An Intelligent Systems Approach to Reservoir Characterization

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ABSTRACT

Today, the major challenge in reservoir characterization is integrating data coming from different sources in varying scales, in order to obtain an accurate and high-resolution reservoir model. The role of seismic data in this integration is often limited to providing a structural model for the reservoir. Its relatively low resolution usually limits its further use. However, its areal coverage and availability suggest that it has the potential of providing valuable data for more detailed reservoir characterization studies through the process of seismic inversion. In this paper, a novel intelligent seismic inversion methodology is presented to achieve a desirable correlation between relatively low-frequency seismic signals, and the much higher frequency wireline-log data. Vertical seismic profile (VSP) is used as an intermediate step between the well logs and the surface seismic. A synthetic seismic model is developed by using real data and seismic interpretation. In the example presented here, the model represents the Atoka and Morrow formations, and the overlying Pennsylvanian sequence of the Buffalo Valley Field in New Mexico. Generalized regression neural network (GRNN) is used to build two independent correlation models between; 1) Surface seismic and VSP, 2) VSP and well logs. After generating virtual VSP's from the surface seismic, well logs are predicted by using the correlation between VSP and well logs. The values of the density log, which is a surrogate for reservoir porosity, are predicted for each seismic trace through the seismic line with a classification approach having a correlation coefficient of 0.81. The same methodology is then applied to real data taken from the Buffalo Valley Field, to predict inter-well gamma ray and neutron porosity logs through the seismic line of interest. The same procedure can be applied to a complete 3D seismic block to obtain 3D distributions of reservoir properties with less uncertainty than the geostatistical estimation methods. The intelligent seismic inversion method should help to increase the success of drilling new wells during field development.

EXECUTIVE SUMMARY

A 3D seismic data set was acquired for the project from WesternGeco. The survey covers the Buffalo Valley oil field in southeastern New Mexico. Donated data included zero-offset and 3D VSP's and a dipole sonic from a key well located within the 3D survey area. Oil production in the survey area is from channel sands in the Lower Pennsylvanian Morrow Formation. The producing channel deposit in the field is referred to as the Harris Channel which is incised into the Mississippian age Barnett Shale. The channel sand is not distinctly resolvable in the seismic data. Channel thickness is below the resolution limit of the data. The relatively thin reservoir interval serves as an excellent test of the potential of neural nets to accurately estimate log scale reservoir properties from the seismic response. A partial tie between the synthetic and surface seismic was achieved by first making a tie to the near-offset. Time shifts in the stacked seismic data introduced by processing led to difficulties in correctly registering the synthetic in two-way time. Use of the well velocity survey and near-offset VSP helped identify the existence of a time shift between processed surface and well seismic travel times.

A fully known seismic and petrophysical dataset that could be used for development, training, and validation of the Intelligent Systems Approach to Reservoir Characterization was developed. A detailed geological interpretation of the lower Pennsylvanian Atoka-Morrow sequence in the Buffalo Valley Field (SE New Mexico) using the available wells, 3D seismic, and VSP data was carried out. On the basis of geological and geophysical analysis, a 2D density and acoustic velocity model was designed to represent the main geological characteristics of the Atoka-Morrow sequence of Buffalo Valley. The 2D petrophysical model was then used to generate synthetic seismic data with a frequency content equivalent to that of the real field data. Synthetic seismic data with a frequency content and resolution equivalent to that of the VSP of the Lula-3 well that was used as an intermediate step between seismic data and well data during the neural network inversion was also generated. A variety of seismic attributes were extracted from the synthetic data in order to use them for training of the neural network and to establish which attributes are most useful for deriving petrophysical properties on the basis of the seismic data.

Generalized regression neural network (GRNN) was used to build two independent correlation models between; 1) Surface seismic and VSP, 2) VSP and well logs. After generating virtual VSP's from the surface seismic, well logs were predicted by using the correlation between VSP and well logs. The values of the density log, which is a surrogate for

reservoir porosity, were predicted for each seismic trace through the seismic line with a classification approach having a correlation coefficient of 0.81. The same methodology was then applied to real data taken from the Buffalo Valley Field, to predict interwell gamma ray and neutron porosity logs through the seismic line of interest. The same procedure can be applied to a complete 3D seismic block to obtain 3D distributions of reservoir properties with less uncertainty than the geostatistical estimation methods.

INTRODUCTION

Reservoir characterization requires building a spatial model of the reservoir by using appropriate data gathered from previous studies. This spatial model is then used in flow simulators, which can predict reservoir performance. An accurate and reliable reservoir characterization study is indispensable in reservoir management. The major challenge in today's reservoir characterization is to integrate all different kinds of data to obtain an accurate and high-resolution reservoir model.

The concept of data analysis forms the basis of reservoir characterization. Uncertainty, unreliability, and large variety of scales due to the different origins of the data must be taken into consideration. Together with the immense size of the data sets that must be dealt with, these issues bring complex problems, which are hard to address with conventional tools. That's why unconventional computation tools have gained much interest in data analysis in recent years. Among those modern tools; intelligent systems, which mimic the mechanism of the human mind, are a way of dealing with imprecision and partial truth¹. It should not surprise us that using intelligent systems in reservoir characterization studies has become a widely-used method in the petroleum engineering literature. Some previous intelligent reservoir characterization applications include, but are not limited to, synthetic log generation^{2,3,4}, permeability estimation from logs^{5,6}, and predicting bulk volume of oil⁷.

Let us consider different types of data used in reservoir characterization: core samples provide very high resolution information about the reservoir (fraction of inches), while seismic data have a resolution in tens of feet, and well logs have in one of inches. Because of its low resolution, seismic data is routinely used only to attain a structural view of the reservoir. On the other hand, unlike core samples or well logs, which are only available at isolated localities of a reservoir, seismic data frequently provides 3D coverage over a large area. Because of this areal coverage, researchers have always aimed to use seismic data in reservoir description. Inverse modeling of reservoir properties from the seismic data is known as *seismic inversion* in the literature. The process presented in this paper includes modeling of the well logs from seismic data, which is also an inverse modeling process (Figure 1). This approach attracts a lot of interest and is very important because of the necessary shift from exploration to development of existing fields⁸.

Seismic inversion has been applied by several authors with different approaches. Hampson *et al.*⁸ and Leiphart and Hart⁹ have compared different techniques such as multiple linear regression, backpropagation

and probabilistic neural networks. They have predicted porosity logs from seismic attributes and both have suggested using probabilistic neural networks in this type of problems considering its mathematical simplicity and success.

Balch *et al.*¹⁰ have used fuzzy ranking to see which type of seismic attribute is related to the target reservoir property. They have modeled correlations between those selected attributes and porosity, water saturation and net pay thickness by using a backpropagation neural network. Chawathe *et al.*¹¹ used neural networks to predict gamma ray log from seismic attributes; amplitude, phase, frequency, reflection strength, and quadrature. However, they have used higher-resolution crosswell seismic data instead of surface seismic as a new approach. Soto and Holditch¹² have used the same types of attributes from surface seismic to predict the gamma ray log with neural networks.

Reeves *et al.*¹³ introduced a new methodology, which divides the whole seismic inversion problem into two parts. They have considered cross-well tomography as an intermediate step in their procedure, after finding a correlation between surface seismic and cross-well seismic. They have suggested producing virtual cross-well seismic data, before dealing with logs. Giving Chawathe *et al.*'s¹¹ work as an example, they stated that well logs can easily be predicted from virtual cross-well seismic data. According to the authors, using crosswell seismic as an intermediate scale data can provide improved vertical resolution, increase constraints and reduce the uncertainty of reservoir description.

In this study, a similar methodology is followed. Instead of cross-well seismic which is rather hard to obtain, vertical seismic profile (VSP) is incorporated into the study as the intermediate scale data. This is due to the fact that VSP is available more frequently, and is less expensive to obtain than cross-well tomography. It is a common type of data that can be found in many fields.

Together with the integration of a third type of data, another unique feature of this study was developing and integrating a synthetic model to the research, before dealing with real data. Having a synthetic model that we had full control of gave us the opportunity to develop and test the proposed methodology better before applying it to real data. Our synthetic model represents the gas-producing Atoka and Morrow formations and the overlying Pennsylvanian sequence in the Buffalo Valley Field in New Mexico. Surface seismic and VSP responses of this model are computed. Artificial neural networks are used to develop two independent correlation models between; 1) Surface seismic and VSP, 2)

VSP and well logs. Density log has been selected as the target log, and is predicted from the seismic line. In the second case, seismic field data have been used to predict gamma ray and neutron porosity distributions through a seismic section.

This study was divided into three specific tasks. This report, therefore, has been organized to reflect each of the tasks in detail. Following are the list of the tasks that each will be covered in a chapter in this report.

1. Geophysical analysis of the formation being studied;
2. Modeling study of the geophysical phenomena;
3. Neural Network modeling and analysis.

CHAPTER ONE: GEOPHYSICAL ANALYSIS

A 3D seismic data set was acquired for the project from WesternGeco. The survey covers the Buffalo Valley oil field in southeastern New Mexico. Donated data included zero-offset and 3D VSP's and a dipole sonic from a key well located within the 3D survey area.

Oil production in the survey area is from channel sands in the Lower Pennsylvanian Morrow Formation. The producing channel deposit in the field is referred to as the Harris Channel which is incised into the Mississippian age Barnett Shale. The channel sand is not distinctly resolvable in the seismic data. Channel thickness is below the resolution limit of the data. The relatively thin reservoir interval serves as an excellent test of the potential of neural nets to accurately estimate log scale reservoir properties from the seismic response. A partial tie between the synthetic and surface seismic was achieved by first making a tie to the near-offset. Time shifts in the stacked seismic data introduced by processing led to difficulties in correctly registering the synthetic in two-way time. Use of the well velocity survey and near-offset VSP helped identify the existence of a time shift between processed surface and well seismic travel times. The match between the surface seismic and synthetic was fairly good for reflection events from the near-surface Permian strata (<0.8 seconds) but generally poor from the deeper intervals including the lower Pennsylvanian target strata. The difficulties in making a good tie are attributed to local heterogeneity in the depositional environments. The Fresnel zone scale seismic response is controlled by bulk properties of strata covering an area of approximately 80,000 square meters (a circular area with radius of approximately 160 meters). The seismic response provides information about the properties of a larger rock volume and the properties of the larger volume are often dissimilar to the properties observed within a foot or so of the well bore sampled by the well logs.

The location of the Harris Channel is inferred from the distribution of oil production. It was also located by isopaching the Barnett shale. Identification of the Harris Channel sands in logs was not easy to do directly because of variable log quality. On the other hand, the high gamma ray response of the underlying Barnett Shale was easy to pick. Since the Harris channel eroded the Barnett Shale along its course, thinning of the Barnett Shale was used to identify the location of the channel. The correlation between the oil production trend and thinned Barnett Shale is remarkable. Clear identification of the channel in the 3D seismic was not achieved. The channel is thin and the bounding strata are complex.

Although the Harris channel is below the seismic resolution is thick enough to significantly influence composite seismic response. Attempts were made to locate the channel by mapping various attributes in addition to amplitude. A variety of attribute maps were compiled and interpreted. Approximately 30 post stack attributes were derived from the seismic data for neural net training. The correlation of attributes to well log measurements was evaluated for all attributes derived in the task using standard using a standard Pearson product-moment correlation. A clear association to production distribution in the field was obtained using the RMS acoustic impedance and integrated seismic amplitude over smaller time windows including Atoka-Chester reflection events. The results indicate that the acoustic properties of the reservoir interval can be detected and mapped. Seismic response can be directly related to the distribution of production in the Buffalo Valley field. Neural nets offer the potential to better refine the information content obtained from the seismic signal.

1.1 Introduction

Data used in this project consist of a 3D seismic data set donated to the Department of Geology and Geography by WesternGeco. The study area is located within the Buffalo Valley field in the southern part of Chavez County, New Mexico (Figure 1.1). The area lies on the Northwest Shelf of the Delaware Basin. Oil production in the field is from a channel sand (the Harris Channel) at the base of the Pennsylvanian age Morrow Formation. Reservoir depth in the field is approximately 9000 feet subsurface. The Morrow Formation is quite heterogeneous, and consists mostly of interbedded sand, shale and thin limestone deposits. The reservoir quality sandstone lies in the lower part of the Morrow Formation and is interpreted to be an inter-distributary channel fill deposit. The base of the Pennsylvanian Morrow Formation lies unconformably on the Mississippian. Channels at the base of the Morrow scour into the Mississippian Barnett shale, which overlies the Chester Formation. The top of the Morrow is overlain by the Atoka Formation which is comprised mostly of sand shale and carbonate (Figure 1.2).

Formation top picks for most of the wells in the area were based on the gamma ray and density log response. The top of the Morrow (Figure 1.2) was generally difficult to pick but is often associated with a drop in density associated with the predominantly clastic Morrow deposits. The basal Morrow channel is a low γ ray, high porosity zone that overlies the high γ ray Barnett shale (Figure 1.2).

The main problem encountered in the seismic interpretation is that these channels are much thinner than the resolution limit. Resolution limits

were evaluated using calibration curves¹³⁻¹⁵. Based on the calibration curves shown in Figure 1.3, the two-way travel time resolution limit is approximately 0.0075 seconds. Using a 16000 foot per second average velocity for the Harris Channel yields a resolvable thickness of approximately 60 feet. The thickness of the Harris Channel varies from approximately 5 to 30 feet in the area. As an illustration, the two-way travel time through a 20 foot thick channel is approximately 2.5 milliseconds. Note that on the normalized amplitude plot (red curve in Figure 1.3) the amplitude associated with this travel time will be nearly 40 -50% of the peak amplitude. Thus, while the channel may not be resolvable, it may be detectable; it may have significant influence on the composite response of reflection events in the vicinity of the target horizon. Detectability depends on several factors including background noise levels, and the level of interference from nearby reflection events. The challenge of 3D interpretation in this area is to hunt down the subtle indicators for the presence of the Harris Channel in the seismic response.

Figure 1.1: Southeastern New Mexico study area and location of the 3D seismic survey.

