

**INTEGRATED APPLICATION OF SEISMIC INVERSION AND ARTIFICIAL
NEURAL NETWORKS FOR RESERVOIR CHARACTERIZATION AND PROSPECT
DE-RISKING OF OA-FIELD**

BY

Adedolapo Ayomide OGUNSADE

(B.Tech FUTA. M.Sc. IFP SCHOOL, FRANCE, M.Sc. O.A.U)

(SCP11/12/H/3280)

**A THESIS SUBMITTED TO THE DEPARTMENT OF GEOLOGY, FACULTY OF
SCIENCE OBAFEMI AWOLOWO UNIVERSITY, ILE-IFE IN PARTIAL
FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF DOCTOR OF
PHILOSOPHY (Ph.D) IN APPLIED GEOPHYSICS**

2016

CERTIFICATION

This research work by Mr. OGUNSADE, Adedolapo Ayomide has been read and approved as meeting part of the requirement for the award of Ph.D. Applied Geophysics of Obafemi Awolowo University, Ile-Ife, Nigeria.

.....
Dr. A.A. Adepelumi
Supervisor

.....
Dr. S.A. Adekola
Chief Examiner

OBAFEMI AWOLOWO UNIVERSITY

ACKNOWLEDGEMENTS

My sincere gratitude goes to God Almighty who has made this work possible and granted me the strength and perseverance to complete it. I also appreciate my parents for their wonderful contributions and support in ensuring that this dream is fulfilled.

My thanks go to my supervisor, Dr. A.A. Adepelumi for his support throughout the duration of the program and for giving me this splendid opportunity to contribute to the body of knowledge. I salute you sir. I won't fail to mention Dr. O.A. Alao for helping me sustain my drive towards completing this work. Thank you so much for your great kindness and encouragement through the years. My appreciation goes to all the academic and non-academic staff of the Department of Geology, Obafemi Awolowo, University, Ile-Ife.

Special thanks to my colleagues in the academia and the industry for their assistance in one way or the other during the course of this work. I also acknowledge the Department of Petroleum Resources (DPR) for the provision of the data used for this study.

To my lovely wife, Mrs. Temidayo Ogunsade, I say thank you, God will bless and lift you up for showing me the love that surpasses every challenge and for standing by me through it all. To my son Adedayo, in some years to come, I will remind you of how you always wanted to help daddy type on the computer anytime you were with me while working. These are sweet memories I will cherish forever.

And lastly, to the One who has made everything good in His own time, I give all glory, adoration and praise. Amen

TABLE OF CONTENTS

TITLE PAGE	i
CERTIFICATION	ii
ACKNOWLEDGEMENTS	iii
TABLE OF CONTENTS	iv
LIST OF FIGURES	viii
LIST OF TABLES	xii
ABSTRACT	xiii
CHAPTER ONE: INTRODUCTION	1
1.1 Statement of the Problem	2
1.2 Objectives of the Research	3
1.3 Contribution to Knowledge	3
1.4 Research Materials and Location of the Field	4
1.5 Research Methodology	4
CHAPTER TWO: LITERATURE REVIEW	7

2.1	Geology of the Niger Delta	7
	2.1.1 Regional Stratigraphy and Structural Style	
7	2.1.1.1 Stratigraphy	
	9	
	2.1.1.2 Structural Styles	11
	2.1.2 Petroleum Systems of the Niger Delta	15
	2.1.3 Petroleum Potential of the Niger Delta	15
2.2	Seismology	17
	2.2.1 Principles of the Seismic Method	19
	2.2.1.1 Compressional Waves	20
	2.2.1.2 Shear Waves	23
	2.2.1.3 Surface Waves	23
	2.2.1.4 Rayleigh Waves	23
	2.2.1.5 Love Waves	23
	2.2.1.6 Acoustic Impedance (Z)	26
	2.2.1.7 Reflection Coefficient	26
	2.2.2 Seismic Data	28

2.2.2.1	Polarity and Phase of Seismic Data	31
2.2.2.2	Amplitude of Seismic Data	34
2.2.3	Seismic Tuning, Detection, and Resolution	34
2.2.4	Seismic Attributes	40
2.2.4.1	Treatise on Types of Seismic Attributes	42
2.3	Rock Physics: A Critical Tool for the Success of Seismic Inversion	45
2.3.1	Gassmann Fluid Substitution	46
2.3.2	Zoeppritz Equations	48
2.3.3	Bortfeld Approximation	51
2.3.4	Aki, Richards and Frasier Approximation	51
2.3.5	Shuey Approximation	52
2.3.6	Amplitude Variation with Offset/Angle (AVO/A)	53
2.3.6.1	Principles of Amplitude Variation with Offset	53
2.3.6.2	AVO Class Definition	54



