



بسم الله الرحمن الرحيم

∞∞∞∞

تم رفع هذه الرسالة بواسطة / حسام الدين محمد مغربي

بقسم التوثيق الإلكتروني بمركز الشبكات وتكنولوجيا المعلومات دون أدنى

مسئولية عن محتوى هذه الرسالة.

ملاحظات : لا يوجد





APPLICATION OF NON-PARAMETRIC REGRESSION TECHNIQUES TO ESTIMATE THE RESERVOIR PERMEABILITY OF BAHARIYA FORMATION

By

Hesham Mokhtar Ali El Shahat

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
Giza, Egypt
2022

APPLICATION OF NON-PARAMETRIC REGRESSION TECHNIQUES TO ESTIMATE THE RESERVOIR PERMEABILITY OF BAHARIYA FORMATION

By

Hesham Mokhtar Ali El Shahat

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

Under the Supervision of

Prof. Dr. Mahmoud Abu El-Ela Prof. Dr. Ahmed Hamdy El-Banbi

.....
Professor of Petroleum Engineering
Faculty of Engineering, Cairo University

.....
Professor and Chair of Petroleum and Energy
Engineering Department
The American University in Cairo

Faculty of Engineering, Cairo University
Giza, Egypt
2022

APPLICATION OF NON-PARAMETRIC REGRESSION TECHNIQUES TO ESTIMATE THE RESERVOIR PERMEABILITY OF BAHARIYA FORMATION

By

Hesham Mokhtar Ali El Shahat

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

Approved by the Examining Committee

Prof. Dr. Mahmoud Abu El Ela Mohamed,

Thesis Main Advisor

Prof. Dr. Ahmed Hamdy El Banbi,

Advisor

- Professor of Petroleum Engineering (The American University in Cairo)

Prof. Dr. Khaled Ahmed Abdel-Fattah,

Internal Examiner

Eng. Nabil Abdel-Sadek Abdel-Aleem,

External Examiner

- Chairman of General Petroleum Company

Faculty of Engineering, Cairo University
Giza, Egypt
2022

Name: Hesham Mokhtar Ali El Shahat
Date of Birth: 25/09/1988
Nationality: Egyptian
E-mail: hesham.mokhtar@gpc.com.eg
Phone: +2 01210718755
Address: Nasr City, Cairo, Egypt
Registration Date: 01/03/2016
Awarding Date: / /2022
Degree: Master of Science
Department: Petroleum Engineering



Supervisors

Prof. Dr. Mahmoud Abu El-Ela
Prof. Dr. Ahmed Hamdy El-Banbi

Examiners

Prof. Dr. Mahmoud Abu El-Ela Mohamed (Thesis Main Advisor)
Prof. Dr. Ahmed Hamdy El-Banbi (Advisor)
- Professor of Petroleum Engineering (The American University in Cairo)
Prof. Dr. Khaled Ahmed Abdel-Fattah (Internal Examiner)
Eng. Nabil Abdel-Sadek Abdel-Aleem (External Examiner)
- Chairman of General Petroleum Company

Title of Thesis

Application of Non-Parametric Regression Techniques to Estimate the Reservoir Permeability of Bahariya Formation

Key Words

Alternating Conditional Expectation (ACE), Artificial Neural Networks (ANN), Bahariya Formation, Permeability Estimation, Western Desert of Egypt

Summary

The objective of this work is to introduce a systemic workflow for a regional understanding of Bahariya reservoir characteristics, identification of rock units, and reservoir permeability. Specifically, the Alternating Conditional Expectation (ACE) algorithm and the Artificial Neural Networks (ANN) were applied on well log data from about 100 cores covering the different geological and depositional features. This approach was applied to different testing wells addressing different geological and sedimentary features with variable log characteristics from the convention high-resistivity to low-contrast (LRLC) behaviors. The established permeability profiles exhibit high correlation coefficients for training and testing datasets. Additionally, it shows high accuracy that matches the field experience even with LRLC characteristics.

Disclaimer

I hereby declare that this thesis is my own original work and that no part of it has been submitted for a degree qualification at any other university or institute.

I further declare that I have appropriately acknowledged all sources used and have cited them in the references section.

Name: Hesham Mokhtar Ali El Shahat

Date: / /2022

Signature:

Dedication

To **my parents**, my wife, my beloved girls (*Shams* and *Lilian*),
my sisters (*Doaa* and *Abeer*), and my brother (*Ahmed*).

