ABSTRACT BOOK

INTERNATIONAL CONFERENCE ON OIL AND GAS INDUSTRY, TECHNOLOGIES AND APPLICATIONS 2022

"Current and Emerging Trends in Oil and Gas Industry Technologies and Applications"

Virtual Event
14 - 15 Sept 2022

ORGANIZER

UMS
UNIVERSITI MALAYSIA SABAH

OIL AND GAS ENGINEERING PROGRAMME
FACULTY OF ENGINEERING

THE SECOND INTERNATIONAL CONFERENCE ON OIL AND GAS INDUSTRY, TECHNOLOGIES AND APPLICATIONS (ICOG-ITA 2022)

ABSTRACT BOOK

ORGANIZED BY

OIL AND GAS ENGINEERING PROGRAMME

FACULTY OF ENGINEERING

UNIVERSITI MALAYSIA SABAH

CONFERENCE ORGANIZING AND SCIENTIFIC COMMITTEE

Advisors

YBhg. Associate Professor Dr. Raman Noordin
Acting Vice Chancellor, Universiti Malaysia Sabah, Malaysia

Associate Professor Ts. Dr. Ismail Saad
Dean of Faculty of Engineering, Universiti Malaysia Sabah, Malaysia

Conference Chair

Professor Ir. Ts. Dr. Zainal Zakaria

Vice Chair

Dr. Emma Suali
Dr. Norfazliana Abdullah

Secretariat & Co-Secretariat

Dr. Mohd Syazwan Mohd Musa (Chief)
Ms. Wann Mas Anum Mohd Yakub
Mr. Muhamad Afif Naqiudien Aladin
Ms. Carla Goncalves De Oliveira Sarmento

Technical

Ms. Zykamilia Kamin (Chief)
Mr. Mohd Hardyianto Vai Bahrun

Promotion & Publicity

Dr. Chiam Chel Ken (Chief)
Mrs. Hafeza Abu Bakar

Protocol & Event

Ts. Dr. Lim Kit Guan (Chief)
Dr. Fiona Ling Wang Ming
Mr. Mohd Afif Naqiudien Aladin

Treasurer & Co-Treasurer

Dr. Mohd Syahlan Mohd Syukri (Chief)
Dr. Helen Chuo Sin Ee
Representative of UMS Bursar

Publication

Dr. Norsuhadat Nordin (Chief)
Dr. Emma Suali
Dr. Norfazliana Abdullah
Ts. Dr. Norzilawati Mohamad

Website & IT

Ts. Dr. Norzilawati Mohamad (Chief)
Mr. Mohd Hardyianto Vai Bahrun

Registration

Dr. Wan Mohd Shaharizuan Mat Latif (Chief)
Ms. Elysandra Peter

Scientific Committee

Professor Dr. Md. Mizanur Rahman (World University of Bangladesh, Bangladesh)

Professor Dr. Rajesh @ Rajasekaran Nithyanandam (Sri Venkateswara College of Engineering, India)

Dr. Mohd Shahrizan Moslan (Universiti Teknologi MARA, Malaysia)

Dr. Syafikah Huda Paiman (Universiti Teknologi Malaysia, Malaysia)

Dr. Nabilah Zaini (Malaysia-Japan International Institute of Technology, Malaysia)

Dr. Emma Suali (Universiti Malaysia Sabah, Malaysia)

Dr. Norfazliana Abdullah (Universiti Malaysia Sabah, Malaysia)

Dr. Chiam Chel Ken (Universiti Malaysia Sabah, Malaysia)

Ts. Dr. Norzilawati Mohamad (Universiti Malaysia Sabah, Malaysia)

Dr. Norsuhadat Nordin (Universiti Malaysia Sabah, Malaysia)

Dr. Mohd Ridhwan Adam (Universiti Sains Malaysia, Malaysia)

ABOUT THE CONFERENCE

The Second International Conference on Oil and Gas Industry, Technologies and Application 2022 (ICOG-ITA2022) is a virtual conference to be held on 14th – 15th September 2022, hosted from Kota Kinabalu, Sabah, Malaysia.

This conference is organized by the Oil and Gas Engineering Programme, Universiti Malaysia Sabah, with the theme of "Current and Emerging Trends in Oil and Gas Industry Technologies and Applications".

