



**ARTIFICIAL INTELLIGENCE APPLICATIONS FOR
PORE PRESSURE AND FRACTURE PRESSURE
PREDICTION FROM SEISMIC ATTRIBUTES
ANALYSIS AND WELL LOGS DATA**

By

Mohamed Atta Farahat Mohamed

A Thesis Submitted to the
Faculty of Engineering at Cairo University
In Partial Fulfillment of the
Requirements for the Degree of
MASTER OF SCIENCE
In
Petroleum Engineering

FACULTY OF ENGINEERING, CAIRO UNIVERSITY
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Artificial Intelligence Applications for Pore Pressure and Fracture Pressure Prediction from Seismic Attributes Analysis and Well Logs Data

Keywords:

Pore Pressure, Fracture Pressure, Neural Network, Seismic Inversion, Seismic Attributes

Summary:

This study aims to investigate the pore and fracture pressure of sub-surface formations. Eaton's method is applied to predict pore and fracture pressure of wells. Inversion process with numerous algorithms are applied to seismic area of the field. Prediction methods are applied to investigate best attributes such as single, multiple seismic attribute analysis and neural network. Well logs and seismic attributes obtained from inversion process and seismic data are used to train ANN. ANN is validated using blind wells which are not included in training process. The correlations of ANN training and validation are good so ANN is applied for prediction of pore and fracture pressure for 3D seismic area of field.

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Dedication

This work is dedicated to
My father Mr. Atta and my mom, Mrs. H. Abdullah
For their love, understanding and support.
They are the reason why this is life. Love them dearly.

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Nomenclature

ENGLISH

AI	Acoustic Impedance
ANN	Artificial Neural Networks
Pp	Pore Pressure
Ph	Hydrostatic Pressure
Po	Overburden Pressure
Vp	Compressional Velocity
OBG	Overburden Gradient
Vml	Compressional Velocity in Mud Line
Pulo	PORE PRESSURE for UNLOADING
U	Uplift Parameter
V _{max}	Velocity at start of unloading
V _m	Sonic Interval velocity of shale
Vulo	Velocity of unloading
GR	Gamma Ray
GOR	Gas Oil Ratio
IGR	Index of Gamma Ray
I _p	P-impedance
MLFN	Multi-layer Feed Forward
PNN	Probabilistic Neural Network
RBF	Radial Basic Function
RC	Reflection Coefficient
SCF	Standard Cubic Foot
STB	Stock Tank Barrel
Sw	Water Saturation
TD	Total Depth
Vsh	Volume of Shale
Vp	P-wave Velocity
Ro	Observed Resistivity from log
S	Total Stress
F/D	Fracture Gradient
K	Stress Ratio
TVD	True Vertical Depth
MD	Measured Depth
Ft	Foot
ms	Millisecond
ppg	Pound per Gallon
R	Resistivity Value at Interested Depth

GREEK

σ_e	Effective Stress
σ_v	Vertical Stress
α	Biot Effective Stress Coefficient
σ_{max}	Effective Stress at Start of Unloading

ϕ	Porosity
ϕ_D	Porosity from Density log
ϕ_N	Porosity from Neutron log
$\mu\text{s/ft}$	Micro second / feet
ρ	Density
ρ_{ma}	Matrix Density
ρ_{obs}	Observed Density of Log
ρ_f	Fluid Density
Δt	Sonic Travel Time
τ	Tau Variable
μ	Poisson's ratio