UNIVERSITI PUTRA MALAYSIA

ANOPTIMIZEDENSEMBLEFOR PREDICTING RESERVOIR ROCK PROPERTIES IN PETROLEUM INDUSTRY

SEYED ALI JAFARI KENARI

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By

SEYED ALI JAFARI KENARI

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfillment of the Requirement for the Degree of Doctor of Philosophy

October 2013

DEDICATION

I would like to dedicate my thesis to

Spirit of my father

and

My dear mother

and

Mydear wife

and

My cute sons

Abstractof thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

AN OPTIMIZED ENSEMBLEFOR PREDICTING RESERVOIR ROCK PROPERTIES IN PETROLEUM INDUSTRY

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October 2013

Chairman: SyamsiahMashohor, PhD

Faculty: Engineering

The estimation of initial hydrocarbon in place before investing in development and production is the main objective in petroleum industry. Porosity, permeability and water saturation are the most important key variables to quantitatively describe petroleum reservoir. However, identification of these parameters which relies on core data analyses is expensive and time consuming. A lot of researches have been done to predict the reservoir parameters using well log data through applying various methods.

To predict theaforementioned parameters, we need a method with high accuracy, good generalization, fast and low in cost. In the present thesis, we proposed a new method named optimized ensembleto improve the prediction of these reservoirs parameters from well log data with the aid of available core data.
Ensemble is a learning algorithm that combines some experts instead of considering a single best expert for the predictions.The thesis proposed anoptimizing method leading to small structure of assemble GA.

After constructing suitable ensemble members, we need to combine them with a propermethod to improve the accuracy.So, we proposed two combining methods to improve the prediction accuracy while maintaining the generalization. The first method isbased on fuzzy genetic algorithm to overcome the premature convergence. The second method is based on two other functions instead of traditional fitness function in genetic algorithmnamely MSE to determine the individual's weight in an ensemble.This approach is based on Huber and Bisquare functions which are meant to avoid the influence of outliers that can be found in many real data such as geosciences data.

In the present thesis, we implemented our method for predicting these three most important reservoir parameters namely porosity, permeability and water saturation.The real field data is obtained from Iranian offshore and onshore oil fields. A total of 3695 data points from the 5 wells having conventional well log data and core data were used. Threeperformance measurements for analysing and comparing the predicted results and target values including correlation coefficient (R),Root Mean Squared Error (RMSE) and related RMSE were selected.

The results on pruning method show that the memory requirements for porosity, permeability and water saturation decreased to 68.75, 68.75 and 81.25 percent respectively.The results on pruned ensemble with FGA based weighted averaging also show that triple performance measure (RMSE, RRMSE, R/R^2) improved (9.95, 12.50, 1.16) percentfor porosity, (6.6, 16.21, 1.17) percentfor permeability and (37.56, 28.08, 1.52) percentfor water saturation in comparison to the whole ensemble.A comparison results between the Huber and MSE based GA show that that triple performance measure (RMSE, RRMSE, R^2) improved (17.3, 25.2, 1.0) percent for the permeability data set.

Abstraktesis yang dikemukakankepadaSenatUniversiti Putra Malaysia sebagaimemenuhikeperluanuntukijazah Master Sains

SATU KESATUAN YANG DIOPTIMUMKAN UNTUK MERAMAL SIFAT BATUAN TAKUNGAN DALAM INDUSTRI PETROLEUM

Oleh

SEYED ALI JAFARI KENARI

Oktober2013

Pengerusi: SyamsiahMashohor, PhD

Fakulti: Kejuruteraan

Anggaran awal hidrokarbon pada peringkat sebelum melabur dalam pembangunan dan pengeluaran merupakan objektif utama dalam industri petroleum. Keliangan, kebolehtelapan dan ketepuan air merupakan pembolehubah utama paling penting dalam menerangkan takungan petroleum secara kuantitatif. Walau bagaimanapun, mengenal pasti parameter ini yang bergantung kepada analisis data teras adalah mahal dan memakan masa. Banyak kajian telah dijalankan untuk menganggar parameter takungan dengan menggunakan log data telaga minyak menerusi pelbagai kaedah.