Figure 1.2: Type log response of the Harris Federal (30-005-61038) well in the southern part of the Buffalo Valley field¹⁶.

Figure 1.3: Resolution calibration curves. A) The yellow line defines an idealized relationship between actual travel time through a thinning layer and that observed using seismic data. B) The actual versus apparent travel time curve reaches a resolution limit and breaks away from the idealized curve at point B. Curve C) is the normalized peak-to-trough amplitude difference in reflections from the top and bottom of the thinning layer. D) Normalized peak-to-trough amplitudes reach a peak at D associated with maximum constructive interference between the two reflections¹⁷.

1.2 Synthetic Seismic Response

Establishing a good tie between the synthetic seismogram and the surface seismic data presented several difficulties. Use of the near offset VSP provided a critical link between the surface and synthetic seismic responses. The tie between seismic reflection events and formation tops was established at the Read and Stevens, Inc., Lula #3 well (API No. 30-005-60481). Data available for the Lula #3 well include a near offset VSP and near offset corridor stack (Figure 1.4). Arrival times of reflection events in the surface seismic data were approximately 44 milliseconds early relative to those in the VSP corridor stack. Identification of this shift helped reconcile differences between the synthetic and surface seismic responses. Weathering corrections and surface consistent static corrections are the likely cause of the relative time shift introduced into the surface seismic data set.

Surface seismic data in the vicinity of the Lula #3 well (Figure 1.5) along with the near offset corridor stack and bandpass filtered synthetic seismic traces compiled from the Lula #3 sonic illustrate the seismic tie used to

interpret reflection events. The east-west inline is split at the Lula #3 well. The corridor stack along with a series of bandpass filtered synthetics has been inserted into the gap at the well location for comparison to surrounding seismic data. Formation top correlations to reflection events are illustrated.

The section is quite heterogeneous at local scales, and Fresnel zone effects likely prevent a good match of synthetic to corridor stack, and VSP corridor stack to surface seismic. Some of this heterogeneity can be observed in the 3D VSP data around the Lula #3 well (Figure 1.6). The 3D VSP view of the lower Pennsylvanian reflection events (Atoka to 1st Chester (At to 1C) in Figures 1.6A and B) reveals discontinuity of reflection events in the form of reflector terminations and reflector merging within approximately 300 feet of the well. Significant dip and additional reflector heterogeneity are also observed along a north to south transect through the 3D VSP (Figure 1.3B).

The Fresnel zone radius at lower Pennsylvanian Morrow depths is liberally estimated to be approximately 520 feet using an RMS velocity of 16400 feet per second derived from the well velocity survey, and dominant frequency of approximately 62.5 Hz. This corresponds to a surface area of approximately 80,000 square meters. Given the 3D VSP response, it is not surprising to see disagreement in the details of the seismic response observed between the various data sets and the synthetic seismogram. Based on the above comparisons the base of the Morrow (top of the Chester) is interpreted at 1.074 sec in the surface seismic; the reflection from the top of the Atoka arrives at approximately 1.041 sec.

Figure 1.4: Zero-offset VSP and corridor stack.

Figure 1.5: Surface seismic, VSP near-offset corridor stack, and synthetics.

Figure 1.6: The Atoka reflection event (At) arrives at approximately 1.082 seconds in the above 3D VSP profiles from the Lula #3 well. A) west to east profile through the 3D data. B) South to north profile. Considerable heterogeneity can be observed over short distances in reflections from the lower Pennsylvanian section.

1.3 Attribute Analysis and Interrelationships

Experiments were designed to evaluate the relationship of various seismic data sets to well log properties. Neutron porosity is a critical reservoir parameter. The sonic log provides information on fundamental acoustic properties. The basal Morrow sand is identifiable as a high porosity, low velocity interval (see Figures 1.7 and 1.8). These parameters are good indicators of the basal Morrow sand. Comparison of seismic attributes to the log data often help establish a direct link between seismic response and reservoir properties.

Table 1.1 below lists several attributes derived for this study. These attributes were calculated for each of the test data sets mentioned earlier (Lula #3 VSP corridor stack, the surface seismic trace at the Lula #3 well, 3D VSP and the synthetic seismic traces computed from the sonic log). The relationship of these attributes to well velocity (determined from the VSP well velocity survey), neutron porosity log response, surface seismic, and interval velocity derived from the sonic log are evaluated in Tables 1.2 through 1.8.

Figure 1.7: Conversion of Lula 3 neutron porosity data to two-way time from 8000 to 8700 feet subsurface. The Lula 3 well velocity survey was used for velocity control.

Figure 1.8: Velocities derived from the Lula #3 sonic log have been converted to 2-way travel times. Resampling at 1 and 2 millisecond intervals is illustrated, along with the resampled well velocity function (far right).

Seismic Attribute List			
1. Amplitude of the Seismic Trace (i.e. real part of complex trace)	$= r(t)$	Kingdom	A
2. Average Energy	$\langle E(t) \rangle = \sum_{t=i-k}^{t+k} r^2(t) / (2k+1)$	Kingdom	AE
3. Instantaneous Amplitude (also known as envelope, reflection strength)	$e(t) = \sqrt{r^2(t) + i^2(t)}$	Kingdom	IA
4. Finite Difference		Kingdom	FD
5. Instantaneous Frequency	$\omega(t) = d\phi/dt$	Kingdom	IF
6. Hilbert Transform (imaginary part of complex trace)	$h(t) = i(t)$	Kingdom	H
7. Para phase		Kingdom	PP
8. Peak to Trough		Kingdom	PT
9. Instantaneous Phase (L&H)	$\phi(t) = a \tan(i(t)/r(t))$	Kingdom	IP
10. Signed Frequency		Kingdom	SF
11. 1 st Derivative of Seismic Trace (L&H)	$= dr(t)/dt$	Excel	1DA
12. 2 nd Derivative of Seismic Trace	$= d^2 r(t)/dt^2$	Excel	2DA
13. 1 st Derivative of Envelope	$= de(t)/dt$	Excel	1DIA
14. 2 nd Derivative of Envelope	$= d^2 e(t)/dt^2$	Excel	2DIA
15. Instantaneous Energy	$E = e^2(t)$	Excel	IE
16. Instantaneous Power	$= dE/dt$	Excel	IP
17. Instantaneous Acceleration	$\alpha(t) = d\omega/dt$	Excel	IAcc
18. Decay	$d(t) = \frac{de(t)/dt}{e(t)}$	Excel	Dcy
19. Instantaneous Q Quality Factor	$q(t) = \pi \cdot \omega(t) / d(t)$	Excel	IQF
20. Amplitude Weighted Phase (L & H)	$= e(t) * \phi(t)$	Excel	AWP
21. Average Frequency (L & H)	$\langle \omega(t) \rangle = \sum_{t-k}^{t+k} \omega(t) / (2k+1)$	Excel	AF
22. Residual Envelope	$= e(t) - \left(\sum_{t-k}^{t+k} e(t) / (2k+1) \right)$	Excel	RIA
23. Integrated Residual Amplitude	$= \sum_t \left[e(t) - \left(\sum_{t-k}^{t+k} e(t) / (2k+1) \right) \right]$	Excel	IRE
24. Smoothed Envelope	$e_s(t) = \sum_{t-k}^{t+k} e(t) / (2k+1)$	Excel	SIA
25. Integrated Absolute Amplitude (L&H) = Integrated Residual Amplitude	$IA(t) = \sum_0^t e(t) - \sum_0^t e_s(t)$	Excel	IAA
26-30. Relative Acoustic Impedance (high frequency using low pass filters with 0, 5, 10, 20, 40 Hz cutoff)	$Z_n = Z_1 \prod_{i=1}^{n-1} \left[\frac{1+r_i}{1-r_i} \right]$	Kingdom	AI _x

31. Smoothed Inversion (L&H) We can modify this by using the log data to provide the low frequency component which can be added in to the high frequency inversion.	$\sum_{i=j}^k Z(i) / (k-j)\Delta t$	Excel	Sinv
SQRT (minimum continuity) (L&H)	Requires coherency volume	Not available	

Table 1.1: Attributes calculated in Kingdom Suite or derived separately as part of this study for use in neural net training and design.

A comprehensive analysis was undertaken between the various attributes and the surface seismic data, synthetic data, some of the log data (neutron porosity and sonic compressional wave velocity), and VSP (3D and near-offset). The correlation tables (Tables 1.2 through 1.8) indicate that a few surface seismic attributes do correlate with neutron porosity and sonic. Surface seismic attributes such as envelope (instantaneous amplitude), peak to trough amplitude, smoothed envelope, acoustic impedance and smoothed impedance correlate to neutron porosity with p-values ≤ 0.01 (Table 1.2). The correlations of surface seismic response to the sonic log response are similar to those with neutron porosity, but a correlation is also observed with average frequency and a correlation to smoothed envelope is not observed. A greater number of near-offset VSP attributes correlate to the neutron porosity log than do for the surface seismic attributes (see Table 1.3). As might be expected from the earlier difficulties encountered in establishing a tie between the synthetic and surface seismic response, the near-offset VSP does not correlate well with the surface seismic. A small number of attributes (instantaneous amplitude and energy, and smoothed envelope) correlate with p-values less than 0.01. The near-offset VSP also has very limited correlation to the sonic and well velocity responses. Interestingly, 3D VSP attributes do not show good a correlation to the neutron porosity or sonic (Table 1.4). When we break the synthetic response down into different frequency components, by continually broadening the bandwidth of the wavelet, we do not see what we might have expected: the neutron porosity response seems to be better predicted by the low frequency narrow bandwidth wavelet than with the broader bandwidth wavelets. The prediction of sonic, however, does improve, as it should, with increased bandwidth (see Tables 1.6 through 1.8). This is also expected since increased frequency content yields an increase in resolution of subsurface acoustic impedance variations and contrasts.

Correlation coefficients in the attribute tables below (Tables 1.2 through 1.8) are classified on the basis that the computed correlation coefficient might statistically be no different from zero. The probability that the correlation coefficient could be 0 is referred to as the p-value. The larger the p-value is, the greater the likelihood that the correlation coefficient could be 0. The correlation coefficients were grouped into 4 color-coded categories based on p-value (see table below).

Reference p-value color bar

p-value			
≤ 0.01	$>0.01 \leq 0.06$	$0.06 \leq 0.1$	$0.1 \leq 0.12$

Attribute Surface Seismic	Well Velocity	Neutron Porosity	Surface Seismic (A)	Sonic Velocity
1. A	-0.17	-0.02	1.00	-0.43
2. AE	-0.09	-0.38	0.33	-0.25
3. IA	-0.04	-0.49	0.12	-0.05
4. FD	0.12	-0.24	-0.28	0.14
5. IF	0.02	0.32	0.29	-0.35
6. H	-0.34	0.28	0.49	-0.33
7. PP	-0.08	0.40	-0.30	-0.05
8. PT	0.14	0.51	0.16	-0.57
9. IP	-0.28	0.25	0.39	-0.27
10. SF	0.02	0.32	0.29	-0.35
11. 1DA	0.16	-0.28	-0.27	0.14
12. 2DA	0.09	0.29	-0.34	0.18
13. 1DIA	0.32	0.18	-0.30	0.02
14. 2DIA	-0.12	0.21	-0.02	0.08
15. IE	-0.11	-0.43	0.17	-0.15
16. IP	0.28	0.16	-0.31	0.06
17. IAcc	-0.22	-0.14	0.49	-0.29
18. Dcy	0.30	0.13	-0.29	0.06
19. IQF	-0.20	0.15	0.01	-0.13
20. AWP	-0.32	0.30	0.36	-0.33
21. AF	-0.07	0.34	0.44	-0.55
22. RIA	-0.19	-0.27	0.24	-0.13
23. IRE	-0.35	-0.24	0.22	0.04
24. SIA	0.04	-0.45	0.03	0.00
25. IAA	-0.35	-0.24	0.22	0.04
26. AI _x	-0.09	0.57	0.16	-0.51
27. Sinv	-0.07	0.58	0.15	-0.54

Table 1.2: Correlation of attributes computed from the surface seismic trace nearest the Lula #3 well with the well velocity function, neutron porosity, and compressional wave velocity derived from the sonic log.