This modest work is a sign of my love to you!

Acknowledgments

First of all, I would like to express my endless thanks to **ALLAH** for giving me the ability to perform this research.

Secondly, I am extremely grateful to the supervisors of this thesis: **Prof. Dr. Mahmoud Abu El-Ela** and **Prof. Dr. Ahmed Hamdy El-Banbi**, for their helpful advices, sincere assistance, continuous guidance, and encouragement in creating this work. Simply, without their kind helps, this work would not come to light.

I would like also to direct my gratitude to the management of General Petroleum Company specially **Eng. Nabil Abd El-Sadek** (Chairman of the Board) for giving me the opportunity to work on this study, and providing the support to accomplish this work. Special thanks is sent to **Eng. Khaled Moafi** (Chairman and Managing Director of Petroleum Engineering - Khalda Petroleum Company) for his approval for core and well log data release. Meanwhile, I would like to send my gratitude to **Eng. Mohamed Gallab** (Reservoir Engineer - Khalda Petroleum Company) for his help during the phase of the data collection. Additionally, I am especially thankful to **Eng. Hesham Saied** (Reservoir Engineer - General Petroleum Company) for his technical support during this study.

Finally, words will not adequate to credit my parents the praise they deserve. Their encouragement did not diminish at any moment rather than during this research. Everything written here is owing to their powerful ability to strengthen my will at all times. In addition, my close friends have never let down at assisting me with everything from the technical information I needed to their encouragement messages.

Hesham Mokhtar Ali

Cairo, Egypt, 2022

Table of Contents

	Page
Acknowledgments	I
Dedication	II
Table of Contents	III
List of Tables	VI
List of Figures.....	VII
Nomenclature	XII
Abstract.....	XVI
Chapter 1: Introduction	1
Chapter 2: Literature Review.....	3
2.1. Introduction.....	3
2.2. Permeability Prediction Methods.....	3
2.3. Bahariya Formation.....	6
2.3.1. Production Contribution	7
2.3.2. Stratigraphical Settings	9
2.3.3. Depositional Settings	10
2.4. Lithofacies Identification.....	12
2.4.1. Hydraulic Flow Unit (HFU) Analysis.....	12
2.4.2. Flow Zone Indicator (FZI) Probability Plot.....	13
2.4.3. Ward's Algorithm	13
2.4.4. Winland's R35 Method.....	14
2.5. Data Mining Techniques	15
2.5.1. Definition of Data Mining	15
2.5.2. Applications of Data Mining in Petroleum Industry	17
2.6. The Non-Parametric Regression Techniques.....	22
2.7. Alternating Conditional Expectation (ACE)	24
2.7.1 Concept of the ACE Algorithm	24
2.7.2. Applications of the ACE Algorithm	26
2.8. Artificial Intelligence Techniques.....	29
2.9. Artificial Neural Networks (ANN)	31
2.9.1 Concept of the ANNs.....	31
2.9.2. Applications of the ANNs.....	33
2.10. Concluding Remarks	37

Chapter 3: Statement of the Problem, Objectives, and Methodology	39
3.1. Statement of the Problem.....	39
3.2. Objectives.....	40
3.3. Methodology	40
Chapter 4: Methodology Implementation	43
4.1. Introduction.....	43
4.2. Coring Datasets Preparation	43
4.2.1. Statistical Analysis of Core Data	44
4.2.2. Lithofacies Identification Techniques.....	49
4.2.2.1. Hydraulic Flow Unit (HFU) Analysis.....	49
4.2.2.2. Flow Zone Indicator (FZI) Probability Plot.....	50
4.2.2.3. Ward's Algorithm	50
4.2.2.4. Winland's R35 Method.....	50
4.3. Logging Datasets Classification.....	51
4.3.1. Logging Data Normalization	53
4.3.2. Electrofacies Identification Techniques.....	57
4.3.2.1 Principle Component Analysis (PCA)	58
4.3.2.2. Self-Organizing Map (SOM)	58
4.3.2.3. Linear Discriminant Analysis (LDA)	60
4.4. Coring and Logging Data Integration.....	60
4.5. Permeability Prediction Techniques	60
4.5.1 Alternating Conditional Expectation (ACE) Approach	60
4.5.1.1. Core-Log Depth Matching	61
4.5.1.2. Log Selection and Correlation	62
4.5.1.3. Data Transformation	64
4.5.1.4. Permeability Prediction.....	68
4.5.2. Artificial Neural Network (ANN) Model	70
4.5.2.1. ANN Model Design	70
4.5.2.2. ANN Model Training and Validation	71
4.5.3. Model Evaluation.....	82
Chapter 5: Results and Discussion	85
5.1. Introduction.....	85
5.2. Results of Lithofacies Identification.....	85
5.2.1. HFU Analysis Results.....	85
5.2.2. FZI Probability Plot Results.....	86
5.2.3. Ward's Algorithm Results.....	89
5.2.4 Winland's R35 Results	89