Untuk meramal parameter tersebut, kami memerlukan kaedah yang kukuh dengan ketepatan yang tinggi, generalisasi yang baik, cepat dan dengan kos yang rendah. Di dalam tesis ini, kami mencadangkan kaedah baru yang dinamakan *optimized ensemble* bagi menganggar parameter takungan ini daripada log data telaga minyak dengan bantuan data teras yang sedia ada.

*Ensemble*merupakan algoritma pembelajaran yang menggabungkan banyak kepakaran berbandinghanya mempertimbangkan satukepakaran tunggal yang terbaik untuk ramalan. Tesis ini mencadangkan kaedah paling optimum berdasarkan *genetic algorithm* yang dapat mengurangkan keperluan memori dan masa ramalanyang biasanya berlaku di dalam *ensemble* yang biasa.

Setelah mendapatkan ahli *ensemble*yang sesuai, kami perlu menggabungkannya dengan kaedah yang betul bagi meningkatkan ketepatan. Oleh itu, kami mencadangkan dua kaedah penggabungan untuk meningkatkan ketepatan ramalan disamping mengekalkan generalisasi. Kaedah yang pertama adalah berdasarkan *fuzzy genetic algorithm* untuk mengatasi penumpuan pramatang. Kaedah kedua ialah berdasarkan dua fungsi kukuh dan bukannya fungsi kecergasan tradisional dalam *genetic algorithm* untuk mengenalpasti berat individu dalam sesuatu *ensemble*.

Pendekatan adalah berdasarkan fungsi *Huber* dan *Bisquare* yang mana untuk mengelak pengaruh unsur luaran yang boleh didapati di pelbagai data sebenar seperti data geosains.

Di dalam tesis ini, kami mengaplikasikan kaedah kami untuk meramal tiga parameter takungan yang paling penting ini. Data sebenar diperoleh daripada medan minyak di luar pesisir dan di pantai Iran. Sebanyak 3695 titik data daripada 5 telaga minyak yang mempunyai log data telaga yang konvensional dan data teras telah digunakan. Tiga kaedah pengukuran untuk menganalisis dan membandingkan hasil ramalan dan data sasaran termasuk pekalikorelasi (R), Min Ralat Kuasa Dua (RMSE) dan RMSE yang berkaitan telah dipilih.

Hasil menunjukkan bahawa kaedah yang kami cadangkan ini memberikan pekali korelasi yang tertinggi dan RMSE dan RMSE berkaitan yang paling rendah berbanding dengan pakar tunggal dan menghasilkan ketepatan yang signifikan bagi ramalan-ramalan ini. Keputusan pada kaedah mencantas menunjukkan bahawa keperluan memori untuk keliangan, kebolehtelapan dan air tepu menurun kepada (68.75, 68.75 dan 81.25) peratus. Keputusan pada kaedah mencantas menunjukkan bahawa keperluan memori untuk keliangan, kebolehtelapan dan air tepu menurun kepada (68.75, 68.75 dan 81.25) peratus. Satu perbandingan keputusan antara Huber dan MSE berasaskan GA menunjukkan bahawa tiga ukuran prestasi (RMSE, RRMSE, R^2) bertambah baik kepada (17.3, 25.2, 1.0) peratus bagi kebolehtelapan set data.

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APPROVAL

I certify that an Examination Committee has met on 11 October 2013 to conduct the final examination of SEYED ALI JAFARI KENARI on his Doctor of Philosophythesis “AnOptimizedEnsembleforPredicting Reservoir Rock Properties in Petroleum Industry”in accordance with UniversitiPertanian Malaysia (Higher Degree) Act 1980 and UniversitiPertanian Malaysia (Higher Degree) Regulations 1981. The Committee recommends that the candidate be awarded the relevant degree.