ICOG-ITA2022 act as a platform to spur and strengthen the bonding between the oil and gas players, which include the oil and gas companies, industries, technology expert, as well as policymakers to harmonize the way forward for the oil and gas industry in the future.

This conference is also in line with the avenue of the post COVID-19 pandemic, innovative strategies, and best practices to catalyze the exponential growth in moving forward in propagating the technologies and applications with emphasis on the oil and gas arena.

The conference will focus on the keynote addresses, paper presentation, and discussions on the key area of technologies and applications, which impelling sustainability and industrial revolution 4.0 (IR4.0) technologies in the oil and gas industry and other relevant key areas. This is critical to stay relevant in this challenging and competitive climate of the oil and gas landscape.

The Organizing Committee invites technical papers on substantial, original, and unpublished research in the areas relevant to the oil and gas. ICOG-ITA2022 welcomes contributions in the following areas but not limited to:

- Enhanced oil recovery
- Flow assurance (Drag reduction)
- Advanced materials/nanomaterials
- Environment
- Nanotechnology
- Simulation in oil and gas
- Oil and gas applications
- Safety (Oil and gas leak detection)

- Fluid dynamic
- Energy application
- Polymer
- Control and intelligent system
- Renewable energy (Bioenergy)
- Membrane application in oil and gas
- Sustainability in oil and gas
- IR4.0 in oil and gas

We hope the participants of this conference will find something interesting, useful, and informative and inspire them for more advanced and innovative research on the current trend in this field.

CONTENTS

CONFERENCE ORGANIZING AND SCIENTIFIC COMMITTEE **i**

ABOUT THE CONFERENCE **iii**

CONTENTS **v**

SESSION A: ENHANCED OIL RECOVERY **1**

ICOG-ITA125 1

ICOG-ITA135 2

ICOG-ITA143 3

ICOG-ITA145 4

ICOG-ITA146 5

SESSION B: APPLICATION OF MACHINE LEARNING **6**

ICOG-ITA127 6

ICOG-ITA129 7

ICOG-ITA136 8

ICOG-ITA137 9

ICOG-ITA138 10

ICOG-ITA151 11

SESSION C: ADVANCED MATERIALS **12**

ICOG-ITA124 12

ICOG-ITA131 13

ICOG-ITA147 14

ICOG-ITA148 15

ICOG-ITA149 16

ICOG-ITA150 17

SESSION D: SEPARATION TECHNOLOGY/BIOENERGY/STRUCTURE **18**

ICOG-ITA126 18

ICOG-ITA140 19

ICOG-ITA142 20

ICOG-ITA152 21

ICOG-ITA153 22

SESSION E: MODELLING AND SIMULATION/FLUID DYNAMICS 23

ICOG-ITA121 23

ICOG-ITA122 24

ICOG-ITA139 25

ICOG-ITA141 26

ACKNOWLEDGMENTS 277

APPLICATION OF MACHINE LEARNING

ICOG-ITA138

Using Artificial Neural Network to Evaluate the Performance of Cyclic Steam Stimulation on Recovering Crude Oil

Ade Junastri, Fiki Hidayat*

Department of Petroleum Engineering, Universitas Islam Riau, Jl. Kaharuddin Nasution No 113, Pemberhentian Marpoyan, Pekanbaru 28284, Indonesia

*Corresponding author. E-mail: fikihidayat@eng.uir.ac.id

Abstract

Currently, more and more heavy crude oil reserves are found, so it is necessary to apply enhanced oil recovery (EOR) technology which is considered effective in increasing oil recovery. Cyclic Steam Stimulation (CSS) method is a thermal EOR method with a mechanism that goes through the steam injection, immersion, and oil production cycle. Therefore, it is necessary to conduct research on the performance of the cyclic steam stimulation parameter to increase oil recovery. Analysis of the performance of the cyclic steam stimulation parameter on the increase in oil recovery in this study was carried out by simulation research using CMG-STARTS software and Python. The aim is to investigate the performance of cyclic steam stimulation to increase oil recovery from several operational parameters tested, namely injection volume, steam quality, injection rate, soaking time, injection temperature, and injection pressure. This ANN method is a deep learning method from input data and produces output data. By using 516 data ratio 80% of the RF and SOR calculation model results from CMG software for training data and 20% of the model results for testing. To get prediction results using the ANN method optimally, trial and error will be carried out on the number of hidden layer nodes. The optimal and stable hidden layer nodes are obtained at nodes 14 with a value of R2 train 0.9976 and R2 test 0.9882. RMSE train 0.0501 and RMSE test 0.1126 and MAPE train 0.1767 and MAPE test 0.2697. It can be concluded in this study that using ANN in RF and SOR prediction using 14 nodes hidden layer proved to be very good and successful.