Reference p-value color bar			
p-value			
≤ 0.01	$>0.01 \leq 0.06$	$0.06 \leq 0.1$	$0.1 \leq 0.12$

Attribute Near-Offset VSP	Well Velocity	Neutron Porosity	Surface Seismic (A)	Sonic Velocity
1. A	0.01	-0.23	0.23	0.16
2. AE	-0.24	0.42	0.24	-0.35
3. IA	-0.25	0.32	0.50	-0.19
4. FD	0.00	0.20	-0.21	-0.28
5. IF	0.07	0.46	-0.08	-0.07
6. H	-0.05	-0.05	0.29	-0.06
7. PP	-0.12	-0.07	0.29	-0.1
8. PT	-0.07	-0.58	-0.26	0.53
9. IP	-0.06	0.11	0.23	-0.26
10. SF	0.05	0.45	-0.15	0.06
11. 1DA	-0.05	0.06	-0.22	-0.01
12. 2DA	0.02	0.12	0.14	-0.10
13. 1DIA	-0.03	-0.57	0.35	0.11
14. 2DIA	0.01	0.03	-0.26	0.00
15. IE	-0.31	0.27	0.48	-0.16
16. IP	0.02	-0.51	0.18	0.23
17. IAcc	-0.18	-0.19	0.43	-0.16
18. Dcy	0.14	-0.35	0.19	0.08
19. IQF	0.04	0.01	-0.05	0.05
20. AWP	0.32	-0.49	-0.26	0.34
21. AF	-0.11	0.63	-0.09	-0.30
22. RIA	-0.03	0.15	0.18	-0.03
23. IRE	0.06	0.59	-0.27	-0.18
24. SIA	-0.27	0.31	0.49	-0.20
25. IAA	0.06	0.59	-0.27	-0.18
26. AI _x	-0.18	0.45	0.32	-0.35
27. Sinv	-0.18	0.45	0.32	-0.41

Table 1.3: Correlation table for attributes computed from the near offset VSP corridor stack

Reference p-value color bar

p-value			
≤ 0.01	$>0.01 \leq 0.06$	$0.06 \leq 0.1$	$0.1 \leq 0.12$

Attribute 3D VSP	Well Velocity	Neutron Porosity	Surface Seismic (A)	Sonic Velocity
1. A	-0.09	0.01	0.17	-0.159
2. AE	-0.19	-0.09	0.43	0.08
3. IA	-0.34	-0.02	0.48	0.02
4. FD	0.06	-0.21	-0.07	0.13
5. IF	-0.1	0.21	0.38	-0.37
6. H	0.05	0.24	-0.06	-0.01
7. PP	0.27	0.03	-0.35	0.35
8. PT	0.05	0.33	0.09	-0.24
9. IP	-0.07	0.32	-0.01	-0.17
10. SF	-0.08	0.17	0.36	-0.33
11. 1DA	0.08	-0.22	-0.03	0.11
12. 2DA	-0.02	0.25	-0.11	-0.01
13. 1DIA	0.06	-0.38	-0.22	0.24
14. 2DIA	0.22	0.06	-0.07	-0.07
15. IE	-0.34	0.00	0.45	0.04
16. IP	0.14	-0.26	-0.22	0.24
17. IAcc	-0.11	-0.18	-0.05	0.11
18. Dcy	-0.02	-0.37	-0.23	0.24
19. IQF	0.01	0.07	0.06	0.02
20. AWP	0.11	0.20	-0.32	-0.14
21. AF	-0.37	0.18	0.50	-0.46
22. RIA	-0.11	0.05	0.23	-0.06
23. IRE	-0.09	0.38	0.23	-0.25
24. SIA	-0.35	-0.03	0.49	0.03
25. IAA	-0.09	0.38	0.23	-0.25
26. AI _x	0.10	0.16	-0.08	0.02
27. Sinv	0.15	0.08	-0.09	0.05

Table 1.4: Correlation table for attributes computed from the 3D VSP response observed in the Lula #3 well.

Reference p-value color bar

p-value			
≤ 0.01	$>0.01 \leq 0.06$	$0.06 \leq 0.1$	$0.1 \leq 0.12$

Attribute Synthetic Seismogram	Well Velocity	Neutron Porosity	Surface Seismic (A)	Sonic Velocity
1. A	0.14	0.02	-0.28	0.35
2. AE	0.11	-0.17	0.49	-0.41
3. IA	0.15	0.18	0.35	-0.56
4. FD	-0.28	-0.05	0.25	-0.29
5. IF	0.06	0.11	0.34	-0.02
6. H	0.26	0.03	-0.24	0.21
7. PP	-0.07	0.03	0.12	-0.30
8. PT	0.13	-0.18	-0.59	0.25
9. IP	0.23	-0.23	-0.03	0.27
10. SF	0.06	0.11	0.34	-0.02
11. 1DA	-0.33	-0.03	0.11	-0.22
12. 2DA	0.23	0.06	0.01	-0.05
13. 1DIA	0.08	0.39	0.15	-0.36
14. 2DIA	0.25	0.08	-0.10	0.16
15. IE	0.04	0.09	0.38	-0.58
16. IP	0.27	0.17	-0.329	0.10
17. IAcc	0.03	-0.12	-0.04	0.04
18. Dcy	-0.02	0.27	0.09	-0.15
19. IQF	0.09	0.35	0.42	-0.43
20. AWP	-0.12	0.25	-0.38	0.31
21. AF	-0.03	0.22	0.45	-0.13
22. RIA	-0.15	-0.17	0.23	-0.20
23. IRE	-0.08	-0.42	-0.07	0.35
24. SIA	0.18	0.21	0.34	-0.56
25. IAA	-0.08	-0.42	-0.07	0.35
26. AI _x	0.32	-0.14	-0.44	0.42
27. Sinv	0.25	-0.25	-0.59	0.54

Table 1.5: Correlation table for attributes computed from the synthetic seismogram from the Lula #3 well. The synthetic was constructed using a wavelet extracted from the seismic data in the vicinity of the Lula #3 well.

Reference p-value color bar

p-value			
≤ 0.01	$>0.01 \leq 0.06$	$0.06 \leq 0.1$	$0.1 \leq 0.12$

Attribute 10-35 Hz Synthetic	Well Velocit y	Neutron Porosit y	Surface Seismic (A)	Sonic Velocity
1. A	-0.03	-0.03	-0.01	-0.30
2. AE	0.06	-0.08	0.50	-0.42
3. IA	0.14	-0.30	0.49	-0.28
4. FD	0.04	0.36	0.33	-0.38
5. IF	-0.06	0.37	-0.07	-0.07
6. H	0.06	-0.41	-0.19	0.32
7. PP	0.32	-0.01	0.20	0.08
8. PT	0.05	-0.14	-0.66	0.26
9. IP	0.09	-0.21	-0.20	0.16
10. SF	-0.06	0.37	-0.07	-0.07
11. 1DA	-0.18	0.19	-0.04	-0.16
12. 2DA	0.31	0.06	-0.06	0.11
13. 1DIA	0.21	0.14	-0.03	-0.28
14. 2DIA	0.18	0.01	-0.15	-0.07
15. IE	0.00	-0.28	0.49	-0.38
16. IP	0.34	0.14	-0.41	0.12
17. IAcc	-0.14	-0.22	0.37	-0.15
18. Dcy	0.29	0.24	-0.25	-0.11
19. IQF	0.18	-0.02	-0.01	0.10
20. AWP	0.01	0.13	0.29	-0.05
21. AF	-0.18	0.40	-0.22	-0.12
22. RIA	0.11	-0.23	0.22	0.02
23. IRE	-0.30	-0.15	0.24	0.24
24. SIA	0.13	-0.29	0.50	-0.32
25. IAA	-0.30	-0.15	0.24	0.24
26. AI _x	0.11	-0.60	-0.33	0.44
27. Sinv	0.10	-0.62	-0.40	0.47

Table 1.6: Correlation table for attributes computed for Lula #3 synthetic generated with 10 – 35 Hz Butterworth filter.

Reference p-value color bar

p-value			
≤ 0.01	$>0.01 \leq 0.06$	$0.06 \leq 0.1$	$0.1 \leq 0.12$

Attribute 10-60 Hz Synthetic	Well Velocity	Neutron Porosity	Surface Seismic (A)	Sonic Velocity
1. A	-0.09	-0.01	0.05	-0.21
2. AE	0.07	-0.07	0.38	-0.42
3. IA	0.18	-0.19	0.35	-0.36
4. FD	-0.02	0.11	0.27	-0.27
5. IF	0.30	0.25	0.01	-0.18
6. H	0.17	-0.22	-0.35	0.39
7. PP	0.30	-0.01	-0.13	0.23
8. PT	-0.08	-0.67	-0.01	0.28
9. IP	0.23	-0.16	-0.43	0.23
10. SF	0.33	0.08	0.05	-0.06
11. 1DA	-0.26	0.04	0.15	-0.26
12. 2DA	0.34	0.06	-0.17	0.19
13. 1DIA	0.15	0.37	0.03	-0.35
14. 2DIA	0.24	0.03	-0.20	-0.02
15. IE	0.01	-0.15	0.36	-0.46
16. IP	0.30	0.20	-0.34	0.09
17. IAcc	-0.17	0.06	0.37	-0.21
18. Dcy	0.09	0.26	-0.15	-0.12
19. IQF	-0.14	0.12	0.13	-0.13
20. AWP	-0.15	-0.02	0.44	0.09
21. AF	0.28	0.39	-0.02	-0.36
22. RIA	0.11	-0.40	0.36	-0.04
23. IRE	-0.23	-0.38	0.08	0.32
24. SIA	0.18	-0.14	0.32	-0.38
25. IAA	-0.23	-0.38	0.08	0.32
26. AI _x	0.25	-0.51	-0.55	0.57
27. Sinv	0.20	-0.55	-0.58	0.56

Table 1.7: Correlation table for attributes computed for Lula #3 synthetic generated with 10 – 60 Hz Butterworth filter.

Reference p-value color bar

p-value			
≤ 0.01	$>0.01 \leq 0.06$	$0.06 \leq 0.1$	$0.1 \leq 0.12$

Attribute 10-100 Hz Synthetic	Well Velocit y	Neutron Porosit y	Surface Seismic (A)	Sonic Velocit y
1. A	-0.14	0.09	0.00	-0.08
2. AE	-0.03	-0.15	0.51	-0.47
3. IA	0.10	-0.10	0.52	-0.45
4. FD	0.22	-0.17	0.18	-0.04
5. IF	-0.21	0.03	0.30	0.04
6. H	0.07	0.02	-0.34	0.36
7. PP	0.32	-0.29	-0.05	0.34
8. PT	-0.47	0.15	-0.29	-0.04
9. IP	0.11	0.07	-0.24	0.22
10. SF	-0.21	0.03	0.30	0.04
11. 1DA	-0.29	0.02	0.18	-0.37
12. 2DA	0.48	-0.11	-0.10	0.33
13. 1DIA	0.35	0.30	-0.11	-0.13
14. 2DIA	-0.11	0.06	-0.16	0.01
15. IE	-0.01	-0.13	0.48	-0.48
16. IP	0.32	0.19	-0.35	0.11
17. IAcc	0.17	-0.33	-0.03	0.06
18. Dcy	0.31	0.22	-0.03	-0.09
19. IQF	0.21	-0.12	-0.06	-0.12
20. AWP	-0.01	-0.08	-0.12	0.30
21. AF	-0.16	-0.14	0.41	0.14
22. RIA	-0.03	-0.29	0.25	-0.03
23. IRE	-0.37	-0.30	0.10	0.15
24. SIA	0.12	-0.04	0.51	-0.48
25. IAA	-0.37	-0.30	0.10	0.15
26. AI _x	0.39	-0.41	-0.59	0.69
27. Sinv	0.24	-0.48	-0.70	0.63

Table 1.8: Correlation table for attributes computed for Lula #3 synthetic generated with 10 – 100 Hz Butterworth filter.

p-value	
≤ 0.01	$>0.01 \leq 0.05$

Attribute SurfSeis	Gamma Ray	Neutron Porosity	Sonic P-Wave	Sonic S-Wave	VSP Corridor
1. A	0.02	-0.04	-0.01	-0.07	-0.42
2. AE	-0.18	-0.19	0.13	0.09	0.00
3. IA	-0.33	-0.22	0.29	0.22	0.03
4. FD	0.20	-0.10	-0.02	0.06	0.38
5. IF	-0.06	0.00	-0.14	-0.14	0.06
6. H	-0.17	0.18	0.01	-0.07	-0.38
7. PP	-0.01	0.11	0.02	0.03	0.08
8. PT	-0.02	0.05	0.00	-0.08	0.11
9. IP	0.00	0.20	-0.06	-0.08	-0.16
10. SF	-0.06	0.00	-0.14	-0.14	0.06
11. 1DA	0.03	-0.11	0.04	0.09	0.36
12. 2DA	0.08	0.05	-0.08	-0.08	0.08
13. 1DIA	0.18	0.07	-0.11	-0.10	-0.07
14. 2DIA	-0.06	-0.04	0.01	0.02	0.02
15. IE	-0.34	-0.21	0.24	0.17	0.07
16. IP	0.16	0.04	-0.08	-0.09	-0.05
17. IAcc	0.07	0.06	-0.02	-0.03	-0.05
18. Dcy	0.18	0.12	-0.15	-0.14	-0.09
19. IQF	0.00	-0.02	-0.04	-0.03	0.06
20. AWP	-0.10	0.04	-0.01	-0.04	-0.45
21. AF	0.02	0.05	-0.36	-0.37	-0.02
22. RIA	-0.08	0.04	0.19	0.19	-0.12
23. IRE	0.22	0.09	-0.24	-0.16	0.01
24. SIA	-0.32	-0.22	0.26	0.19	0.05
25. IAA	0.22	0.09	-0.24	-0.16	0.01
26. AI _x	-0.09	0.18	-0.07	-0.11	-0.29
27. Sinv	-0.06	0.17	-0.09	-0.12	-0.24

Table 1.9: Table of correlation coefficients between attributes computed for the surface seismic trace (0.9425 to 1.09 seconds) and well log and VSP seismic responses over the same time interval. The surface seismic trace was resampled to a 0.0005 second sample interval. N = 296.

Additional analysis of seismic attributes was undertaken for the much larger time window extending from 0.92 to 1.1 seconds along the length of the northwest-southeast arbitrary line selected by a Task 3 for neural net evaluation (see Table 1.9). As shown in Figure 1.10 this window of time extends from the middle Canyon into the upper Mississippian formations and covers approximately 2500 feet of vertical section. Five Wells are located close to this arbitrary line. Logs available from these wells were transformed from depth to time using velocity functions derived from a combination of synthetic seismic ties and seismic interpretation of travel times to key reflection events along the arbitrary line.

The correlations presented in Table 1.9, overall, are much lower than those obtained for the smaller analysis window due to the larger window of data used in the analysis and associated variability in lithology over this 2500 foot interval. Attributes derived from the surface seismic that have the best overall correlation to the log response include: integrated absolute amplitude, integrated residual amplitude, average frequency, decay constant and 1st derivative of the envelope.

Evaluation of correlations found between surface seismic attributes and log properties for the smaller time window (Table 1.2) reveal best overall correlation to acoustic impedance inversion, smoothed acoustic impedance inversion, peak-to-trough amplitude, and average frequency.

1.4 Subsurface interpretation

The conversion of formation top depths to surface seismic time, their placement in the near offset VSP, and subsequent tie of the near-offset VSP to the surface seismic allowed us to make direct correlation of the surface seismic response to subsurface geology (Figure 1.10).

Time structure on the Chester and Atoka reflection events (Figures 1.11 and 1.12, respectively) reveals that the field is bounded along its western and eastern margins by two faults across which the strata drop to the east. Seismic profiles from the 3D survey reveal that these faults are nearly vertical.