2.3.6.3	Data Processing for AVO/AVA Analysis	58
2.3.6.4	Noise Attenuation	59
2.3.6.5	AVO Attributes Analysis	59
2.4	Seismic Inversion	62
2.4.1	Prestack Inversion Method	67
2.4.1.1	Tomography Travel time Inversion	68
2.4.1.2	AVO Inversion	68
2.4.1.3	Elastic-Impedance Inversion	69
2.4.1.4	Simultaneous Inversion	70
2.4.1.5	Waveform Inversion	71
2.4.2	Post-Stack Inversion Methods	72
2.4.2.1	Amplitude Inversion	73
2.4.3	Model Based Inversion	75
2.4.4	Stochastic (Geostatistical) Inversion	77

2.4.5	Use of Petroelastic Models for Inversion	79
2.5	Artificial Neural Networks	79
2.5.1	The Artificial Neuron	81
2.5.2	Characteristics of Artificial Neural Networks	89
2.5.3	Structure/Architecture of Neural Networks	89
2.5.3.1	Feed Forward Artificial Neural Networks	90
2.5.3.2	Feedback Artificial Neural Networks	93
2.5.4	Training of Artificial Neural Networks	96
2.5.5	Applications of Artificial Neural Networks	97
CHAPTER THREE: MATERIALS AND METHODS		101
3.1	Data Description	101
3.2	Research Methodology	101
3.2.1	Data Loading and QC	103



3.2.2	Well Log Interpretation	103
3.2.2.1	Lithology	104
3.2.2.2	Water Saturation	104
3.2.2.3	Porosity	106
3.2.3	Well-To-Seismic Tie	108
3.2.4	Seismic Data Interpretation	113
3.2.5	Derivation of Shear Velocity from Compressional Velocity	114
3.2.6	Building of the <i>A Priori</i> Model	114
3.2.7	Generation of Inversion Cubes and Attributes	115
3.2.8	Network Selection and Training	116
CHAPTER FOUR: RESULTS AND DISCUSSION		117
4.1	Identification of Reservoir Intervals	117
4.2	Well to Seismic Calibration	117
4.3	Seismic Data Interpretation	122
4.4	Building the <i>A Priori</i> Model for Inversion	128

4.5	Back propagation Neural Network Results	145
CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS		157
5.1	Conclusions	157
5.2	Recommendations	158
REFERENCES		159

OBAFEMI AWOLOWO UNIVERSITY

LIST OF FIGURES

Figure	Caption	Page
1.1:	Map showing the Location of the Study Area	6
2.1:	Niger Delta Morphology and the various Depobelts	8
2.2:	Stratigraphic Columns showing the Three Formations of the Niger Delta	10
2.3:	Regional Western Niger Delta Structure	12
2.4:	Examples of Niger Delta Oil Field Structures and Associated Trap Types	14
2.5:	Distribution of Oil Fields in the Niger Delta	16
2.6:	Reflection of a Seismic Wave Incident upon a Layer (Geological Boundary) having Constant Velocities	21
2.7:	A compressional wave travels through a medium by means of compression and dilation	22

2.8: A Shear Wave Travels through a Medium in a Perpendicular Direction to Particle Motion	24
2.9: Particle Motion for Surface Waves	25
2.10: Normal Incidence Coefficients of Reflection, RC, and Transmission, TC	27
2.11a: Actual and Assumed Raypaths from a Subsurface Horizon	29
2.11b: A Typical Convolutional Model illustrating how a Seismic Volume is derived	29
2.12: A Graphical Illustration of 2-D and 3-D Survey Acquisition Layout with respect to Surface and Subsurface Geology	30
2.13: Polarity of Seismic Data, (a) SEG Convention, (b) Reverse Polarity	32
2.14: Two Main Types of Wavelet Phase used in Seismic Reflection Method	33
2.15: Illustration of Seismic Tuning	35
2.16: Resolution depends on Wavelet Interference	37
2.17a: Fresnel Zone	39
2.17b: Comparison between High and Low Frequency Filtered by the Earth	39