Keywords: *Cyclic steam stimulation, CMG-STARS, Python, artificial neural networks*

1. Introduction

Currently, world oil production comes from old wells. To Increase oil recovery from old wells, one of the problems in the implementation of the oil and gas industry. Cyclic steam stimulation referred to as the steam soaking or huff and puff method, was discovered incidentally in Venezuela in 1959, by one of steam injector wells being flowed back to release reservoir pressure(Trebolle et al., 1993). The cyclic steam stimulation project started decades ago in several different reservoir conditions such as Tar sand, Heavy oil and light oil (Hidayat & Abdurrahman, 2018). It is estimated that the world total heavy oil reserves are around 3,396 billions barrels, there are about 30 billions barrels of prospective heavy oil reserves that have not been discovered (Suranto et al., 2016). Cyclic steam stimulation is a thermal method by injecting steam using one well that functions as an injection well production well.

There are also stages of cyclic steam stimulation as follows:

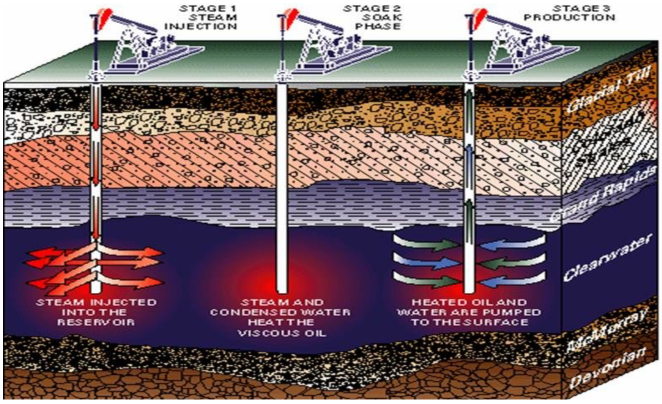

Figure 1. Process stage cyclic steam stimulation (Stark, 2011)

1) Injection Stage, this injection stage is the first stage where the CSS cyclic operates. Which steam is injected into the production well to introduce the characteristic of the steam to the reservoir. At the increase in temperature is inversely proportional to the viscosity to the oil.
2) Soaking stage, in the soaking stage the well is closed for a few days in order to get the heat spread in the reservoir.
3) Production stage, the production stage is the last phase in the CSS cycle after closing a short period of soaking duration. With steam injection much that heated, and temperature greatly affects the initial oil rate which will increase

Gu et al. (2015) present the modelling of heat in the wellbore efficiency and performance of the steam injection. In this study, a comprehensive mathematical model the efficiency of the wellbore heat and analyse the performance of the steam injection for heavy oil recovery. The result is to increase the heat efficiency in the wellbore by increasing the wellhead injection the wellhead injection rate of steam quality.

Artificial Neural Network is a parallel distributed information processing model that can recognize very complex patterns in the available data. The AAN design that produces the best blind test performance will be selected as the optimized ANN model. Parallel computing technique is used to train and test. Multiple AAN designs synchronously to increase workflow execution speed (Sun & Ertekin, 2015). Back-Propagation is one of the learning algorithms in ANN. This algorithm has 2 calculation stages, namely forward calculations which are carried out to calculate the error between the ANN output and the desired target (Ervina et al., 2018). The Back Propagation Algorithm architecture consists of 3 layers, namely, input layer, hidden layer, and output layer. At the input layer there is no computational process, only sending the input signal to the hidden layer. In the hidden and output layers, there is a computation process on the weights and biases, and the magnitude of the output from the hidden and out layers is calculated based on the activation function. In this back propagation algorithm, a binary sigmoid activation function is used, because the expected output is between 0 to 1 (Kholis, 2015).