However, an evaluation of fault dip through the area reveals that these faults shift from steeply west dipping to east dipping along their length (Figure 1.13). This suggests that the fault is not a simple reverse fault or normal fault but may be a strike slip fault. Pyakurel's interpretation¹⁷ reveals what may be the presence of flower structures providing additional evidence for a strike slip interpretation.

Figure 1.10: Seismic profile passing through the Lula #3 well.

Can – top of the Canyon Formation;

St – top of the Strawn Formation;

At – top of the Atoka Formation (yellow line);

1C – top of the Mississippian Chester Formation (red).

The dark green line is the Morrow; the light green line is the middle Canyon.

Figure 1.11: Time structure on the top of the Chester reflection event.

Figure 1.12: Time structure on top of the Atoka reflection event.

Figure 1.13: Two-way travel times to the fault along the eastern margin of the survey area reveal the fault is steeply dipping with dip reversals along its length.

The isochore map for the Atoka to Chester (Atoka through Morrow) reflection events (Figure 1.14) suggests that some movement occurred along these faults during deposition of this lower Pennsylvanian interval.

Figure 1.14: Atoka to Chester (or Atoka through Morrow) isochore map.

Structure on the top of the Chester and Atoka formations is shown in Figures 1.15 and 1.16, respectively. In general the structure follows the northeast trend of the Northwestern Shelf; however, north trending structural indentations interrupt the regional trend within the field. Comparison of the time and structure maps suggests that the north trending faults observed in the 3D seismic data are probably associated with the structural indentation portrayed in the well derived structure maps.

Figure 1.15: Structure on the top of the Chester Formation¹⁷.

Figure 1.16: Structure on the top of the Atoka Formation¹⁷.

The isochore map of the Atoka to Chester top (Atoka through Morrow) reflection times (Figure 1.14) shows thickening along the westernmost fault as well as across the southern extent of the fault block in the survey area. The southern part of the block appears to have rotated south-southwest during deposition, and at the same time there appears to have been local subsidence across the western fault that diminished to the north along its length. Reduced travel time differences observed in the Atoka-Morrow isochore to the north, along the trend of the western fault, show some similarity to the decreased thickness of the interval observed in the isopach map (Figure 1.17).

The Atoko-Morrow isopach map (Figure 1.17) reveals a belt of thickened section running NW to SE through the 3D survey area. In the northern part of the 3D survey area the Atoka-Morrow interval is over 100 feet thick, and increases to over 200 feet thick in the south. The well derived maps provide a much coarser view of the subsurface, with well spacing of about 2000 feet on average. However a pronounced trend of thickened Atoka-Morrow is clearly revealed along the trend of the seismic interpreted fault block.

Figure 1.17: Isopach map showing variations in the thickness of the Atoka-Morrow interval through the 3D survey area¹⁷.

1.5 Production Data

The oil production trend from the Buffalo Valley field outlines the course of the Harris Channel through the area (Figure 1.18). The thickness of the channel varies roughly between 10 and 20 feet through the area. Total production from the field is ** barrels of oil. The sinuous channel trends roughly north to south through the area and may have been diverted from a course normal to the shelf by the north-south trending faults that border the field on its east and west. The origin of these faults is debatable, but would appear to be either normal faults or part of a larger strike slip fault system. Thinned intervals in the isopach map of the Barnett Shale have trend and distribution similar to that of oil production from the field. The Morrow channels were incised into the shale, thinning it along its course. Five year cumulative production data from the Buffalo Valley field is shown in Figure 1.16. The average 5 year cumulative production per well calculated from 57 wells in the field is 4842.07 Bbl. High producing regions in the field (Figure 1.18) trend roughly N30W and N70E. Thickening observed in the isopach map (Figure 1.19) between the northern and southern halves of the field may be associated with segmentation of the channel sands.

Figure 1.18: Five year cumulative oil production. The highlighted yellow dots indicate two wells with very high production. These wells were omitted so that the general outline of production trends through the field could be portrayed¹⁷.

Figure 1.19: Thinned areas in the Barnett Shale are superimposed on production from the field. Shale thinning coincides well with the major production trends. Note that the highest producing wells in the field (yellow dots) also lie within or on the edge of thinned Barnett Shale¹⁷.

1.6 Seismic Attribute Maps

Attribute maps were compiled for a variety of intervals surrounding the lower Morrow reflection event. In addition various attribute properties were mapped and examined within time windows straddling the producing interval. These included root mean square (RMS) value of attribute, average absolute value of attribute, maximum absolute value, minimum absolute value, etc. Analysis of attributes presented earlier (Table 1.2) indicates that acoustic impedance had significant correlation to log properties in the Atoka to Chester time interval.

The RMS impedances between the Atoka through Morrow shown in Figure 1.20 reveal a trend of impedances that roughly coincides with the trend and distribution of production through the area covered by the 3D seismic survey. The correlation analysis helped to identify potential attributes that might highlight producing stratigraphic intervals. Although the correlation of seismic amplitude to log responses was not good, a smaller window of data associated with the Lower Pennsylvanian and Upper Pennsylvanian section, which includes the Harris Channel, was analyzed. A map of integrated trace amplitudes in a 20 millisecond window including the lower Morrow, Barnett Shale, and 1st Chester reveals a pattern similar to that observed in the acoustic impedance data (Figure 1.20). Overall, it is possible to establish a general connection between the production distribution, presence of the Harris Channel and 3D seismic response.

Figure 1.20: Root mean squared acoustic impedance for the Atoka to Chester interval. Intermediate impedance zones (greens, yellows and orange colors) coincide roughly with the production trend in the field. Interpreted channel sand distribution is outlined in the duplicate map at right (Figure 1.20).

Figure 1.21: Integrated amplitude over a 20 millisecond time window extending from the base of the 1st Chester through the Lower Morrow

The interpretation presented by Sanchez^{18,19} (Figure 1.22) presents a meandering channel system that courses along the high production trend through the survey area. Portrayal of the channel course is enhanced in the RMS acoustic impedance map and in the integrated seismic amplitude map. Interpreted channel sand distribution through the central block stands in greater contrast to the surrounding seismic response.

Figure 1.22: Channel interpretation presented by Sanchez^{18,19}.

1.7 Conclusions

A tie between synthetic and surface seismic proved difficult to establish. Comparison of well log derived synthetics to the VSP near-offset corridor stack was essential to identifying two-way travel times to formation tops and corresponding reflection events observed in the 3D surface seismic. The response of the Atoka-Morrow intervals observed in the 3D VSP confirms observations of the well log response in the field that the Atoka-Morrow interval is heterogeneous at interwell and seismic (Fresnel Zone) scales. The seismic response is controlled by Fresnel zone scale acoustic properties. Because of significant heterogeneity in the distribution of acoustic properties associated with the Morrow and surrounding strata, well log responses do not accurately portray the larger scale properties of the reservoir and surrounding intervals.

The 3D seismic data from the field reveal that the Buffalo Valley field is bounded by nearly vertical faults that step down to the east. The faults are oriented roughly north-south at an angle to the NE trending Northwestern Shelf on which the field is located. There appears to have been some movement along these boundary faults during deposition of the Atoka-Morrow interval. Observable fault offsets are located near the center of the field on the western fault and near the southern end of the field along the eastern fault during lower Pennsylvanian time. Production from the Pennsylvanian Morrow Formation along the Northwest Shelf of the Permian Basin is confined to basal Harris Channel. These sands are generally identifiable by a high neutron porosity, low sonic velocity (higher interval transit times) and low γ ray log responses. Log derived structure and isopach maps reveal the influence of the faults observed in the seismic. Structure maps clearly reveal that the field sits on an interruption in the regional trend of the Northwest Shelf. The Atoka-Morrow isopach reveals thickening of the Atoka-Morrow interval along the trend of the fault block. Atoka-Morrow thickening increases from north to south suggesting that the fault block may have rotated to the south during deposition of the Atoka-Morrow interval, consistent with observations made in the 3D seismic data volume.

Approximately 30 seismic attributes were derived for the study. These attributes were calculated for surface seismic, near-offset VSP, 3D VSP, and several synthetic seismograms located at the Lula #3 VSP well. Correlation coefficients (Pearson Product Moment) were computed between each attribute and neutron porosity, sonic velocity, and well velocity. Correlations obtained between surface seismic attributes and log responses were much lower for the longer data sets than were those obtained from a smaller analysis window restricted to the Atoka through Morrow intervals. This is likely due to the larger window of data used in

the analysis and the greater variability in depositional environments and lithology encountered in the longer 2500 foot thick section. Attributes derived from the surface seismic that have the best overall correlation to the log responses for the longer time window include: integrated absolute amplitude, integrated residual amplitude, average frequency, decay constant, and 1st derivative of the envelope. Correlations found between surface seismic attributes and log properties for the smaller time window extending from the Atoka through Morrow reflection intervals reveal best overall correlation to peak-to-trough amplitude, acoustic impedance inversion, smoothed acoustic impedance inversion, amplitude weighted phase and average frequency.

Efforts to identify a correlation between seismic attributes and production/channel sand distribution were examined within the context of attribute analysis and the traditional analysis of seismic amplitudes. Acoustic impedance computed using a recursive inversion approach had high overall correlation to log response. A map consisting of the root mean squared acoustic impedance computed in a window of data extending from the Atoka to Chester reflection events revealed a trend of impedance with intermediate value that extend along the general trend of production through the area. The attribute analysis helped highlight the course of the Harris Channel through the area and could be used to locate additional wells in future in-field development efforts. The conventional seismic amplitude response was also investigated for its potential use in detecting production related seismic features. A map of integrated reflection amplitudes in the Morrow through 1st Chester interval also yielded enhanced positive amplitude trends that coincided roughly with production distribution.

Seismic analysis yields information that can be directly related to the distribution of production in the Buffalo Valley field. Future application of the neural net design effort undertaken in Task 3 offers the potential to better refine the information content obtained from the seismic signal.

CHAPTER TWO: GEOPHYSICAL MODELING

The objective of our modeling studies was to provide a fully known seismic and petrophysical dataset that could be used for development, training, and validation of the Intelligent Systems Approach to Reservoir Characterization. To this end we carried out a detailed geological interpretation of the lower Pennsylvanian Atoka-Morrow sequence in the Buffalo Valley Field (SE New Mexico) using the available wells, 3D seismic, and VSP data (Fig. 2.1). On the basis of our geological and geophysical analysis, we created a 2D density and acoustic velocity model designed to represent the main geological characteristics of the Atoka-Morrow sequence of Buffalo Valley (Fig. 2.2). We then used this 2D petrophysical model to generate synthetic seismic data with a frequency content equivalent to that of the real field data. We also created synthetic seismic data with a frequency content and resolution equivalent to that of the VSP of the Lula-3 well that was used as an intermediate step between seismic data and well data during the neural network inversion. A variety of seismic attributes were extracted from the synthetic data in order to use them for training of the neural network and to establish which attributes are most useful for deriving petrophysical properties on the basis of the seismic data. The methodology and results of our modeling work are summarized below and are described in more detail in the M.S. thesis attached to this report¹⁹.

2.1 Database

We had five sets of data available for this study:

1. A 3D seismic survey covering an area of 24 sq. mi with a vibroseis source, and sweep frequencies ranging from 8 to 98 Hz. This data set was loaned to the Department of Geology and Geography of West Virginia University by WesternGeco, Houston, TX (Fig. 2.1).
2. A vertical seismic profile volume, with a two-vibrator source, covering an area of approximately 3.5 sq. mi in the southeast corner of the area.
3. 64 raster well logs including gamma ray, spontaneous potential, resistivity, neutron, density and sonic logs.
4. 20 digital well logs files. The typical depth of the Atoka and Morrow Formations in the Buffalo Valley Field ranges from 8000 to 9000ft.
5. Well drilling reports, headers, complementary well logs, and production data were incorporated in the interpretation and analysis.

Figure 2.1. Location and data base of the Buffalo Valley Field. Selected wells and seismic sections are displayed on the map.

Figure 2.2. Generalized stratigraphic section of the Northwest Shelf areas in the Permian Basin and Pennsylvanian plays in the Permian Basin.

2.2 Seismic Interpretation Methodology

An integrated seismic interpretation of the Atoka and Morrow sequence (Fig. 2.2) was carried out using the 3D seismic volume, the post stack trace correlation seismic volume, and the well log response tied to the seismic data. Time slices of the seismic volume were used to identify the morphology of stratigraphic features and to help interpret the paleoenvironment of deposition that predominated during Atoka-Morrow time. Additionally, the synthetic seismic models of the Atoka-Morrow sequence were used to evaluate the seismic response of different stratigraphic features and to verify the proposed interpretations.

In order to carry out the seismic interpretation, a tie of the well logs was done by using the synthetic seismogram derived for the well Lula #3 and the two-way time data from the near-offset VSP (Fig 2.3). Thus, the tops of the Strawn, Atoka, Morrow, and Chester Formations and the remaining overlying Pennsylvanian sequence and lower Permian (Canyon, Cisco, Wolfcamp, Abo, and Tubb) were picked in the 3D seismic data. Synthetic seismograms from 4 more wells were derived and used to tie and control the velocity function across the field.

Because the correlation between the synthetic seismogram, the VSP, and the seismic survey was not perfect, adjustment was necessary to obtain a match (Fig. 2.3). The check shot provided additional confidence to tie the wells to the seismic reflectors. The lack of correlation between the synthetic seismogram and the seismic data is probably due to the vertical and lateral stratigraphic variability of the Atoka and Morrow sections. Thus, local features observed in the synthetic seismogram (high resolution) vary compared to the ones observed in the seismic traces of the VSP and 3D survey (low resolution). The local character of the seismic traces at the well location reflects additional lateral information from a radius equal to the Fresnel zone (horizontal resolution). The width of the Fresnel Zone is about 1200 ft for the 3D survey and 1000 ft for the VSP²⁰.