2.18: Attributes Derivable from the Seismic Data	41
2.19: Reflections and Transmissions at a Single Interface between Two Elastic	
Half-Space Media for an Incident Plane P-wave	49
2.20: Illustration of Amplitude Variation with Offset and corresponding CMP gather	55
2.21: Zoeppritz P-wave Reflection coefficients for a shale – gas sand interface	56
2.22: AVO Responses for the Four Classes of Sand	57
2.23: Illustration of the Intercept - Gradient Method	61
2.24: Seismic Inversion Techniques	63
2.25: Illustration of the Seismic Inversion Technique	64
2.26: Basic Workflows employed in Forward and Inverse Modelling	65
2.27: Illustration showing the differences between Forward and Inversion Modelling	66
2.28: The Recursive Inversion Technique	74



2.29: The Philosophy of Sparse Spike Inversion Method	76
2.30: Flowchart for the Model-based Inversion Technique	78
2.31: Representation of a biological neuron	80
2.32: Illustration of a Typical Connection between Two Biological Neurons	82
2.33: Nonlinear Model of an Artificial Neuron	83
2.34(a): Threshold Function	86
2.34(b) Piecewise-Linear Function	86
2.34(c) Sigmoid Function for Varying Slope Parameter 'a'	86
2.35: Affine Transformation Produced by the Presence of a Bias	88
2.36: Single Layer Feed Forward Network	91
2.37: Feed forward Multi-Layer Perception with Two Hidden Layers	92
2.38: Calculations for each Layer of a Three-layer, One-middle Layer ANN	94

2.39: A Typical Example of a Recurrent Network with Hidden Neurons	95
3.1: Basemap of the Study Area	102
3.2: Typical Depths of Investigation of Different Logging Tools	109
3.3: Drift Correction of Sonic Logs Preparatory to Developing the Time-Depth Law	111
3.4: A Typical Well-seismic Calibration Panel	112
4.1: Well-OA showing RESV_A and RESV_B Reservoirs	118
4.2: Well-OA showing RESV_C and RESV_D Reservoirs	119
4.3: Well-OA showing the Full Stack of the Four Reservoirs	120
4.4: Drift Correction of Sonic Log using Checkshot Data	121
4.5: Extraction from Near Stack showing its Wavelet and the Frequency Spectrum	123
4.6: Well to Seismic Calibration Panel	124
4.7: Crossline 22245 showing Faults E, A, C, D and B	125
4.8: Crossline 22265 showing Faults E, C, D, F and B	126



4.9: Three Dimensional View of the Fault Interpretation in the “OA”-Field	127
4.10: Extraction from Mid Stack showing its Wavelet and the Frequency Spectrum	129
4.11: Extraction from Far Stack showing its Wavelet and the Frequency Spectrum	130
4.12(a): Well Data Crossplot of P-impedance vs. S-impedance	131
4.12(b): Well Data Crossplot of P-impedance vs Density	131
4.13: The a Priori P-impedance Section	133
4.14: The a Priori S-impedance Model	134
4.15: The a Priori Density Model	135
4.16: Inverted Pre-stack P-impedance Section	136
4.17: Inverted Density Section.	137
4.18: Inverted Vp/Vs Ratio Section	138
4.19: Residuals from the Inversion Process	139
4.20a: Inversion Analysis Crossplot of Inverted P-impedance vs Original Impedance	140
4.20b: Inversion Analysis Crossplot of Inverted Vp/Vs Ratio vs Inverted Impedance	140

4.21: Quality Check Plot of the Inverted Pre-stack Data	141
4.22: Comparison of the Original Seismic Section and the Inverted Impedance Section within the established Reservoir Intervals	143
4.23: Selected Inversion Section showing Impedance-supported Possible Exploration Prospects in the “OA”-Field	144
4.24: CDP showing Potential Targets within an Interval of 1750 Milliseconds to 2150 Milliseconds	146
4.25: Crossplot of “SoPhi” Attribute and Inverted P-impedance Attribute	147
4.26: Panel showing the Desired Output and the Input extracted from a Radius of 150 m around Well-OA	148
4.27: Input Parameters in the Multi-layer Feed forward Neural Network Scheme	149
4.28: Crossplot of the BPNN predicted “SoPhi” Attribute Correlates well with the desired SoPhi Attribute	150

4.29: Comparison of the Original “SoPhi” Log and the extracted “SoPhi” from the Final Integrated ANN-Inversion	152
4.30: Bright Amplitudes on an Inline Cross-section showing clearly Possible Hydrocarbon Bearing Reservoirs	153
4.31: Another ANN cross-section in the Crossline Direction	154
4.32: Possible Hydrocarbon bearing Zones can be clearly seen on the “SoPhi” attribute Section	155
4.33: Comparison of the Original Seismic, inverted P-impedance and ANN-derived “SoPhi” attribute at “OA”-well Location	156

LIST OF TABLES

Table	Caption	Pages
2.1	Seismic Attributes	43

OBAFEMI AWOLOWO UNIVERSITY

ABSTRACT

The study modified seismic inversion algorithm which incorporated artificial neural networks for reservoir characterization to pre-stack seismic data acquired in the “OA”-Field. The adopted workflow was used to transform the seismic data to acoustic impedance and petrophysical attribute “SoPhi”; considered to be a direct hydrocarbon indicator, in an integrated inversion scheme. This was with a view to characterizing “OA”-Field reservoirs, identifying the exploratory prospects and proposing possible development opportunities.

