



# Development of Proxy Models for Screening Water Flood and Gas Flood Candidates

Moyosore, Olanipekun<sup>1</sup>, Akpabio, Julius U.<sup>2\*</sup> and Isehunwa, Sunday O.<sup>1</sup>

<sup>1</sup>Department of Petroleum Engineering, University of Ibadan, Ibadan, Nigeria.

<sup>2</sup>Department of Chemical and Petroleum Engineering, University of Uyo, Uyo, Nigeria.

## Authors' contributions

This work was carried out in collaboration among all authors. Author MO designed the study, performed the statistical analysis and wrote the protocol Authors AJU and ISO wrote the first draft of the manuscript and managed the analyses of the study. All authors read and approved the final manuscript.

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## ABSTRACT

Fluid-flood and other improved oil recovery techniques are becoming prominent in global petroleum production because a large proportion of production is from mature oil fields. Although water flooding and gas injection are well established techniques in the industry, several of the screening criteria in literature are discipline which could sometimes be subjective. This work used experimental design techniques to develop proxy models for predicting oil recovery under water-flood and gas-flood conditions.

The objective of the study is to develop a quantitative screening method that would allow for candidates to be evaluated and ranked for water flood or gas injection. The model was applied to some field cases and compared with published models and the well-known Welge Analysis method. The coefficient constants for the oil formation volume factor for water flooding and gas injection was 0.0139 and 0.0434 respectively. Similarly, the coefficient constants for water injection and gas injection for the generated proxy model was  $-2.34 \times 10^{-8}$  and  $-6.1 \times 10^{-5}$  respectively. The results show that the proxy models developed are quite robust and can be used for first pass screening of water and gas flood candidates.

\*Corresponding author: Email: [juliakpabio@yahoo.com](mailto:juliakpabio@yahoo.com), [akpabiojulius@gmail.com](mailto:akpabiojulius@gmail.com);

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## ABBREVIATIONS

ANN	: Artificial Neural Network
DOE	: Design of Experiment
RSM	: Response Surface Methodology
IOR	: Improved Oil Recovery
EOR	: Enhanced Oil Recovery
PVT	: Pressure Volume Temperature
ED	: Experimental Design
EOS	: Equation of State
BWPD	: Barrels of Water per day
MMSTB	: Million Stock tank barrels
MMSCF	: Million Standard Cubic Feet
BSCF	: Billion Standard Cubic Feet
K	: Permeability
∅	: Porosity
μ	: Viscosity
h	: Formation Thickness
S	: Saturation
RF	: Recovery Factor
P	: Pressure
PV	: Pore Volume
B	: Formation Volume Factor
OOIP	: Original Oil In Place

## SUBSCRIPTS

o	: Oil
w	: Water
g	: Gas
I	: Initial
Wc	: Connate Water
av	: Average

## 1. INTRODUCTION

Improved oil recovery comprises any of the various methods apart from the primary recovery method (reservoir drive mechanism) designed to improve the flow of hydrocarbons from the reservoir to the wellbore; it is the second stage of hydrocarbon production during which an external fluid such as water or gas is injected into the reservoir through injection wells located in rocks that has fluid communication with the production wells. Many researchers have performed laboratory studies to show that CO<sub>2</sub> injection is a very effective enhanced oil recovery process for light and medium gravity reservoir oils [1]. Shtepani [2] discussed PVT experiments, special coreflood experiments and numerical coreflood simulations to determine the micro-scale conformance of the CO<sub>2</sub> displacement and identify CO<sub>2</sub> breakthrough characteristics. He gave serious attention to the importance of water

injection and other factors related with CO<sub>2</sub> injection, which could extend the miscible CO<sub>2</sub>-EOR technology to a broader range of oil reservoirs. He concluded that an accurate EOS characterization and phase behavior of reservoir fluids, based on extensive PVT measurements was key for a successful design.