5.3. Results of Electrofacies Identification.....	90
5.3.1. PCA Results	90
5.3.2. SOM Results	95
5.3.3. LDA Results.....	99
5.4. Permeability Prediction Using ACE Algorithm.....	101
5.5. Permeability Prediction Using ANNs.....	105
5.6. Discussion.....	110
Chapter 6: Conclusions and Recommendations	115
6.1. Conclusions	115
6.2. Recommendations	116
References	117
Appendices	127
Appendix A: Artificial Intelligence Techniques	127
Appendix B: Calculation of Permeability by the ACE Algorithm	130

List of Tables

No.	Title	Page
2.1	Permeability prediction models (modified after Balan et al. 1995; Babadagli and Al-Salmi 2004)	5
2.2	Literature review of permeability prediction using the non-parametric transformation	28
2.3	Literature review of permeability prediction using the ANNs	35
4.1	Statistical analysis for the core data of BAH formation	44
4.2	Statistical analysis for the core data of UBAH formation	45
4.3	Statistical analysis for the core data of LBAH formation	45
4.4	Typical ranges of Winland's R35 values corresponding to different pore types	50
4.5	Network parameters applied using one hidden-layer structure network	74
4.6	Network parameters applied using two hidden-layer structure network	74
5.1	Basic parameters of the four rock units of BAH formation	88
5.2	Correlation Table of seven well log responses	91
5.3	Eigenvectors for seven log responses (RHOB, LLD, GR, LLS, MSFL, NPHI, and PEF)	92
5.4	Correlation Table of 8 log responses	93
5.5	Eigenvectors representing five log responses (RHOB, LLD, GR, NPHI, and PEF)	94
5.6	PCs of 3 log responses (GR, LLD, and NPHI)	95
5.7	PCs of 3 log responses (GR, LLD, and RHOB)	95
5.8	Variable ranking using 4 different well log responses (GR, RHOB, NPHI, and PEF)	96
5.9	Variable ranking using 3 log responses (GR, RHOB, and NPHI)	97
5.10	Variable statistics of the assigned four groups or rock units	98
5.11	Variable ranking for facies prediction using four log responses and core permeability	98
5.12	Accuracy of the developed ACE model against several prediction techniques	102
5.13	Accuracy of the developed ANN model against several prediction techniques	110
B.1	Calculation of the ACE-derived permeability	131

List of Figures

No.	Title	Page
2.1	Oil and gas concessions across the WD of Egypt (after Kitchka et al. 2015)	6
2.2	The generalized stratigraphic column of the WD (after Temraz et al. 2018)	7
2.3	Contribution of main producing areas to total crude oil production during September 2019 (after Hussein 2018)	8
2.4	Annual crude oil production by area during the period 2013-2018 (after Hussein 2018)	8
2.5	Contribution of main producing areas to Egypt's annual crude oil production during the period 2013-2018 (after Hussein 2018)	9
2.6	Depositional basins of the WD of Egypt (after Petroleum 2020)	10
2.7	Depositional environment of BAH formation (after Conway et al. 1988)	11
2.8a	Sequence of Ward's algorithm to cluster seven different points	14
2.8b	Sequence of Ward's algorithm to cluster seven different points (after Schlumberger 2015)	14
2.9	The concept of SOM artificial neural network classification procedure	17
2.10	Contributions of different AIPA techniques for E&P disciplines (after Shujath et al. 2013)	18
2.11	The SOM of 6 wells in Alfadl and Alqadr fields, Abu Gharadig Basin, Egypt (after El-Bendary et al. 2017)	19
2.12	Projection circle of GR, RHOB, and NPHI logs in BED field (top) and correlation table for 3 well each other's (after Mabrouk et al. 2017)	20
2.13	Variance and cumulative contribution of the principal components for well log data of three wells (after Sharma et al. 2011)	20
2.14	Scatter plot of petrophysical reservoir properties vs. the first 3 principal components for North Robertson Unit, west Texas (after Mathisen et al. 2001)	21
2.15	Results of LDA for well responses of 12 wells in Delaware Basin, West Texas, US	22
2.16	Parametric (a) vs. non-parametric (b) regression for a dataset of permeability vs. porosity and Uranium content	23