The data used for the study included pre-stack seismic substacks (near-, mid-, and far) and data for one well “OA” comprising gamma ray, resistivity, density, sonic, caliper, and neutron logs. Schlumberger’s Petrel and CGG Veritas’s Hampson Russell softwares were used for the analyses of the data. The hydrocarbon-bearing reservoirs were identified from the well logs using petrophysical parameters such as porosity, water saturation and the volume of shale. Well-to-Seismic calibration was used to tie the formation tops to seismic, thereafter, faults and horizons interpretation were carried out on the pre-stack seismic data. Wavelets were extracted from all the seismic substacks, while a priori impedance (Z_p , Z_s) and density models were generated from the P-impedance, computer S-impedance (using a modified form of Castagna’s equation) and density logs, within a time window that covered the full extent of all observed hydrocarbon bearing intervals. The pre-stack seismic inversion workflow was run on the initial model for the selected time window and was progressively iterated over 100 runs to minimize the residual difference between the inverted model and the original seismic data. The inversion results with other seismic attributes were then fed as input into a back propagation neural network (BPNN) algorithm which learned the relationship between the desired output and the

training data. This was then used to convert the original seismic data into a hydrocarbon presence indicator.

Four hydrocarbon bearing reservoirs (A, B, C and D) were delineated from the OA well log. Reservoirs A and B were oil bearing, C was gas and oil bearing while reservoir D was gas-filled. Average porosity progressively decreased from Reservoir A (23%) to the deepest Reservoir D (at 16%). Hydrocarbon saturations of the reservoirs A, B, C and D were 55%, 66%, 58% and 68% respectively. Six faults (A, B, C, D, E and F) and seven horizons (HOR A, B, C, D, E, F and G) were interpreted in the “OA”-Field. Horizons E and F defined the upper and lower boundaries of the interval of the seismic inversion. The pre-stack seismic inversion data showed that in the reservoirs already found by the OA well, the impedance attribute could be directly correlated to hydrocarbon presence as was the case in Reservoirs A, B and C that had thicknesses in excess of 190 feet. Integration of the parameters from the inversion with six other seismic attributes in a back propagation neural networks (BPNN) scheme resulted in the identification of five exploration prospects (A, B, C, D and E) with different characters. Prospects A and C were identified as flat spots; with very good hydrocarbons presence. Prospect E was a possible anticlinal structure which extended beyond the limits of the study area and would require additional data to completely evaluate its potential. Prospects B and D were stratigraphic targets which would require two wells to be drilled to rest them.

The study concluded that the integration of pre-stack seismic inversion and artificial neural networks enhanced the exploration potentials of the “OA”-Field in terms of prospect delineation which could eventually lead to identification of additional hydrocarbon reserves and resources.

CHAPTER ONE

INTRODUCTION

Seismic exploration methods have developed a steadily increasing power and complexity during the past 50 years and the use of seismic data has advanced greatly with improvement in technology over these years. A typical interpretation workflow today goes beyond using maps and sections with computerized visualization and display techniques. It is now common to apply techniques such as rock physics, amplitude versus offset (AVO) and seismic inversion to reservoir characterization. The ultimate goal is to reduce exploration and production risks and optimize the recoverable hydrocarbon volumes from producing oil and gas fields.

Reservoir characterization, in spite of all these advances in interpretation techniques remain an onerous task due to the fact heterogeneity is an inherent property of most reservoirs. Recreating these heterogeneities in the reservoirs as accurately as possible is therefore, of utmost importance as the results impact the simulation processes and history matching carried out by reservoir engineers and also the hydrocarbon reserves estimated for prospects and of course the economic viability of any exploration or development projects.