Members of the Examination Committee are as follows:

Chairman, PhD
Assoc. Prof. Dr. SitiAslinaHussain
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Examiner 1, PhD
Assoc. Professor Dr. MdNasirSulaiman
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Internal Examiner)

Examiner 2, PhD
Dr. Wan Azizun Wan Adnan
Faculty of Engineering
Universiti Putra Malaysia
(Internal Examiner)

External Examiner, PhD
Prof. Dr. Bjorn Ursin
Department of Petroleum Engineering and Applied Geophysics
The Norwegian University of Science and Technology
(External Examiner)

Noritah Omar, PhD
Assoc. Prof. and Deputy Dean
School Of Graduate Studies
University Putra Malaysia

Date:

This thesis submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfillment of the requirement for the degree of Doctor of Philosophy.The members of the Supervisory Committee are as follows:

SyamsiahMashohor, PhD
Senior Lecturer
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Abd.RahmanRamli, PhD
AssociateProfessor
Faculty of Engineering
Universiti Putra Malaysia
(Member)

MohdHamiruceMarhaban, PhD
AssociateProfessor
Faculty of Engineering
Universiti Putra Malaysia
(Member)

BUJANG BIN KIM HUAT, PHD
Professor and Dean
School Of Graduate Studies
Universiti Putra Malaysia

Date:

DECLARATION

I hereby declare that the thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UniversitiPutra Malaysia or other institutions.

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SEYED ALI JAFARI KENARI

Date: 11 October 2013

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
BFG	Broyden-Fletcher-Goldfarb-Shanno Quasi-Newton
BR	Bayesian Regularization
CANFIS	Coactive Neuro-Fuzzy Inference System
CGB	Conjugate Gradient With Powell-Beale Restarts
CGF	Conjugate Gradient With Fletcher-Reeves Updates
CGP	Conjugate Gradient With Polak-Ribiere Updates
CM	Committee Machine
DHC	Directed Hill Climbing
DIVACE	Diverse and Accurate Ensemble
DT	Sonic Logs
FCM	Fuzzy C Mean
FGA	Fuzzy Genetic Algorithm
FIS	Fuzzy Inference System
FL	Fuzzy Logic
GA	Genetic Algorithm
GASEN	Genetic Algorithm Based Selective Ensemble
GD	Gradient Descent
GDA	Gradient Descent With Adaptive Learning Rate
GDX	Gradient Descent With Momentum &Adaptive Learning Rate
GR	Gamma Ray
LM	LevenbergMarquardt
LS	Least Square Error
LWD	Logging While Drilling
ME	Mixture Of Experts
MF	Membership Function
MSE	Mean Square Error
NF	Neuro-Fuzzy
NPHI	Neutron Log

OSS	One Step Secant
RHOB	Density Log
RP	Resilient Back Propagation
SCG	Scaled Conjugate Gradient
SDP	Semi Definite Programming
SP	Spontaneous Potential

CHAPTER 1

INTRODUCTION

1.1 Background

Reliable predictions of reservoir rock properties such as porosity, permeability and water saturation are very important in the evaluation of hydrocarbon accumulations in a petroleum reservoir. Porosity is described as the ratio (usually expressed as a percentage) of the aggregate volume of all pores or interstices in a rock over its total volume. Porosity can be split into two sections named connected and unconnected porosity. The connected porosity means that the fluids can flow into the rock, whereas in unconnected porosity the fluids cannot flow. Permeability is another most important parameter for the petroleum reservoirs evaluation. It is defined as the capacity of a rock or other porous media for transmission of the fluid. The standard unit for permeability is Darcy (D). Depending on the available data, permeability can be determined by three methods including: well test and core analysis in laboratory, and well logging data. Fluid saturation is defined as the fraction of pore space which is filled with fluid (oil, water or gas). Therefore, water saturation means the fraction of this space filled by water which is between 0 and 1.