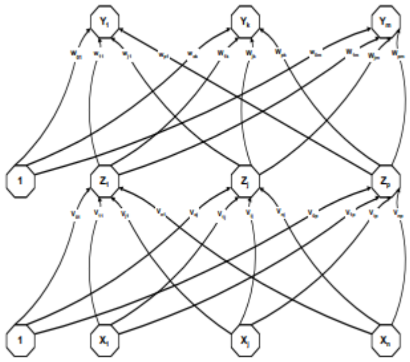

Figure 2 Back Propagation ANN Architecture (Kholis, 2015)

In a study (Ersahin & Tpao, 2019) to study CSI in heavy oil reservoirs, 3 expert systems were developed naturally. The ANN model managed to produce a good level of accuracy in seconds. The trial-and-error method should be used for this process. Applying parallel training algorithms to data sets is an important step to save time. Artificial Neural Network (ANN) works well to solve and classify non-linear relationships between input and output parameters.

2. Methodology

To the best of our knowledge, to investigate the performance of cyclic steam stimulation on the recovery factor. Therefore, in this study 516 experimental designs were made using CMOST from CMG to meet the dataset requirements to be analysed by machine learning algorithm Artificial neural network Back Propagation random.

2.1 Simulation data and design experiment

there is also the property data used in making the reservoir model of this research sourced from (Suranto et al., 2016)

a) Rock properties

Table 1. rock properties

No	Parameter	Unit	Value
1.	Oil Density	°API	12,4
2.	Oil Viscosity	Cp	320
3.	Formation volume factor	bbl/STB	1.02
4.	Steam Quality	-	0,9
5.	Porosity	%	0.34

b) Reservoir model

This study is conducted using a conceptual reservoir model (Figure 3) with the characteristic of model can be seen in (table 2)

Table 2. data characteristics of the reservoir model

Simulator	CMG STARS
Grid Type	*Cartesian*
Grid System	20 x 20 x 5
Grid Thickness	15 ft
Layer	5
Water Saturation	0.5
Reservoir Depth	100 ft
Soi	0.8
Permeability	1500

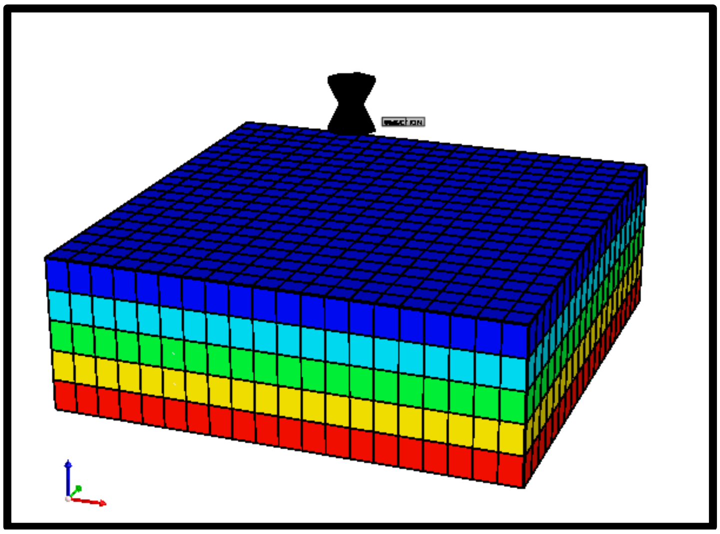

Figure 3. Reservoir model

2.2 Parameters tested

Parameters tested in this study were Soaking Time, Injection Temperature, Injection Rate, Steam Quality, Injection Volume, Injection Time, and Injection Pressure. This parameter is obtained from reliable sources who have previously discussed the cyclic steam stimulation method.