Seismic inversion is a technique used to extract quantitative information about reservoir rocks and fluid parameters from seismic data. It involves integration of both seismic data and well data, where well data may serve to add the low frequency component below the

seismic band and to constrain the inversion. While seismic migration is aimed at imaging the reflectors or the interfaces at their correct subsurface locations, seismic inversion attempts to estimate elastic and flow properties of the layers bounded by these interfaces. Seismic data are sensitive essentially to seismic wave velocity and density contrasts in the subsurface rocks. Compared to seismic amplitudes, inversions show higher resolution and support for more accurate interpretations. This, in turn facilitates better estimations of reservoir properties such as porosity and net pay (Pendrel, 2006). However, there is significant overlap in elastic properties among different rock types, thus, mapping of these elastic properties to rock types and estimating porosity are not trivial.

Neural networks, on the other hand, are adaptive statistical models based on an analogy with the structure of the brain. They are adaptive because they can learn to estimate the parameters of some population using a small number of exemplars (one or a few) at a time. They do not differ essentially from standard statistical models. An artificial network consists of a pool of simple processing units which communicate by sending signals to each other over a large number of weighted connections (Krose and Smagt, 1996). The ability of neural networks to learn and generalize in addition to their wide range of applicability makes them very powerful tools.

1.1 STATEMENT OF THE PROBLEM

Hydrocarbon exploration and production is a risky and capital intensive venture. As a result of this, several techniques of data mining and analysis are employed to increase the value derived from very expensive field data sets. Seismic inversion is one of such

techniques and has been used by several analysts in conjunction with soft computing techniques such as artificial neural networks to enhance seismic data analysis with the aim of associating subsurface rock properties with seismic amplitude response. However, most of the current workflows for integrated seismic inversion and neural networks application has so far succeeded in transforming originally acquired seismic data into impedance and porosity cubes. None of these methodologies has attempted to relate inversion results particularly from known hydrocarbon bearing zones to other areas of the field where only seismic data is available with no information about rock properties and hydrocarbon presence. This research will develop and optimize workflows that will result in a robust reservoir characterization scheme that will use artificial neural networks to learn the relationship between subsurface rock properties, inversion amplitude response and hydrocarbon presence in the “OA”-Field.

1.2 OBJECTIVES OF THE RESEARCH

The specific objectives of this research were to:

- i. interpret pre-stack 3-D seismic data to obtain two-way travel times for major horizons;**
- ii. analyze well data for petrophysical properties and establish relationships between these subsurface rock properties and the seismic data;**
- iii. carry out seismic inversion analysis for the “OA”-Field; and**
- iv. integrate results from (iii), with an artificial neural networks scheme to characterize hydrocarbon bearing reservoirs and prospects in the “OA”-Field.**

1.3 CONTRIBUTION TO KNOWLEDGE

This research takes to a new frontier, the level to which pre-stack seismic data and well logs can be used. Likewise, it establishes the important use of integrating seismic inversion with artificial neural networks in correlating known hydrocarbon response in already discovered hydrocarbon bearing reservoirs with other possible exploratory and infill targets. Finally, this work shows that it is feasible to identify transform a raw seismic data into a volume that can indicate hydrocarbon presence, even though well information might be sparse. Thus new prospects can be identified in areas where it otherwise would have been impossible, and the possibility of targeting multiple prospects with a single well helps to reduce the risks associated with drilling such multi-million dollar wells for exploration, appraisal and hydrocarbon field development purposes.

1.4 RESEARCH MATERIALS AND LOCATION OF THE FIELD

The data used to carry out this research comprised three-dimensional (3D) digital Pre-stack seismic volumes (Near-, Mid- and Far- substacks), a suite of well data comprising of gamma ray, resistivity, density, neutron, sonic logs and checkshot data for one well. Data for the study was sourced through my supervisor from the Department of Petroleum Resources. Data analysis was carried out by using Petrel (a Schlumberger software) for interpretation and Hampson-Russell software (provided to the Department of Geology Obafemi Awolowo University by CGG Veritas) for the inversion and neural network analysis. The field is an onshore oil acreage located in the Niger Delta Basin and has been renamed as the “OA”- Field for proprietary reasons (Figure 1.1). It covers an area of 318 sq.km.

1.5 RESEARCH METHODOLOGY

In order to achieve the objectives of this study, the following workflow was adopted:

- i. Petrophysical analysis of the well logs was done to determine the reservoir targets, and parameters such as volume of shale (V_{sh}), porosity (ϕ) and water saturation (S_w) were determined.
- ii. Well-to-Seismic calibration was done using the checkshot data to tie to formation tops to the seismic data.

The pre-stack 3D seismic data volume was interpreted for faults and horizon using the workstation based interpretation software, Petrel by Schlumberger. 3D subsurface