Core analysis data, may not be possible for all boreholes, and in many soft and friable rocks is only feasible in a few intervals of the borehole. The well testing also provides some information to determine average permeability, thickness, initial pressure and etc. However, both well test and core analysis methods are expensive to obtain and takea lot of time to be implemented. The estimation of some reservoir characterizations can be done by using well log data anda limited number of core data. During all phases of a well development, well logging has been done for almost all wells. Many investigations have been conducted to predict reservoir parameters such as porosity, permeability and water saturation using well log dataand a limited core data. Nowadays, there are various types of logging tools to serve the variety of information that we need. Some of the most important well logging tools are Spontaneous Potential (SP), Resistivity Log (HLLD, HLLS), Sonic Logs (DT), Gamma Ray Log (GR), Neutron Log (NPHI), Density Log (RHO), Caliper log(Cali x) and Nuclear Magnetic Resonance (NMR) Logging.Several techniques have been used to infer reservoir properties from well logging data including empiricalformula, proper cross plot, and a wide range of Artificial Intelligence (AI) techniques.

1.2 Problem Statement

One of the most important objectives in the petroleum industry is to obtain an accurate estimation of the hydrocarbon in place before the exploration or production stages. Accurate determination of reservoir characterizations such as porosity,permeability and saturation are very helpful for evaluating and designing any development plan for production of the field. However, despite its importance, estimating such parameters through the reservoir is not a trivial task and is normally obtained by core analysis and well test methods, which are costly and time-consuming tasks. Almost all of the methods utilized for predicting reservoir rock properties are still not sufficiently reliable when working with the real noisy data from petroleum industry. Therefore,it is significantand beneficial to propose an accurate method for predicting reservoir properties based on well log data (which are available in all of the wells) in petroleum industry.Hence, a study to utilize acollection of different machine learning techniquesso that the method is capable to predict reservoir parameters with an improved accuracy rather than the single expert alone should be made.

The firstlimitation of the existing methods that estimate the petrophysical properties based on ensemblemethod is that the individual members are selected only based on their accuracy level.It means theydidn't pay any attention to diversity that is important issue in ensemble. The academic and experimental study in ensemble methods significantly shows that this machine learning technique will be effective if their members are both diverse and accurate.The second drawback is that genetic algorithm is often used combining method to determine the weights of each individualmember in reservoir prediction research. Premature convergence is one of the main limitations of Genetic Algorithm (GA)which means the sampling process converges on a local optimum rather than the global.

Ensemble pruning is a very important additional stage in designing an ensemble because of its capability to overcome the disadvantages of this machine learning technique. The related limitations are:occupying extra memory, necessitating computational overhead and sometimes decreasing effectiveness. The overall performance of anensemble may also create negative effects due to the existence of some experts with low predictive performance.Therefore, the purpose of this stage is finding an optimum subset of individual members that performs as well as, or better than, the original ensemble.In an ensemble, it is expected that differentmembers converge to differentlocal minima on the error surface with the aim of improving performance. Hence, further research on finding an optimal subset of individuals byensemble pruning to achieve accuracy and diversity has to be made.

Many researches have been conducted to find combining methods to combine the output of the experts and produce the final outputs. Some of them are: simple averaging, weighted averaging and majority voting. The most significant method for calculating the weight of each expert in regression or approximation function is based on GA.

Another problem todetermine the weight of each individual member is utilizing Mean Square Error (MSE) or Least Square Error (LS) as fitness function in genetic algorithm. Unfortunately, this popular objective function can perform badly when the error distribution is not normal. Therefore, a study toovercome this limitation has to be made.

1.3 Research Aim and Objectives

This thesis intends to propose anoptimized ensemble method to improve the prediction accuracy of the reservoir rock parameters such as porosity, permeability and water saturation by utilizing the well log data which are available from most wells in the field and a limited core data. Thedetailed objectives are as follows:

a) To propose a genetic algorithm method for ensemble pruning based on semi definite programming problem to improve the generalization, fast and low in cost in comparison to the whole ensemble.

b) To propose a combining method based on fuzzy genetic algorithm to overcome the premature convergence and implement it for improving the prediction of reservoir parameters.

c) To propose a genetic algorithm based combining method by using Huber and Bisquare as the fitness function instead of MSE to overcome the effect of outliers.