Table 3. Parameter Setting on CMG CMOST

No	Name	Data Range Settings	Default Value	Source
1	InjectorPinjw	Lower Limit: 270 and Upper Limit: 450	360.0	Continuous Real
2	InjectorQual	Real Value: 0.7,0.8,0.9 and Prior: 1	0.9	Discrete Real
3	InjectorStw	Lower Limit: 750 and Upper Limit: 1250	1000.0	Continuous Real
4	InjectorTinjw	Lower Limit: 315 and Upper Limit : 525	420.0	Continuous Real
5	Injector_Time	Real Value : 710,720,730 and Prior : 1	730	Discrete Real
6	Soaking_Time	Real Value : 8, 9, 10 and Prior : 1	10	Discrete Real
7	InjectorVol	InjectorVol = Injector_Time*InjectorStw	730000	Formula

In table 3 by using the 7 operation parameters, a random sample is formed for each parameter as shown in (Table 3). then a random sample is formed according to the lowest and highest limits of the predetermined standard so that 516 Design of Experiment (DoE) are accessed via CMOST from the Computer Modelling Group (CMG).

2.3 Artificial Neural Network Modelling

After running the input data according to a predetermined range using CMG CMOST, then 516 Design of Experiment (DoE) are obtained which will be used to build an artificial neural network model using the Anaconda Navigator 3.0 simulator with the Python programming language.

Of the 516 DoE, 80% of the data or 416 data will be used for training and 20% of the data or 100 data for testing and validating the accuracy of the model. In this study, starting from 1 node to 14 nodes in the hidden layer. In this study, the algorithm used is backpropagation and uses a bipolar sigmoid activation function with a range of (-1.1).

3. Result and discussion

In this study, predictions of the parameters that affect the increase in oil recovery (recovery factor & steam oil ratio) in the cyclic steam stimulation process using ANN Back Propagation (BP). The application of ANN in this study aims to strengthen the value of recovery factor & steam oil ratio to the parameters of cyclic steam stimulation injection in heavy oil type oil wells using the CMG reservoir simulation application. In this study using back propagation programming using Anaconda Navigator 3.0 software with Python programming language. Python is a high-level programming language that is widely used today. The application of Artificial Neural Network-Back Propagation consists of 2 stages, namely the first training (Training) where at this stage a number of target data training data are given and the second stage is testing (Testing) (Siregar & Wanto, 2017).

3.1 analysis of artificial neural network modelling results

As for how the Min-Max Normalization works with a range of 0 and 1. Then to get a good Artificial Neural Network model, optimization must be done using the trial-and-error method. It aims to make it easier to determine the number of nodes in the hidden layer to be able to obtain the optimal number of nodes in the hidden layer. In this research, the number of hidden layers is 1,2,3,4,5,6,7,8,9,10,11,12,13 and 14 nodes. The following are the results of each trial and error.

Table 4. Coefficient of Determination (R^2), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) values on different hidden layer nodes

Number of Nodes	**R^2 (Train)**	**RMSE (Train)**	**MAPE (Train)**	**R^2 (Test)**	**RMSE (Test)**	**MAPE (Test)**
1	0.98749	0.11395	0.38259	0.99174	0.09776	0.35236
2	0.99081	0.10031	0.32198	0.98745	0.10821	0.38086
3	0.99147	0.09502	0.30413	0.99217	0.09124	0.33282
4	0.99169	0.09475	0.30921	0.99169	0.09655	0.34267
5	0.99380	0.08159	0.25622	0.99456	0.07402	0.27128
6	0.99664	0.05950	0.19914	0.98734	0.11727	0.24194
7	0.99491	0.07260	0.21908	0.99666	0.06218	0.22827
8	0.99513	0.07046	0.21187	0.99614	0.06897	0.23297
9	0.99480	0.07189	0.23597	0.99534	0.07189	0.27207
10	0.99571	0.06910	0.19418	0.99705	0.05014	0.18515
11	0.99545	0.07092	0.19888	0.99544	0.07092	0.22022
12	0.99535	0.07047	0.22130	0.99697	0.05609	0.20857
13	0.99531	0.07074	0.21509	0.99433	0.07658	0.26130

14	0.9976	0.05014	0.0.1767	0.9882	0.11265	0.26979

Based on the rule of thumb, the best nodes in the hidden layer to obtain optimal results start with the number of input layers. However, in this study observe how the results obtained if starting from a random number of nodes. Table 4.1 is a collection of run results from R2, RMSE, and MAPE values using 1,2,3,4,5,6,7,8,9,10,11,12,13 and 14 hidden layer nodes. From the results of trial and error that have been obtained, the value for the number of hidden layers. The 14 nodes is much different from the number of other hidden layers. The optimum value for the hidden layer 14 nodes is 0.9976 for training and 0.9882 for testing. The following is the result of the optimum graph between the actual data and the predicted data.