The wavelet in 3D seismic survey has a bandwidth of approximately 11 to 90 Hz, a dominant frequency of 45 Hz, a dominant period of 0.022 sec, at an interval velocity ranging from 15000-15500 f/sec. For the VSP volume, the wavelet content had a bandwidth of approximately 20 to 90 Hz, a dominant frequency of 65 Hz, a dominant period of 0.0154 sec, and the same interval velocity. Under these conditions the vertical seismic resolution for the Atoka and Morrow in the 3D seismic survey is between 83-88 ft and the 57-61 ft in the VSP volume.

The formation tops were interpreted by correlating the well log character and the seismic response under the assumption that these reflectors

correspond to chronostratigraphic depositional lines. Thus, time slices flattened at the top of the Atoka to eliminate structural effects on the seismic character, would represent depositional surfaces, and a can be used for paleoenvironmental interpretation. Synthetic modeling (Fig. 2.5) demonstrated that the tops of vertically stacked packages of sands embedded in shales produced a positive reflection event (peaks, visualized in black) (Fig. 2.4).

The tops of the Strawn, Atoka, Morrow and Chester were identified in the seismic volume and mapped throughout the area.

Figure 2.3. Seismic trace and synthetic seismic seismogram tie. To the right a visualization of the tops picked in the 3D seismic volume at Well 8.

Figure 2.4 Seismic section 3 (in Figure 2.1). In the seismic section, individual stacked or laterally accreted sands are not resolved, but they are identified in well-logs (high resolution).

Figure 2.5 Amplitude slice map through the Middle Morrow. Yellow- boundary of the meandering system. Blue- Channels. Green- a second meandering system which may have evolved at a slightly different time.

2.3 Results of the Geological Analysis

The Buffalo Valley Field, which is located close to the Pedernal Uplift in the Northwestern Shelf of the Delaware Basin, records both depositional and tectonic characteristics linked to the Marathon-Ouchita Orogeny^{21, 22, 23}. The depositional environments for the Morrow and Atoka Formations ranged from fluvial, to deltaic, and later to shallow marine conditions²⁴. Tectonic effects produced a structurally complex setting, characterized by an approximately north-south trend of steep reverse and perhaps strike slip faults.

The Morrow Formation in the Buffalo Valley Field is mostly composed of interbedded sandstones and shales (Fig. 2.6), which were deposited in an initial progradational fluvial environment with sedimentary transport trending northwest to southeast that gradually transformed into a deltaic environment. This formation is characterized by high reservoir complexity with pinch outs, lateral, and vertical stacking of sand lenses, as well as considerable variations in petrophysical properties, which resulted from the depositional environment, fluctuations of sea level, and syndepositional faulting. The Morrow Formation, as reflected in the structural map, shows deepening to the southeast. The depth ranges from 4350 to 5150 ft subsea, and the thickness is very variable and ranges from 80 ft to 200 ft.

Figure 2.6. East-west cross section across the Buffalo Valley identifying the lower part of the Strawn Fm., sands and shales of the Atoka and Morrow Formations, the Barnett shale, and the carbonates of the Chester Fm. This cross section correspond to the E-W (blue in Fig.1). Datum: Atoka Top.

On the basis of well log characteristics and seismic amplitude analysis the Morrow Formation is divided into three facial units:

1) The lower Morrow is a progradational fluvial unit deposited mostly in a meandering system that flowed with a north-south-southeast trend into the Delaware Basin, cutting into the Barnett Shale and following the topographic lows in-between the structurally higher Chester carbonates. A comparison between cumulative gas production for the lower Morrow and the distribution of interpreted facies reveals that those wells located within the meandering system are also within the bounds of the high gas production trend.

2) The middle Morrow is a sequential continuation of the fluvial environment that dominated the lower Morrow, and it is constituted by a parasequence of stacked sands and interbedded shales (Fig. 2.6).

3) The upper Morrow Formation is constituted by a thin, laterally variable section composed of sands with some carbonate content, and shales. This unit reflects fluvio-deltaic conditions with a marine influence, resulting from the beginning of the general transgression that took place during the upper Morrow and Atoka. Porosity for the upper Morrow is generally lower than in the middle Morrow. Neutron porosity ranges from 0 to 14% with an average of 7%. Calculated porosities based on density, neutron, and sonic logs for this interval varies from 4% to 14% with an average 6-7%. The matrix identification also corresponds to quartz, but with some carbonate content²⁵.

The Atoka in the Buffalo Valley Field is constituted by sands, limestones, and interbedded shales. The Atoka was deposited in a deltaic to shallow marine environment. It represents a transgressional episode with periodic sea level fluctuations, which produced stacked progradating parasequences of sands interbedded with shales and some limestones.

The Atoka, like the Morrow and the rest of the Pennsylvanian sequence, becomes deeper to the southeast of the area. Its thickness varies from approximately 50 to 170 ft and its depth ranges from 4250 to 5050 ft subsea. We divided the Atoka into two units.

1) The lower Atoka is a thin section with sands interbedded with some carbonate and shales. This unit reflects deltaic to shallow marine conditions. The coarsening upward well log character of the parasequences in this unit is commonly interpreted as representing prograding deltaic conditions. Calculated porosities range from 4 to 14% with an average porosity of 8-9%. Neutron porosity for the lower Atoka

ranges from 0 to 14%. The matrix identification also corresponds to Quartz, though with a higher carbonate content than that found in the upper Morrow²⁷.

2) The upper Atoka is composed of sands, carbonates, and interbedded shales. This unit was deposited under shallow marine conditions with a depositional trend parallel to the paleo coastline. In the well logs, the upper Atoka is a coarsening upward parasequence, which is sometimes followed by a fining upward parasequence. This is interpreted as a deltaic sequence that progressively becomes marine. At the top of the Atoka, a thick shale separates it from the carbonate sedimentation of the Strawn Formation. Petrophysical evaluation yields a calculated porosity ranging from 1 to 14% with an average porosity of 4-6%. Neutron porosity ranges from 0 to 12%. Having a density of 2.7g/cc, the matrix identification corresponds to calcite and quartz, with higher carbonate content than found in the lower Atoka. The bulk density log for this unit is very characteristic, showing a bell shape curve with higher values compared to the rest of the Atoka and Morrow Formation. Such a density signature is related to its higher carbonate content.

The Strawn Formation records marine sedimentation in shallow to more open marine environments as the transgression continued.

The structural relief of the area is dominated by two major high-angle reverse faults dipping steeply to the west with a preferential strike direction of between 005 and 015. They are located near the east and west edges of the seismic data block (Fig. 2.7). There is not enough evidence to argue that these faults resulted from wrenching, although they are steeper than typical reverse faults in other areas. The timing of fault movement is inferred to have started some time before the lower Pennsylvanian and could have continued, or been reactivated later, affecting up to Wolfcampian strata (Early Permian). Syn-tectonic sedimentation related to the western and eastern faults occurred during deposition of both units the Morrow and the Atoka Formations, resulting in a thicker section in the down-thrown blocks.

Figure 2.7 Overlay of the structural map of the Atoka with the isopach map of the Atoka-Chester interval.

2.4 Synthetic Modeling Role for Reservoir Characterization Using Neural Networks

Well-log properties have been predicted directly from the surface seismic attributes and the well logs available using neural networks in some previous studies^{26, 27, 28, 29}. A further step of training and testing neural networks in simple synthetic models has proven the effectiveness of neural networks for predicting reservoir properties^{30, 31}. An et al.³⁰, simulated a thin lens-shaped reservoir at the top of a formation boundary. Even though strong seismic noise was included in the simulation, the neural networks predicted the reservoir boundaries accurately.

In this project, a realistic 2D geological model was designed in order to train, test, and determine important factors for the final design of the neural network to be subsequently applied to the real data set. The advantage of using a model is that, unlike the real data, we have complete knowledge of the input interval velocity and density values. The training of the neural networks includes multiple seismic attributes derived from the synthetic seismic model. Therefore, we can precisely evaluate the effectiveness of the neural network prediction.

As primary properties of seismic wavelets, seismic attributes, such as instantaneous amplitude, phase or frequency carry information directly related to the physical properties and/or fluids in each rock unit. This is the reason why the selection of the seismic attributes to be extracted from the seismic data is an important step for the neural network prediction. Leiphart and Hart³⁰ suggest that the attributes that show a clear relationship with the physical property to be predicted should be ranked by correlation with the neutron porosity log. These attributes can be run in a number of neural network iterations and by trial and error choose the attributes that yield the best result when predicting the properties with respect to a geological model.

Banchs and Michelena²⁹ used all seismic attributes the software had available: sample number, in-line coordinate, cross-line, time integral of the amplitude, time integral of the absolute amplitude, instantaneous phase, derivative, second derivative, average frequency, and average amplitude. Leiphart and Hart³⁰ concluded that amplitude is a good indicator for stratigraphic changes, frequency may be related to lithology and stratigraphic changes as well, and phase emphasizes weak coherent events, so it could locate stratigraphic pinchouts and channel features.

In our project a multi-attribute approach was followed using the seismic attributes that the software computed automatically by Kingdom Suite. These included amplitude, average energy, envelope, frequency, Hilbert transform, phase, paraphrase, and peak/trough ratio. These attributes were extracted and handed to the team conducting the neural network inversion. Thus these attributes provided the input data for designing and training the neural networks.

Some of the advantages of applying the neural networks to a synthetic model are:

- 1) Acoustic velocity and density (which can be used as surrogates for petrophysical properties, such as porosity) are available, if desired, for each seismic trace along the section, and the number of traces can be modified as desired as well.

2) Seismic data derived from the model can be easily sampled into a smaller time interval providing the opportunity to match closely the sampling rate of well logs. Real data is typically sampled at 2 ms while the synthetic data can be sampled up to 0.5 ms. In this project, two data sets were generated, one sampled every 2ms, and a second, sampled every 0.5 ms.

3) The synthetic data allows us to test different combinations of seismic attributes to narrow the number or combination of attributes that lead to the best training of the neural network.

4) The synthetic data can be modified to include different degrees of noise to simulate noise in real data. Therefore the training and convergence of the neural network can be tested and probably enhanced when applied to real data.

5) The complexity of the model can be modified in order to test the capabilities of the neural networks approach under different geological scenarios.

This chapter explains the methodology followed in order to develop the synthetic geological model and the synthetic seismic sections of the Pennsylvanian sequence, especially of the Atoka and Morrow Formations. The synthetic seismic sections were generated with the seismic characteristics of the actual 3D seismic data and of the VSP (by deriving a Butterworth wavelet with the same peak domain frequency but wider bandwidth) of the Buffalo Valley Field. Finally, the chapter also describes the models' output data, which will later be used as the input to design, train, and verify reservoir predictions using the neural networks.

2.4.1 Modeling Methodology

Synthetic seismic modeling is a forward process in which a seismic wavelet is convolved with a reflection coefficient train to simulate the seismic response. Reflection coefficient (R) is defined as $R = (\rho_2 v_2 - \rho_1 v_1) / (\rho_2 v_2 + \rho_1 v_1)$, where ρ_1 and ρ_2 are the densities of the upper and lower rock layer respectively; v_1 and v_2 , are their acoustic velocities. These reflection coefficients are convolved with an equivalent wavelet (generally from the real data) to finally model a synthetic seismic trace of a simulated or actual stratigraphic section from a well. This concept can be understood as the superposition of the wavelet, scaled by the reflection coefficients, and delayed by the travel time, $s(t) = w(t) \square r(t)$, where s is the seismic trace, $w(t)$ is the wavelet, and r is the reflection coefficient sequence^{20, 32, 33, 34}.

This study employed STRUCT a modeling software from the Geographix Discovery Suite (Landmark Graphics), which uses a forward modeling approach to simulate straight vertical rays paths traveling down from the surface without diffracting (Figs. 2.8, 2.9). The software calculates the reflection coefficients (in depth) at each interface between layers. Then it converts depth to time using the acoustic velocity entered in the model. Next, it convolves the wavelet (that in this case was extracted from the real 3D and VSP seismic data) with the reflectivity to produce synthetic seismic traces for the modeled stratigraphic section. Results are equivalent to a perfectly migrated seismic line without Fresnel effects (Figs 2.11, 2.12). We also used Kingdom Suite (Seismic Microtechnology) to calculate seismic attributes, and in-house software for converting to and from SEG-Y format to ASCII files that could be utilized by the neural network software.

Modeling Methodology - Input

•Struct: Modeling software from Geographix

1. Design

•Dimensions:
(comparable to
actual
interpretation)

-Extension :7.9 km / 26000ft
-Depth (Subsea) :Morrow: 8300
Pen:7000-9000ft
-Sequence Thickness :Penn:2000ft
-Formations thickness :Morrow 500-300ft
-Channels/Layer Thickness :20-80ft Thickening
below resolution
level

2. Input

Petrophysical:

-Interval Velocity
-Density
(Well logs)

Lithology	Density g/cc	Velocity ft/sec
Limestones	2.5-2.71	12,000- 17,000
Sandstones	2.4-2.7	12,500- 16,000
Shales	1.9-2.1	9,000- 11,000

Figure 2.8 Synthetic modeling design and input methodology.

Figure 2.9 Wavelet extraction method, seismic resolution characteristics of the model, and forward modeling general methodology.

Figure 2.10 Synthetic geological model and location of the wells in the section.

Figure 2.11 Lower resolution synthetic seismic model generated using the seismic wavelet from the surface seismic with 45 Hz dominant frequency.

Figure 2.12 Higher resolution synthetic seismic model generated using the seismic wavelet from the VSP data with 65 Hz dominant frequency.

2.4.1.1 Design of the geological model.

The synthetic modeling process was applied to a geological model proposed as a comparative example of a stratigraphic section in the Buffalo Valley for the Morrow and Atoka Formations and the overlying Pennsylvanian sequence (Fig. 2.10). Thus, the stratigraphic complexity of the Atoka and Morrow Formations within the Buffalo Valley Field were portrayed in the synthetic seismic. The input model was defined using petrophysical properties and vertical and horizontal dimensions consistent with the geological interpretation of the actual data set. Thickness, geometry, lateral distribution, density and interval velocity of the rocks within the unit were similar in both cases.