2.17	Predicted permeability profile using parametric (a) and non-parametric (b) regression for a dataset of permeability versus porosity and Uranium content	23
2.18	Measured vs. predicted permeability by ACE algorithm for three different wells at Salt Creek Field Unit	27
2.19	Measured against predicted permeability using electrofacies analysis and ACE algorithm (west Texas)	27
2.20	The unsupervised learning approach (after Bhattacharya 2021)	30
2.21	The supervised learning approach with three modeling stages (training, validation, and testing (after Bhattacharya 2021)	30
2.22	The biological perspective of neural networks (after Bhatt 2002)	31
2.23	Typical arrangement of an artificial neuron (after Pacheco and Vellasco 2009)	32
2.24	The simplest structure of a neural network with two hidden layers	33
2.25	ANN-predicted against measured permeability for Bangestan field, Iran (after Naeeni et al. 2010)	34
3.1	Block diagram of the study methodology	42
4.1	Locations of the cored wells (after Kitchka et al. 2015)	44
4.2	Histogram plot of core porosity with the corresponding statistical analysis	45
4.3	Histogram plot of core permeability with the corresponding statistical analysis	46
4.4	Histogram plot of measured grain density with the associated statistical analysis	46
4.5	Distribution of the core data throughout different rock unit of BAH formation	46
4.6	Distribution of the UBAH and LBAH formation within every rock unit	47
4.7	Log(k) vs. ϕ plot of the entire core samples available for BAH formation	48
4.8	k - ϕ cross-plot of available core samples for UBAH and LBAH separately	48
4.9	Well log correlation of three wells (samples) with the corresponding core data	51
4.10	Workflow of core and well log data integration	52
4.11	Box plot of GR log for three wells (samples from the data) before normalization	54
4.12	Multi-well histogram of GR log for three wells (samples from the data) before normalization	54

4.13	Box plot of GR log for three wells (samples from the data) after normalization	55
4.14	Multi-well histogram of GR log for three wells (samples from the data) after normalization	55
4.15	Multi-well histogram of GR log for 10 sample wells on BAH formation	56
4.16	Log correlation of BAH formation showing the spatial variations in log characteristics	57
4.17	Structure of a competitive learning ANN while SOM processing	59
4.18	Kohonen's topological SOM	59
4.19	Typical workflow of non-parametric transformation for permeability prediction by ACE algorithm	61
4.20	BAH formation core-log data depth matching (NPHI vs. ϕ_{core})	62
4.21	The relation between the correlation coefficient (R2) for the calculated permeability versus different combinations of log responses	63
4.22	Core permeability vs. GR log	63
4.23	Core permeability vs. LLD log	64
4.24	Core permeability vs. PEF log	64
4.25	Optimal transformation of GR log response generated using the ACE algorithm	65
4.26	Optimal transformation of RHOB log response	65
4.27	Optimal transformation of PEF log response	66
4.28	Optimal transformation of NPHI log response	66
4.29	Optimal transformation of LLD log response	67
4.30	Optimal transformation of LLS log response	67
4.31	Optimal transformation of permeability vs. the summation of the optimal transformations of log data	67
4.32	The ACE-predicted permeability from the optimal permeability transform (k)Tr	69
4.33	Workflow for the ANN modeling (after Beale et al. 2015)	71
4.34	Representation of TANSIG, LOGSIG, and PURELIN activation functions (after Beale et al. 2015)	72
4.35	Behavior of a MLP with (b) and without (a) over-fitting for mapping the function sine(x) (after Da Silva et al. 2017)	76
4.36	Relationship between the convergence error, model complexity, and stopping criterion of a MLP network (after El-Mabrouk 2012)	77
4.37	Neural network performance using 1,000,000 training cycles	78
4.38	Neural network performance using 1,000,000 training cycles	78
4.39	The workflow of the developed ANN model (after Chaki 2015)	79