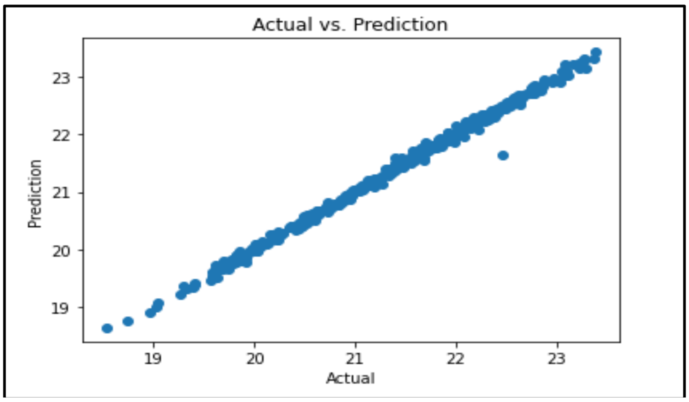

Figure 4. Coefficient of determination (R^2) 0.997 between the value of increasing actual oil recovery and increasing predicted oil recovery of training data with 14 nodes hidden layer

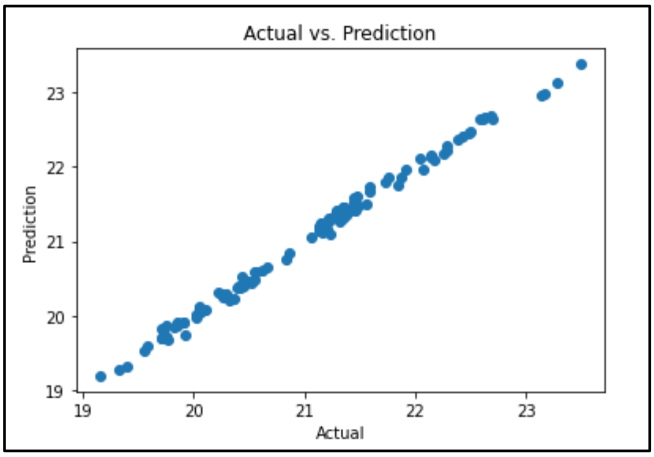

Figure 5. Coefficient of determination (R^2) 0.9882 between the value of increasing actual oil recovery and increasing oil recovery prediction of training data with 14 nodes hidden layer

In this study, the best parameter performance of Artificial Neural Network-Back Propagation in investigating performance on cyclic steam stimulation parameters on recovery factor and steam oil ratio obtained 14 nodes in the hidden layer. The Coefficient of Determination (R^2) value that is closest to 1 for training data and testing data is 0.9976 and 0.9882, respectively. For the error value that does not even reach 1%, namely for RMSE for training data 0.0514 and testing 0.11265, while MAPE for training data is 0.0.1767 and testing 0.26979. this proves that by using the ANN-BP method the value of accuracy in predicting is very high and precise and in a relatively short time of course.

3.2 performance investigation analysis of cyclic steam stimulation parameters to increase oil recovery

In this study, to determine the performance of the cyclic steam stimulation parameter on increasing oil recovery using the importance feature in the neural network. The terms of each test parameter can be seen in the picture 6 and 7