In this model, as in the real stratigraphic section, geological complexity increases with depth. Thus, the Cisco, Canyon, and Strawn Formations are made of relatively continuous beds with no lateral variations of reservoir properties, although there are thickness variations within the layers. The Atoka and Morrow have multiple sand bodies that change laterally, which simulate sand channels (Fig 2.10). The input model was 7.9 km (4.9 mi) wide, equivalent to the dimension of the 3D survey, and approximately 2000 ft thick, starting at about 7000 ft depth.

Sand channels and layers ranged in thicknesses between 10 and 80 ft according to the well log interpretation. Density and interval velocity of shales and sand bodies were derived from the well logs. These values ranged between 2.4-2.7 g/cc for sands, between 1.90-2.10 g/cc for shales, and 2.5-2.7 for limestones. The acoustic velocities ranged from 12,500-16,000 ft/s for sands, 9,000-11,000 ft/s for shales, and from 14,000-17,000 ft/s for limestones.

2.4.1.2 Synthetic wells

Three synthetic well locations were chosen initially to use in the training of the neural net. These wells are located at traces 20 (Well 20), 50 (Well 50), and 80 (Well 80) (Fig. 2.10). The synthetic VSP is located at Well 50 (the center of the model) and consists of 20 traces centered around the well. Density and velocity data were provided for the three well locations, and were sampled in two data sets matching the time sampling of the synthetic seismic section. The first was sampled every 2 ms, and the second one was sampled every 0.5ms.

2.4.1.3 Seismic sections: seismic attributes

In this study, eight seismic attributes were extracted from the synthetic seismic sections using the EarthPak software of Kingdom Suite: amplitude, average energy, envelope, frequency, Hilbert transform, phase, paraphrase, and peak/through ratio^{21, 35}.

2.4.2 Synthetic Model of the Atoka and Morrow Formations

The synthetic seismic response of the model was first computed using a wavelet derived from a time window from the zone of interest in line 1034 of the 3D surface seismic data. This wavelet had a bandwidth of approximately 11 to 95 Hz, a dominant frequency of 45 Hz, and a dominant period of 0.022 sec. Using an interval velocity ranging from 15000-16000 f/sec, the vertical resolution calculated with the equation $VR = v/4f$ where VR is the vertical resolution; v is the interval velocity; and f is the dominant frequency, led to a tuning thickness between 83 and 88 ft. The result is the synthetic seismic line shown in Fig. 2.11. We introduced 1% noise during the computation of the synthetic seismic line. The model has 100 traces spaced every 80 meters.

The process was repeated using a Butterworth wavelet with the same dominant frequency as a wavelet derived from line 2064 of the 3D VSP but with a larger bandwidth (Fig. 2.12). This wavelet had a bandwidth of approximately 20 to 110 Hz, a dominant frequency of 65 Hz, and a dominant period of 0.0154 sec. Using the same interval velocities, the vertical resolution led to a tuning thickness ranging from 57 to 61 feet.

As stated above, the geological complexity of the model increases with depth. Thus, the Cisco Formation is the least complex unit, while the Morrow Formation is the most complex. The tops and internal bedding of the Cisco, Canyon and Strawn Formations produce strong reflectors that are laterally continuous. However, within the Canyon and Strawn Formations, the gradual thinning of some beds is distinguishable in the seismic signal.

The positive amplitudes observed in the section (peaks, in black) are produced at the top of the carbonates (layers in blue in the geological model), reflecting the interface between an overlying rock with weak acoustic impedance (shales, layers in white in the geological model) and an underlying high acoustic impedance (carbonates). The next downward cycle, a negative amplitude (trough) is produced due to the interface between the strong acoustic impedance carbonate, and the underlying weak impedance shale.

When the thickness of the layer exceeds the resolvable thickness, such as in some of the thick shale intervals observed in the seismic section, the amplitude becomes very low, near zero (white in the seismic section) due to the lack of reflectivity contrast or the encounter with a new interface in the down going path of the wave front.

Wedges of laterally thinning carbonates and shales produce tuning and a consequential large amplitude when the bed becomes $1/4$ wavelength. Then, the amplitude progressively decreases, continuing the thinning trend.

For the Atoka and Morrow Formations, the seismic character is considerably variable. The lateral complexity of these units is characterized by a series of lenses and layers of sandstones and sands with carbonate content that are laterally and vertically stacked and embedded in shale. This configuration results in a discontinuous seismic character with undulating reflections and faster lateral variations of the amplitude.

As explained above, the lateral variation of the thickness and acoustic properties result in changes in the amplitude. Thus, sands with stronger acoustic impedance (i.e. related to higher interval velocity) than the shales adjacent to them produce a lateral variation of the velocity above the continuous top of the Chester Formation. These velocity variations produce pull ups and pull-downs additional effects in the time reflection of the Chester (Figs. 2.11, 2.12). These velocity variations modify the time structure of the Chester Formation top by developing a false undulated relief. A pull up in time, is produced where there is a sand (higher velocity) overlying the Chester. Alternatively, a push down (sag) is developed where a lower velocity shale overlies the Chester. Thus, the reflection character is fundamentally related to lateral stratigraphic changes. This qualitative analysis of amplitude showed how lateral variations, such as thinning or lateral variation of the acoustic properties, produce either an increase or decrease of the amplitude.

The modeling of laterally continuous marine sequences, such as the carbonate and interbedded shales of the Strawn, Canyon and Cisco Formations, produce laterally continuous reflectors. Contrarily, discontinuous and laterally variable formations such as the Atoka and Morrow, with lenses of "channel" sands pinching out and stacked on top of each other, produce discontinuous seismic reflectors with more visible amplitude variations.

Figure 2.13 Comparison of the ability of different seismic attributes calculated from the geological model shown at the bottom calculated using a wavelet extracted from the 3D seismic volume and petrophysical properties consistent with the Buffalo Valley wells.

Figure 2.14 Comparison of seismic attributes “phase” and “frequency” extracted from the synthetic seismic line shown on Figure 2.11 and used for training of the neural network.

The comparison of the seismic response in the model with the actual seismic data contributed to an understanding of the type of complexities and characteristics of the Pennsylvanian sequence, especially that of the Atoka and Morrow Formations.

As discussed, the visual comparison of the seismic resolution between the seismic section with the seismic characteristics of the 3D seismic (lower resolution) and the VSP (higher resolution) allowed the verification that the seismic section with the VSP seismic characteristics better defines the geometry and differences in the acoustic impedance between different lithologic units (Fig. 2.11 and 2.12).

Seismic attribute displays of instantaneous frequency and instantaneous phase for this synthetic section were generated. The display of these seismic attributes in the same color scale as used as for amplitude permits the visualization of their response to the differences in the acoustic impedance between the layers included in the model. Amplitude, better defines the geometry and lateral changes in the acoustic impedance (Fig. 2.13). Frequency, compared to amplitude, does not resolve the tops and bottoms of each lithological unit very well (as seen in the Strawn, Canyon and Cisco Formations), but effectively shows the thinning of beds/ and lateral change in the acoustic impedance (as seen for the Atoka and Morrow Formations) (Fig. 2.14). Phase, compared to frequency, better defines the tops and bottoms of the lithologic units (as seen in the Strawn, Canyon and Cisco Formations) but fails in showing a gradual variation in the values according to the variation in thickness (as for the Atoka and Morrow Formations).

2.5 Conclusions

While the advantages of Artificial Neural Networks to reservoir characterization are known, this project expanded such benefits by providing a method by which an Artificial Neural Network can be trained prior to its application to real data. The use of a model provides a complete knowledge of the input interval velocity, density values, and seismic attributes derived from the synthetic seismic model enabling a precise evaluation of the effectiveness of neural network prediction. The synthetic model was provided at three levels of resolution, ranging from high resolution (well-log), to intermediate (VSP improved frequency content "Butterworth wavelet") and low resolution (3D surface seismic frequency content). The VSP data created a bridge to better scale-down the correlation, the well logs, and the conventional seismic data, resulting in more accurate predictions.

The synthetic data allowed different combinations of seismic attributes to be used in training the neural networks, in order to find the best procedure of the neural network application to the real data. Amplitude, phase, and paraphrase have provided better results than using a multi-attribute approach where amplitude, average energy, envelope, frequency, Hilbert transform, phase, paraphrase, and peak/through ratio were employed.

One additional conclusion from this study is that the traces of the synthetic model (synthetic wells) that are chosen for training of the neural network must be picked with care. The training traces must sample as much geological complexity as is expected to be encountered in the real world. Otherwise the ability of the neural network to predict correctly predict petrophysical properties during the production run, will be restricted.

CHAPTER THREE: NEURAL NETWORK ANALYSIS

The seismic method is the most widely used tool in the exploration of hydrocarbon reservoirs. It is useful for obtaining a structural view of the subsurface geology. The basic theory of the seismic method is based on the movements of signals through the subsurface. *Reflection method* is the most widely used seismic method, which is useful in identifying formation tops. A *seismic trace* is the response of a single seismic detector to the seismic energy propagation through the earth. If these traces are displayed side-by-side, then it is called a *seismic record*. A processing stage comes after obtaining a seismic record, to enhance the signal, to minimize the noise and increase the resolution. These processed images are then compiled together to produce the final output of the seismic survey: a *seismic section*³⁶.

Vertical seismic profiling (VSP) differs from conventional seismic surveys in the location of signal receivers. In VSP surveys, the receivers are located in the borehole instead of at the earth's surface. Because the earth acts as a low-pass filter, placing of the receivers at depth reduces the distance that the signal has to travel through the earth, thus yielding higher frequency (higher resolution) data. VSP surveys are very similar to velocity surveys in terms of where the sources and receivers are located. However, they differ from each other with two issues³⁶:

- 1) The distance between geophone recording depths (smaller in VSP, every 15-40 meters)
- 2) Collection of information (Only first break times are collected in velocity surveys. In VSP, upgoing and downgoing events are also collected for several seconds.)

Seismic attributes are all the information obtained from seismic data, either by direct measurements or by logical or experience-based reasoning³⁷. The attributes used in this study can be briefly defined as;

Amplitude: Measure of the strength of the reflected signal. Indicates changes in physical properties of various lithological entities. It can sometimes be used to detect gas presence¹¹.

Hilbert Transform: This amounts to a 90-degree phase rotation. Amplitude and Hilbert transform are combined as Cartesian components of a trace signal³⁸.

Instantaneous Phase: Phase angles range from -180 degrees to +180 degrees. Envelope and phase are combined as polar components of a trace signal³⁸.

Average Energy: This attribute integrates the envelope between paraphase events. It highlights stratigraphic detail through energy fluctuations across traces. Values are in degrees³⁸.

Envelope: Represents the reflection strength. The envelope is independent of the phase and it relates directly to the acoustic impedance contrasts³⁸.

Frequency: This attribute describes how long it takes the phase to complete 360 degrees of rotation³⁸.

Paraphase: This attribute is the instantaneous phase with the predictable trend removed. As such, it assists visualizing the structural picture because phase tracks geologic boundaries³⁸.

3.1 Artificial Neural Networks

Artificial neural networks (ANN) can be broadly defined as information processing systems that mimic the human mind as a mathematical model representation of the biological neural networks. ANN have gained an increasing popularity in different fields of engineering in the past few decades, because of their capability of extracting complex and non-linear relationships. Their mechanism is based on the following assumptions³⁹:

- 1) Information processing occurs in many simple elements that are called neurons (processing elements).
- 2) Signals are passed between neurons over connection links.
- 3) Each connection link has an associated weight, which, in a typical neural network, multiplies the signal being transmitted.
- 4) Each neuron applies an activation function (usually non-linear) to its net input to determine its output signal.

Outputs (I_n) coming from another neuron are multiplied by their corresponding weights (W_n), and summed up. An activation function is then applied to the summation, and the output of that neuron is now calculated and ready to be transferred to another neuron⁴⁰. There are many different types of neural network architectures and algorithms available. In this study, a generalized regression neural network (GRNN) is used. GRNN is a modification to probabilistic neural network that has been suggested by authors, who have studied seismic inversion^{8,9}. GRNN has also been successfully used in geological pattern recognition applications such as synthetic log generation¹⁰ and total organic carbon

content prediction from logs¹⁹. Besides, GRNN has been used in finding a correlation between cross-well seismic and surface seismic^{13,42}. Huang *et al.*⁴¹ described GRNN as an easy-to-implement tool, which has efficient training capabilities, and the ability to handle incomplete patterns.

3.2 Generalized Regression Neural Network

Introduced by Specht⁴³ in 1991, GRNN is a one-pass learning algorithm with a highly parallel structure. It is a memory-based network, which provides estimates of continuous variables, and converges to the underlying regression surface. This approach is freed from the necessity of assuming a specific functional form. Instead, the appropriate form is expressed as a *probability density function* (pdf), which can be determined from the observed data. General regression uses y (a scalar random variable), the X (a particular measured value of a vector random variable x), and the non-parametric estimator of the joint probability density function $f(x, y)$. After defining the scalar *Euclidian distance* function, D_i^2 ;

$$D_i^2 = (X - X^i)^T (X - X^i) \quad (1)$$

performing the integrations results with the following:

$$\hat{Y}(X) = \frac{\sum_{i=1}^n Y^i \exp\left(-\frac{D_i^2}{2\sigma}\right)}{\sum_{i=1}^n \exp\left(-\frac{D_i^2}{2\sigma}\right)} \quad (2)$$

In order to define it in a simpler mathematical form, (4) is proposed instead of (2), which has given similar results. Instead of the Euclidian distance, it uses the city block distance, C_i ;

$$C_i = \sum_{j=1}^p |X_j - X_j^i| \quad (3)$$

$$\hat{Y}(X) = \frac{\sum_{i=1}^n Y^i \exp\left(-\frac{C_i}{\sigma}\right)}{\sum_{i=1}^n \exp\left(-\frac{C_i}{\sigma}\right)} \quad (4)$$

The estimate $Y(X)$ is defined as a weighted average of the observed values, Y_i , where each observed value is weighted exponentially according to its Euclidian or city block distance²¹. σ is the smoothing factor, and optimum smoothing factor is determined after several runs according to

the mean-squared error of the estimate, which must be kept at minimum. This process is referred to as the training of the network. If a number of iterations pass with no improvement in the mean-squared error, that smoothing factor is determined as the optimum one for that data set. In the production phase, that smoothing factor is applied to data sets that the network has not seen before. While applying the network to a new set of data, increasing the smoothing factor would result in decreasing the range of output values.