1.4 Scope of Study

The data samples includingthe training and test data are collected from Iranian Oil Company located at Iranianoffshore and onshore fields.The inputs data were the conventional well log data and the target data was core data..

Only three of the most significant parameters in reservoir rock properties namely porosity, permeability and water saturation are considered in this work due to their important rules to evaluate the hydrocarbon production potential.Thismethodalso can be employedto estimatesome other reservoir parameters in petroleum industry.

The implementation is done by using the Matlab's software for analyzing the data.

1.5 Contribution of Thesis

In this thesis we introduced few frequently used AI techniques to predict reservoir rock properties. In addition, we proposed a novel structure in machine learning techniques that can handle many real data in petroleum industry, based on regression and function approximation problems.

There are some reasons to distribute learning task among a number of individual nets. The main reason is for improving the generalization ability, because the generalization of individual networks is not unique. There are many methods to create individual members for ensemble or committee machine in literature. Some of them are Bootstrap aggregation resampling (Bagging), Cross-Validation, Stacking, boosting by filtering, AdaBoost, Artificial Neural Network (ANN), Fuzzy Logic (FL) and Neural Fuzzy (NF). The ensembles made by existing methods are sometimes needlessly large and have some drawbacks such as: occupying extra memory, necessitating computational overhead and sometimes decreasing effectiveness. In anensemble, there are also some members with low predictive performance that create negative effect on overall performance. Pruning ensemble members, while preserving a high diversity among the individuals is an efficient technique for increasing the predictive performance. In fact,the ensemble pruning is similar to an optimization problem, in which the objective is to find the optimal subset of the whole individual members belonging to the initial ensemble.

After building ensemble members, their generated results will be combined by some methods. In anensemble, the expectation is that distinct experts converge to differentlocal minima on the error surface, and the overall output will improve the performance. Many investigations have been performed to find more suitable fusion methods to combine the output of the experts and produce the final outputs. Some of the fusion methods in regression problems are simple averaging, weighted averaging and majority voting.

Thecontribution of this research is to propose a novel structure named optimized ensemble based on different learning algorithms.In the first step, accurate and diverse experts are selected based on proposed ensemble pruning method. In second step, two combining methods based on FGA and also GA with two other fitness functions instead of MSE are proposed to obtain the optimum weight of each individual members.

1.6 Outline of Thesis

The organization of the remaining chapters of this thesis is as follows:Chapter 2 is divided in three parts. First part gives an introduction to ensemble methods and describes why these machine learning paradigms are useful. The second part is a brief description of petroleum reservoir, the tools and methods for calculating well log and core data. This part continues with a review of related works that have been carried outto estimate reservoir rock properties based on well logging data throughapplying various AI methods. Finally a few more useful performances metric for regression problem will be described.

Chapter 3 is concerned with the methodology used for this study. In this chapter, firstthe ensembleconstruction using artificial neural network, fuzzy logic, and neural fuzzy are explained. Then,the proposed ensemble pruning method based on genetic algorithmwith pay attention to both accuracy and diversity to obtain an optimal subset of individualsintroduced. Finally, the chapter ended with introducing two proposed combining methods that are based on fuzzy genetic algorithm and two fitness functions (e.g. Huber and Bisquare).

Chapter 4 presentsand discusses the results obtained through utilizing individual members,ensemble with the whole and pruned individual members. In the next stage, the results obtained by pruned ensemble based on genetic algorithm and fuzzy genetic algorithm will be compared. Finally, the performances of pruned ensemblewith genetic algorithm based weighted averaging through applying proposed and usual fitness function are compared.

Finally, chapter 5 summarizes and discusses the implementation and performance of the proposed approach to predict three selected parameters in petroleum reservoir; and recommendssome measures to be taken for improvementof the future work in this field.

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