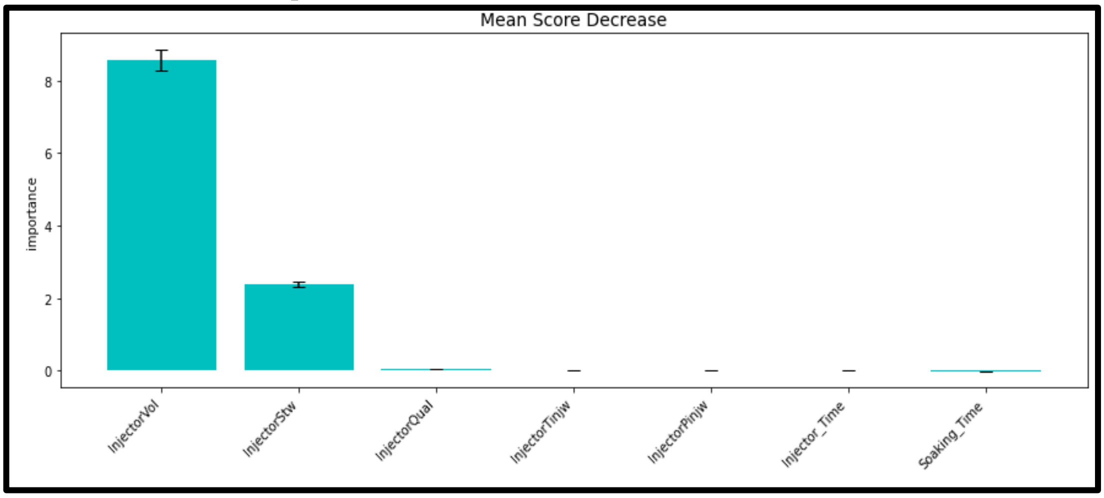

Figure 6. The order of parameters that affect the increase in oil recovery (recovery factor)

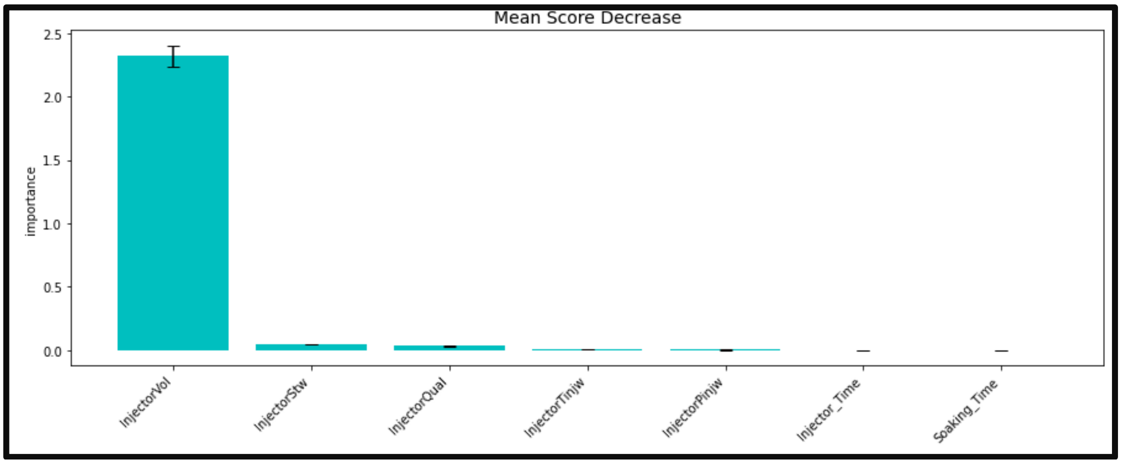

Figure 7. The order of parameters that affect the increase in oil recovery (Steam Oil Ratio)

Based on the results of the study that the injection volume parameter greatly affects the performance of the CSS parameter on increasing oil recovery because within a certain range, the oil production cycle and the volume of the steam injection cycle are proportional (Ma et al., 2013). And other parameters that are dominant to the increase in oil recovery are the injection rate. The steam injection rate on the cyclic steam stimulation parameter has an influence on the cyclic performance. With a low steam injection rate can increase the vapor loss, the steam quality decreases sharply making a significant difference to the quality of the steam on the surface and the quality of the steam in the bottom hole. Because the decreased steam quality can affect the efficiency of the entire cyclic steam stimulation process (Ali et al., 2015).

4. Conclusion

By using a classification or prediction model to investigate the performance of Cyclic Steam Stimulation parameters to increase oil recovery using an Artificial Neural Network with Back Propagation Algorithm, it produces very high accuracy. As evidenced by the 14 hidden nodes, the value of Coefficient of Determination (R^2) in training data and testing data is 0.9976 and 0.9882, RMSE for the value for training data is 0.05014 and testing data is 0.11265, while the MAPE value for data training 0.0.1767 and data testing 0.26979.

Acknowledgment

The author would like to thank the Universitas Islam Riau and Pertamina Hulu Rokan (PHR) who has provided funding for this research under a University Relationship Partner (URP) Program. The author also would like to thank CMG for providing the license for this work.