GRNN is known to be particularly useful in approximating continuous functions, such as logs, or other types of geological patterns. It may have multidimensional input, and it will fit multidimensional surfaces through data⁴⁴. It is a three-layer network. In the hidden layer, there must be one hidden neuron for each training pattern.

3.3 Synthetic Model Study

3.3.1 Methodology

The proposed methodology of this study includes two major steps of correlation (Fig. 3.1); 1) Correlation of surface seismic with VSP; 2) Correlation of VSP with well logs. The data of interval 0.8 - 1.124 seconds (6600 - 9000 ft) are used, as only that interval was rich in terms of geological information. Next, these two steps of correlation will be explained in details.

Figure 3.1: Modeling high-frequency logs from low-frequency seismic signals. Schematic view of seismic inversion process with the proposed correlation map. Two major steps of correlation: 1) Surface Seismic – VSP, 2) VSP – Well logs.

3.3.1.1 Step 1: Correlation of Surface Seismic with VSP

For the first step of the proposed methodology, a correlation between surface seismic attributes and VSP attributes has been looked for. First, the model has been visualized by plotting the cross-sectional distributions of density, velocity and seismic attributes for both surface seismic and VSP. Fig. 3.2 shows the VSP amplitude distribution of the model.

The main aim of visualizing was to determine the most appropriate data that can be used in training before starting to train the network. The predictability of a neural network model highly depends on how and with what data it has been trained. Thus, the data should contain a lot of information regarding the model, to get the most successful results in the production phase. For this purpose, an effort has been made to identify some geological features that can be useful in training the neural network. These include; edges of sand channels, extreme value points, and unique geological structures. Although the model has a uniform

distribution laterally in most of the regions, those kinds of features can be found mostly in the middle zone. In order to include those features in the training model, data of traces 32 and 57 have been decided upon to be used in training after several tests (Fig. 3.3). Number of traces that is used has been kept at two, because of the limitation in optimum number of data rows. Two traces include 326 data rows.

Figure 3.2: VSP amplitude response of the synthetic model.

Figure 3.3: Cross-sectional envelope distribution, which was used to determine special features that can be useful in the network training. Finally, traces 32 and 57 were decided upon to be used in training.

The network structure used in training is shown in Fig. 3.4-a. As shown, data of traces 32 and 57 have been used, to predict a VSP attribute from time and seven available surface seismic attributes. 70% of the data were selected randomly, specifically for training. Among the remaining 30%; 20% were used for calibration, and 10% were used for verification.

At the end, seven separate prediction models have been developed for seven attributes, which are based on data of t-32 and t-57. After having confidence with the prediction abilities of these models, they have been applied to the whole seismic line to obtain network-predicted distributions of available attributes. These distributions were then plotted to be able to compare with the actual ones.

Figure 3.4: Network structures used for training for the synthetic case. a) Data of traces 32 and 57 have been used, to predict a VSP attribute from time and surface seismic attributes. b) Data of Trace - 50 have been used, to predict one of the density classes from time and VSP attributes.

3.3.1.2 Step 2: Correlation of VSP with Well Logs

The second step of the correlation studies is the main goal of this study, which is deriving logs from VSP data. Since Trace 50 is the trace which includes all of the data that we are dealing with theoretically (i.e. surface seismic, VSP and well logs), this trace has been used to develop the model of this part of the correlation. Density log has been selected as the target log, as it was the only log together with the velocity log which has

a very similar structure with density. The methodology that has been developed with the density log was then applied to velocity and acoustic impedance (the product of density and velocity.)

When one looks at the density log of trace 50, one can clearly see that there are a few different averaged values of density (Fig. 3.5), which have been later defined as classes. Each of these classes actually represents a different type of rock layer defined in the model. Finally, instead of using actual values of density, it has been decided to use these classes as the target values. In the initial trial, classes were defined as (Fig. 3.5);

- Class 1: $\rho \approx 1.9$ g/cc
- Class 2: $\rho \approx 2.3$ g/cc
- Class 3: $\rho \approx 2.65$ g/cc

Figure 3.5: Density log of Trace - 50. First classification proposed: Three classes at density values 1.9, 2.3, and 2.65.

The data set has been re-arranged in a way that the corresponding class of that row is equal to 1 and others are 0. Thus, the network structure was like the one in Fig. 3.4-b. All of the VSP attributes with time were used as inputs to predict one of the density classes.

By using the generalized regression neural network algorithm, a reliable training model has been built to be used in density prediction. With that model, the cross-sectional density distribution has been produced through the seismic line, and that distribution has been compared with the actual distribution. Same procedure was applied to velocity and acoustic impedance. Results and discussions are presented in the next section.

3.3.2 Results

3.3.2.1 Step 1: Correlation of Surface Seismic with VSP

Table 3.1 shows the correlation statistics of the training models developed for this step of the study. Correlation coefficient, r , and r -squared values are included as indicators of the accuracy of the match. Results for pattern (overall), training, calibration, and verification sets are included.

	Amplitude		A. Energy		Envelope		Frequency		Hilbert T.		Paraphase		Phase	
	r^2	r	r^2	r	r^2	r	r^2	r	r^2	r	r^2	r	r^2	r
<i>Pattern</i>	1.00	1.00	0.83	0.91	0.97	0.98	0.76	0.87	0.92	0.96	0.88	0.94	0.93	0.96
<i>Training</i>	1.00	1.00	0.84	0.92	0.98	0.99	0.76	0.87	0.93	0.96	0.89	0.94	0.97	0.99
<i>Calibration</i>	1.00	1.00	0.79	0.89	0.90	0.95	0.81	0.90	0.90	0.95	0.85	0.92	1.00	1.00
<i>Verification</i>	1.00	1.00	0.75	0.86	0.92	0.95	0.73	0.86	0.96	0.98	0.85	0.92	0.52	0.72

Fig. 3.6 shows the results of the training as actual vs. network-predicted plots for training, calibration, and verification sets of seven attributes. Each set of data is shown with a different symbol and color.

Statistical and visual results indicate that reliable models have been developed. These models have been applied to the whole line (i.e. other traces of the synthetic model). The seismic attribute distributions have been re-produced. They have been re-plotted to be able to compare with the actual distributions. Figures 3.7, 3.8, and 3.9 show the comparison plots for each attribute, after applying the models for these attributes to the entire line. These plots also include the actual log lines of each attribute at traces 20, 35, 50, 65, and, 80, which makes it easier to assess the accuracy of the produced distributions.

Figure 3.6: Actual vs. network results for each attribute after training the network for surface seismic - VSP correlation. Results for training, calibration, and verification sets are included with different symbols.

Figure 3.7: Actual (left) and network-predicted (right) distributions for VSP attributes: amplitude, average energy, and envelope.

Figure 3.8: Actual (left) and network-predicted (right) distributions for VSP attributes: frequency, Hilbert transform, and paraprphase.

Figure 3.9: Actual (left) and network-predicted (right) distributions for VSP attributes: phase.

3.3.2.2 Step 2: Correlation of VSP with Well Logs

For the second step where the density has been predicted; actual vs. network plot for the pattern set is shown in Fig. 3.10-a. Although the network seemed to be successful in most parts, it has missed some points in the middle-valued region which was assumed to belong to Class 2: 2.3 g/cc. In order to overcome this problem, it has been decided to introduce another class to our model. Class 4 was assigned to density values around 2.09 g/cc (Fig. 3.10-b). That has helped the network to be successful in that region (Fig. 3.10-b), and this network model has been decided upon to be used in further studies. The correlation statistics of this model are shown in Table 3.2 together with the results for the velocity log.

	Density		Velocity	
	r^2	r	r^2	r
<i>Pattern</i>	0.82	0.91	0.90	0.95
<i>Training</i>	0.94	0.97	0.93	0.96
<i>Calibration</i>	0.54	0.73	0.97	0.99
<i>Verification</i>	0.54	0.73	0.49	0.70

Table 3.2: Correlation statistics for density and velocity, for the second correlation step of the synthetic model study.

Actual VSP attributes were applied to this model, and density has been predicted along the seismic line with a correlation coefficient of 0.82. This has been repeated with the predicted VSP attributes coming from the first step of the correlation studies. The density has again been predicted through the seismic line with a correlation coefficient value of 0.81. 87% of the data points have been predicted correctly in terms of the proposed

classes. Fig. 3.11 shows the final actual and network-predicted density distributions. The same procedure has also been applied to velocity and acoustic impedance, and their comparisons are shown in Figure 3.12.

Figure 3.10: Defining density classes, and the corresponding training results. a) Three classes (1.9, 2.3, 2.65). Training $r^2 = 0.82$, b) Four classes (1.9, 2.09, 2.3, 2.65). Training $r^2 = 0.94$

Figure 3.11: Actual (top), and network-predicted (bottom) distributions of density values ($r = 0.81$). In terms of

classes; 87% of the data points have been predicted correctly.

Figure 3.12: Actual (left), and network-predicted (right) distributions of velocity (top), and acoustic impedance (bottom).

3.3.3 Discussions

The synthetic model provided the opportunity to be familiar with the type of data that has been dealt with. Being able to compare the results in a seismic-section basis helped to assess the quality of the developed methodology. Comparisons of the actual and predicted distributions indicate that, VSP attributes can be successfully predicted from surface seismic attributes with the correlation models developed with a generalized regression neural network. The importance of the data that is included in the training set has been seen, with the increased success of the network model after selecting the data with model visualization. In the case of the logs, predicted density and velocity distributions show that the lithological units have been successfully predicted by the neural network.

3.4 Real Case Study: The Buffalo Valley Field, NM

3.4.1 Methodology

The same methodology with the one followed in the synthetic case study, was applied to real field data. Following data were available from the field that can be used in this study:

- 1) A 3D seismic survey covering an area of 24 mi² with a vibroseis source, sweep frequencies ranging from 8 to 98 Hz, and a sweep length of 17 seconds.
- 2) A vertical seismic profile volume, with a two-LRS-315 vibrators source, covering an area of approximately 3.5 mi² in the southeast corner of the area.
- 3) Logs from around 40 wells were available as either paper or electronic copies. Available types of logs included gamma ray, neutron, density, sonic, spontaneous potential, and resistivity. Paper copies have been scanned, and then digitized together with other available electronic copies. Average total depth of those wells were ranging from 8000 to 9000 ft, intersecting the Atoka and Morrow formations.

Unfortunately, not all of the available well logs had a high visual quality. That made them hard to be digitized accurately. It is a proven fact that; quality of the data has an important role in building reliable neural network models. Reasonable amount of noise in the data is acceptable, and even useful for a more realistic model. However, it is impossible to rely on a model, which has been built with unreliable data. After considering these, it has been decided to conduct a quality check of the digitized log files. It was aimed to use data having an acceptable quality not to face with the problem of building poor prediction models.

Considering the qualities of the logs, and the location of the VSP well, a seismic line within the seismic survey area was determined to work on. It is a straight line in the SE-NW direction, and is passing through five wells including the VSP well (Fig. 3.14). The line included 173 seismic traces, with the VSP well, well-1, located on trace 16. Other wells are located on traces 55, 90, 123, and 153, respectively. Table 3.3 shows the available logs for these wells.

Well API #	@ Trace #	Well Logs				
		<i>Gamma Ray</i>	<i>Neutron Por.</i>	<i>Sonic</i>	<i>Velocity</i>	<i>Neutrons</i>
60481	16	0.92-1.092	0.92-1.092		0.92-1.092	
60415	55	0.92-1.089	0.92-1.089	0.92-1.019		
60104	90	0.92-1.07				0.92-1.07
60034	123	0.92-1.042				0.92-1.042
62701	153	0.92-1.0415	0.92-1.055			

Table 3.3: Available logs for the seismic line of interest. Written intervals are time in seconds.

In terms of the seismic data; VSP data were available only for Well-1. Surface seismic data were extracted through the seismic line of interest and were available for an interval of 0.92-1.1 seconds. The surface seismic amplitude distribution of the line is shown in Figure 3.15. A total of 27 attributes were available. 11 of them were provided by the Kingdom Suite, and other 16 attributes were calculated with theoretical relationships.

3.4.1.1 Step 1: Correlation of Surface Seismic with VSP

First, it was aimed to produce the VSP distributions through the seismic line just like the available surface seismic distributions. Since, there was only one available VSP survey, which was on Well-1, the required correlation models could have only been developed by using the data of that well.

The eleven attributes which were obtained from the Kingdom Suite were used since other attributes were derivable from them. As in the synthetic model study, eleven surface seismic attributes were used together with time, as inputs, to predict the single VSP attribute. Thus, eleven neural network models were developed for eleven attributes. The network structure is shown in Figure 3.13-a.

Results were similar to the results of the synthetic model study. They were assumed to be reliable to apply to other sections of the seismic line. Cross-sectional distributions of the eleven attributes were produced from these models for the interval: 0.92-1.1 seconds, passing through 173 traces.

Figure 3.13: Network structures used for training for the real case. a) Data of well-1 have been used, to predict a VSP attribute from time and eleven surface seismic attributes. b) Data of wells 1, 2, 3, 4, and 5 have been used, to predict the gamma ray log, and data of wells 1, and 2 have been used, to predict the neutron porosity log from time and VSP attributes.

Figure 3.14: Map of wells in the Buffalo Valley Field. The red dashed line has been selected as the seismic line to work with. It passes through five wells.

3.4.1.2 Step 2: Correlation of VSP with Well Logs

The approach carried out in this part was to use all the available well data for training, and to apply the model to other parts of the seismic line to obtain the distributions. The main idea is to have a more reliable training model by using all the available data.

In this case, 90% of the total of 871 rows of data from five wells was used for training, while 10% was used for testing during training. Two types of logs; gamma ray and neutron porosity were selected as target logs. Because of the large number of available attributes a Key Performance Indicator study was carried out, to determine the most influential attributes. As a result of this study each attribute had a coefficient between 0 and 1, which basically shows the influence of that attribute on the selected output (i.e. logs). The attributes (including the time) were ranked based on their KPI coefficients, and the ones having a coefficient larger than 0.5 were used as inputs. Those rankings for gamma ray and neutron porosity are shown in Table 3.4. The best thirteen attributes for the gamma ray, and the best eight attributes for the neutron porosity had coefficients higher than 0.5, and they were used as the input attributes. The network structure for this part is shown in Figure 3.13-b.

<i>Rank</i>	<i>Gamma Ray</i>	<i>Neutron Porosity</i>
1	Peak-to-Trough	Amp Weighted Phase
2	Smoothed Envelope	Time
3	Finite Difference	Peak-to-Trough
4	Average Frequency	Instant Energy
5	Instant Energy	Smoothed Envelope
6	Envelope	Envelope
7	Time	Amplitude
8	Amp Weighted Phase	HF Inversion
9	Amplitude	Finite Difference
10	Phase	Average Energy
11	Hilbert	Average Frequency
12	Smoothed Inversion	Paraphase
13	HF Inversion	Hilbert
14	1 st D Amp	Smoothed Inversion
15	Average Energy	Decay Rate
16	Inst. Accel	Phase
17	Inst. Q Fac	Signed Freq
18	Decay Rate	Frequency
19	2 nd D Amp	1 st D Amp
20	Res Env	Int Res Env
21	Frequency	Inst Abs Amp
22	Inst Abs Amp	Inst. Q Fac
23	Int Res Env	1 st D Env
24	1 st D Env	Res Env
25	Inst Power	Inst. Accel
26	Signed Freq	2 nd D Amp
27	Paraphase	2 nd D Env
28	2 nd D Env	Inst Power

Table 3.4: Results of the Key Performance Indicators for gamma ray and neutron porosity. Shaded ones were used as inputs.

Training results were analyzed for each well separately, and upon applying those models to the other traces on the seismic line, distributions of gamma ray logs and neutron porosity logs were produced.

Figure 3.15: Amplitude distribution of the seismic line. Red dashed lines are the five wells that the line is passing through. Well-1 is the well with the VSP survey.

3.4.2 Results

3.4.2.1 Step 1: Correlation of Surface Seismic with VSP

As in the synthetic case, surface seismic - VSP correlation models have been developed, by using time and eleven surface seismic attributes to predict the single VSP attribute. The study was done by using the attributes, which were obtained from the Kingdom Suite as the other attributes can be derived by using those ones.

Table 3.5 shows the correlation statistics for these models for each attribute. Results for pattern, training, calibration, and verification sets are included. Verification results for phase, paraphase, frequency, and signed frequency seemed to be low. However, when plotted it seemed that they were not as bad as they sound with their correlation coefficients. Their actual vs. network graphs are shown in Figure 3.16. Actual vs. network plots for other attributes are shown in Figure 3.17.

	Amplitude		A. Energy		Envelope		Frequency		Hilbert T.		Paraphase		Phase	
	r^2	r	r^2	r	r^2	r	r^2	r	r^2	r	r^2	r	r^2	r
<i>Pattern</i>	0.97	0.98	0.96	0.98	0.98	0.99	0.34	0.58	0.98	0.99	0.79	0.89	0.64	0.80
<i>Training</i>	1.00	1.00	0.98	0.99	0.98	0.99	0.92	0.96	0.98	0.99	0.98	0.89	0.96	0.98
<i>Calibration</i>	0.91	0.95	0.98	0.99	0.98	0.99	0.83	0.91	0.98	0.99	0.90	0.95	0.74	0.86
<i>Verification</i>	0.90	0.95	0.85	0.92	0.85	0.92	0.21	0.46	0.92	0.96	0.29	0.54	0.41	0.64

	Finite Difference		Peak-to-Trough		Signed Frequency		Inversion	
	r^2	r	r^2	r	r^2	r	r^2	r
<i>Pattern</i>	0.92	0.96	0.93	0.96	0.46	0.96	0.98	0.99
<i>Training</i>	0.98	0.99	0.98	0.99	0.98	0.99	0.98	0.99
<i>Calibration</i>	0.98	0.99	0.90	0.95	0.86	0.93	0.98	0.99
<i>Verification</i>	0.83	0.91	0.79	0.89	0.09	0.30	0.98	0.99

Table 3.5: Correlation statistics for eleven VSP attributes, for the first correlation step of the real case study.

Figure 3.16: Actual vs. network plots for paraphrase, phase, frequency, and signed frequency shown as logs. Although having relatively low correlation coefficient values, visual plots show promise.

These models were then applied to other traces on the seismic line, with the available surface seismic data. VSP distribution was produced through the entire seismic line. Figures 3.18 and 3.19 show the produced distributions. Actual log line for the well-1 is also included in these figures to make the comparison easier.

Figure 3.17: Actual vs. network plots for seven of the attributes, that had satisfactory correlation statistics. Training, calibration, and verification sets are included with different symbols and colors.

Figure 3.18: Produced VSP distributions for the selected seismic line in the field study. (Amplitude, average energy, envelope, frequency, Hilbert transform, finite difference).

Figure 3.19: Produced VSP distributions for the selected seismic line in the field study. (Signed frequency, peak-to-trough ratio, paraphrase, inversion, phase).

3.4.2.2 Step 2: Correlation of VSP with Well Logs

Gamma ray and neutron porosity were selected as the target logs. The results for these two types of logs are presented below separately.

3.4.2.2a Gamma Ray Log

Correlation statistics are shown in Table 3.6 for pattern, training, and testing sets, respectively. Results are showing both overall statistics, and separate well statistics. Graphs that show actual and network-predicted log lines are shown in Figure 3.20 for all wells. Figure 3.21 shows the predicted gamma ray distribution of the seismic line using these models. Actual log lines of five wells are also shown in the plot which may give a chance to compare with the predicted one.

	Pattern		Training		Calibration	
	r^2	r	r^2	r	r^2	r
<i>All</i>	0.77	0.88	0.79	0.89	0.60	0.77
<i>Well-1</i>	0.58	0.76	0.57	0.75	0.73	0.85
<i>Well-2</i>	0.75	0.86	0.76	0.87	0.67	0.82
<i>Well-3</i>	0.66	0.81	0.72	0.85	0.27	0.52
<i>Well-4</i>	0.76	0.90	0.77	0.88	0.27	0.52
<i>Well-5</i>	0.81	0.90	0.82	0.91	0.69	0.83

Table 3.6: Correlation statistics for the pattern, training, and calibration sets of the training model for gamma ray log prediction, where VSP attributes were used as input.

The same methodology has been applied by using surface seismic attributes. Table 3.7 shows the correlation statistics. Figure 3.22 show the actual log lines and network-predicted log results of the training models for five wells. Figure 3.23 shows the predicted distribution.

	Pattern		Training		Calibration	
	r^2	r	r^2	r	r^2	r
<i>All</i>	0.94	0.97	0.69	0.83	0.82	0.91
<i>Well-1</i>	0.96	0.98	0.98	0.99	0.82	0.91
<i>Well-2</i>	0.93	0.96	0.95	0.97	0.77	0.88
<i>Well-3</i>	0.95	0.98	0.98	0.99	0.63	0.79
<i>Well-4</i>	0.91	0.99	0.92	0.96	0.80	0.90
<i>Well-5</i>	0.97	0.98	0.97	0.99	0.86	0.92

Table 3.7: Correlation statistics for the pattern, training, and calibration sets of the training model for gamma ray log prediction, where surface seismic attributes were used as input.

Figure 3.20: Actual and network-predicted gamma ray logs for wells 1, 2, 3, 4, and 5. Values for training, and calibration sets are included. VSP attributes were used as inputs.

Figure 3.21: Network-predicted gamma ray distribution through the seismic line of interest. Actual log lines are also shown for five wells on the line. VSP attributes were used as inputs.

Figure 3.22: Actual and network-predicted gamma ray logs for wells 1, 2, 3, 4, and 5. Values for training, and calibration sets are included. Surface seismic attributes were used as inputs.

Figure 3.23: Network-predicted gamma ray distribution through the seismic line of interest. Actual log lines are also shown for five wells on the line. Surface seismic attributes were used as inputs.

3.4.2.2b Neutron Porosity Log

Neutron porosity log was available in only two wells; well-1 and well-2. Thus, these two wells were used in training. Correlation statistics of these models are shown in Table 3.8 and Table 3.9, for the models with inputs of VSP attributes and surface seismic attributes respectively. Figure 3.24 show the actual and network-predicted logs for two wells for the model with VSP attributes. Figure 3.25 shows the distribution, which has been produced with that model. Figure 3.26 shows the logs for the model in which surface seismic attributes were used as inputs. Predicted distribution for this model is shown in Figure 3.27.

	Pattern		Training		Calibration	
	r^2	r	r^2	r	r^2	r
<i>All</i>	0.95	0.97	0.96	0.98	0.82	0.91
<i>Well-1</i>	0.95	0.98	0.97	0.98	0.77	0.88
<i>Well-2</i>	0.94	0.97	0.95	0.97	0.89	0.94

Table 3.8: Correlation statistics for the pattern, training, and calibration sets of the training model for neutron porosity log prediction, where VSP attributes were used as input.

	Pattern		Training		Calibration	
	r^2	r	r^2	r	r^2	r
<i>All</i>	0.85	0.92	0.83	0.93	0.78	0.88
<i>Well-1</i>	0.88	0.94	0.89	0.94	0.81	0.90
<i>Well-2</i>	0.80	0.89	0.81	0.90	0.76	0.87

Table 3.9: Correlation statistics for the pattern, training, and calibration sets of the training model for neutron porosity log prediction, where surface seismic attributes were used as input.

Figure 3.24: Actual and network-predicted neutron porosity logs for wells 1, and 2. Values for training, and calibration sets are included. VSP attributes were used as inputs.

Figure 3.25: Network-predicted neutron porosity distribution through the seismic line of interest. Actual log lines are also shown for two wells on the line. VSP attributes were used as inputs.

Figure 3.26: Actual and network-predicted neutron porosity logs for wells 1, and 2. Values for training, and calibration sets are included. Surface seismic attributes were used as inputs.

Figure 3.27: Network-predicted neutron porosity distribution through the seismic line of interest. Actual log lines are also shown for two wells on the line. Surface seismic attributes were used as inputs.

3.4.3 Discussions

With the proposed methodology, neutron porosity and gamma ray logs have been produced with an acceptable agreement with the actual well logs of five wells. Including 90% well log data in training, instead of using a smaller portion has increased the prediction power of the model. Relatively better results have been obtained when the inputs were surface seismic attributes. This can be explained with the amount of VSP data that have been used in training. Since only one well had a VSP survey, the VSP prediction models were not robust enough to make very accurate predictions. However, in both cases, final log distributions were similar in structure.

3.5 Concluding Remarks

A novel solution for an important problem in reservoir characterization is presented in this report. Integrating data from different sources of varying scales is the main challenge in today's reservoir characterization. The common aim is to obtain a spatial earth model having high-resolution data to input to the reservoir simulators in order to accurately predict the reservoir and well performance.

This study introduces a new methodology for seismic inversion which can be defined as inverse modeling of reservoir properties from seismic data. Intelligent systems have become a widely used method in reservoir characterization mainly for the advantages of being able to deal with uncertainty, imprecision and partial truth. As one of the major tools of soft computing, artificial neural networks have been used to extract the complex and non-linear relationship between low-resolution seismic data and high-resolution well logs.

Considering the results presented in previous sections, the major findings of this study can be summarized as follows:

- 1) It was demonstrated that a relationship (albeit quite complex and non-linear) exists between various seismic attributes and reservoir properties. In this study such relationships were developed using a two-step process. Step 1 included correlating seismic attributes to VSP attributes and step 2 included correlating VSP attributes to well logs. The well logs used for correlation purposes were Gamma Ray and Neutron Porosity and the top six seismic attributes used for each of the correlations are shown below:

Well Log correlated: Gamma Ray

1. Peak to Trough
2. Smoothed Envelope
3. Finite Difference
4. Average Frequency
5. Instant Energy
6. Envelope

Well Log correlated: Neutron Porosity

1. Amplitude Weighted Phase
2. Peak to Trough
3. Instant Energy
4. Smoothed Envelope
5. Envelope
6. Amplitude

- 2) Such a relationship can be extracted by using artificial neural networks, as one of the major soft computing tools. As a useful algorithm in approximating continuous functions, Generalized Regression Neural Network (GRNN) was suggested and applied successfully in this study.
- 3) Benefits of using a synthetic seismic model were clearly demonstrated in developing the appropriate methodology by identifying the most appropriate neural network algorithm as well as identifying the most appropriate seismic attributes to be used in the training process. The synthetic model was also used for a classification (lithology identification) approach, which was not applicable in the field study because of the type of the data available.
- 4) Although there are several examples in using artificial neural networks to correlate seismic attributes to reservoir properties, or well logs, this study is first of its kind to integrate three types and scales of data such as seismic data with low vertical resolution, higher vertical resolution VSP and well logs with much higher vertical resolution.

In this study, vertical seismic profile (VSP) was used as an intermediate scale data that increased the accuracy and constraints the final results. During the synthetic modeling study it was demonstrated that knowledge of the reservoir structure can play an important role in the success of the inversion process using artificial neural networks. When such knowledge is not available, having several wells with VSP data can be a reasonable substitute. However, in the field study, it was seen that in the case of not having sufficient data (VSP was only available from one well), it is not recommended to train and rely on models developed from limited data. In such cases, seismic data acted better than the predicted VSP data, simply because the training models, which were developed with the data of one well, were not powerful enough for VSP prediction. This brought the importance of the amount of data that is used in training. We recommend that VSP data from at least three wells (that are spaced properly in the field) be used in order to train neural networks.

- 5) To determine the data that should be used for training, model visualization can be helpful. It was seen in the first correlation step of the synthetic model study that; including unique geological behaviors in the training set can increase the prediction abilities of the neural network models.

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