References

Ali, H. M. K., Hassan, M. A. A., & Alkhider, M. D. M. (2015). Optimization of cyclic steam stimulation (CSS) using (CMG) software to increase the recovery factor. *This Dissertation Is Submitted as a Partial Requirement of B.Sc. Degree (Honor) in Petroleum Engineering*, *August*.

Ersahin, A., & Tpao, T. P. (2019). *Artificial Neural Network Modeling of Cyclic Steam Injection Process in Naturally Fractured Reservoirs*. *May*, 23–26.

Ervina, M. E., Silvi, R., & Wisisono, I. R. N. (2018). Peramalan Jumlah Penumpang Kereta Api di Indonesia dengan Resilient Back-Propagation (Rprop) Neural Network. *Jurnal Matematika "MANTIK," 4*(2), 90–99. https://doi.org/10.15642/mantik.2018.4.2.90-99

Gu, H., Cheng, L., Huang, S., Li, B., Shen, F., Fang, W., & Hu, C. (2015). Steam injection for heavy oil recovery: Modeling of wellbore heat efficiency and analysis of steam injection performance. *Energy Conversion and Management*, *97*, 166–177. https://doi.org/10.1016/j.enconman.2015.03.057

Hidayat, F., & Abdurrahman, M. (2018). A Prospective Method to Increase Oil Recovery in Waxy-Shallow Reservoir. *IOP Conference Series: Materials Science and Engineering*, *306*(1). https://doi.org/10.1088/1757-899X/306/1/012040

Kholis, I. (2015). Analisis Variasi Parameter Backpropagation Artificial Neural Network Terhadap Pengenalan Pola Data Iris. *Jurnal Teknik & Ilmu Komputer*, *4*(14), 1–10.

Ma, C., Liu, Y., Lian, P., Wang, C., & Li, J. (2013). Study on steam huff and puff injection parameters of herringbone well in shallow and thin heavy oil reservoir. *Open Petroleum Engineering Journal*, *6*(1), 69–75. https://doi.org/10.2174/1874834101306010069

Siregar, S. P., & Wanto, A. (2017). Analysis of Artificial Neural Network Accuracy Using Backpropagation Algorithm In Predicting Process (Forecasting). *IJISTECH (International Journal Of Information System & Technology)*, *1*(1), 34. https://doi.org/10.30645/ijistech.v1i1.4

Stark, S. D. (2011). Increasing cold lake recovery by adapting steamflood principles to a bitumen reservoir. *Society of Petroleum Engineers - SPE Enhanced Oil Recovery Conference 2011, EORC 2011*, *2*, 1503–1509. https://doi.org/10.2118/145052-ms

Sun, Q., & Ertekin, T. (2015). The development of artificial-neural-network-based universal proxies to study steam assisted gravity drainage (SAGD) and cyclic steam stimulation (CSS) processes. *SPE Western Regional Meeting 2015: Old Horizons, New Horizons Through Enabling Technology*, 1140–1166. https://doi.org/10.2118/174074-ms

Suranto, A. M., Permadi, A. K., & Bae, W. (2016). Smart completion design in cyclic steam stimulation process: An alternative for accelerating heavy oil recovery. *International Journal of Oil, Gas and Coal Technology*, *11*(2), 127–140. https://doi.org/10.1504/IJOGCT.2016.074289

Trebolle, R. L., Chalot, J. P., & Colmenares, R. (1993). Orinoco heavy-oil belt pilot projects and development strategy. *Proceedings of the 1993 SPE International Thermal Operations Symposium*, 207–215. https://doi.org/10.2118/25798-ms

ACKNOWLEDGMENTS

Advisors

YBhg. Associate Professor Dr. Raman Noordin

Associate Professor Ts. Dr. Ismail Saad

Keynote Speakers

Tuan Haji Abdul Kadir Haji Abdullah @ OKK Haji Damsal

Professor Ir. Dr. Rosalam Sarbatly

Moderators & Session Chairs

Dr. Norfazliana Abdullah

Dr. Chiam Chel Ken

Dr. Mohd Syahlan Mohd Syukri

Ts. Dr. Norzilawati Mohamad

Dr. Mohd Syazwan Mohd Musa

Dr. S. M. Anisuzzaman

&

Special thanks to our reviewers for giving a timely and quality peer-reviewed comments and suggestions on the manuscripts