According Alvarado and Manrique [3] improved oil recovery methods compass enhanced oil recovery methods as well as new drilling and well monitoring technologies, intelligent reservoir management and control, advanced reservoir monitoring techniques as well as application of different enhancements of primary and secondary recovery processes.

Several methods are available in assessing recoveries; for example laboratory/core analysis as well as intelligent well systems; this research will focus on the use of Design of Experiment and Response surface methodology.

Unlike primary recovery, IOR techniques are technically and economically intensive and require proper planning. This method has been extensively applied in assessing production uncertainties in channelized reservoirs [4] and creating development strategy alternative for Oil fields. Carreras et al., 2006 [5] focused on the Tahiti field in deep water Gulf of Mexico with primary hydrocarbon-bearing turbidite sands. Due to significant uncertainties remaining after appraisal, probabilistic methods were used to assess development alternatives. They applied the classical ED method to generate reservoir simulation models for the P10, P50 and P90 reservoirs of the field. The field development was done by performing ED runs which incorporated uncontrollable uncertainties and decisions as factors such as well counts and injection timing.

This method was used to manage subsurface uncertainties in the Niger Delta by Ogbalor and Peacock [6]. They concluded that experimental design provides a systematic consistent approach to managing uncertainties in field development studies because it reduces the amount of time and cost needed to analyse the impact of a range of subsurface parameters on business decisions. Separate response surface model should be generated for in-place as well as recoverable volumes, as the key sub-surface parameters which drive each model are likely to be different.

Reis [7] applied the Experimental Design and Response Surface Methodology in Risk analysis, where one RSM was built to model the decision variable and another was built to represent an objective function that takes into account dynamic data. A relationship among the uncertainty variables obtained from the RSM of the objective function was applied to the RSM of the decision variable to constrain the model, enabling Risk analysis with history match. The results obtained were compared with that of an Artificial Neural Network (ANN).

Gupta et al. [8] presented a statistical method for performing history matching using experimental design framework. The objective of the experimental design based history matching was to independently quantify ultimate recovery for the studied field based on the production history, primarily water production and pressure matches. Their method quantifies the probability for each scenario based on identified history matching parameters. This methodology can easily be extended to include differential weights for history matching parameters. The success of the method depends on the generation of efficient design and subsequent model for acceptable modeling error.

Cebastian and Osbon [9] presented a comparison between the Experimental Design method and the simpler and quicker Monte-Carlo probabilistic technique used to manage subsurface uncertainty and provide estimates of hydrocarbon in-place and ultimate recovery. Some case studies were used to illustrate this and they concluded that ED tend to produce a wider ultimate recovery distribution compared to the probabilistic because the ED has a tendency to introduce more dependencies between input variables. These dependencies occur as a result of minimizing the simulation runs by combining multiple uncertainties. It was also realized that ED handled the dependencies on recovery factor more thoroughly than the probabilistic method.

Robertson, [10] discussed laboratory works showing examples of improved recovery from low salinity water floods. He tried to quantify the improved oil recovery potentials from low-salinity waterfloods for specific fields. In his conclusion, he showed that oil recovery tended to increase with lower salinity floods.

Li and Friedmann, [11] introduced a new method to effectively generate a response surface although, the input parameters have strong non-

linear effects; the results showed that this method could successfully generate a response surface when the non-linear effects are normally distributed.

## 2. METHODOLOGY

Pareto chart and Plackett Burma design were used to identify the nine imputed factors, and validation was done using Yale's Algorithms:

$$Ex = \frac{\sum Y(+)}{N/2} - \frac{\sum Y(-)}{N/2} \tag{1}$$

Using 20 experiments, a response surface was built using linear Equations (Equation 2) to describe the relationship between the recovery factor and the identified factors [12].

$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k + \varepsilon \tag{2}$$

The fluid proxy models obtained were validated using secondary data: seven cases for the water flooding, and four cases for the gas injection problem. The results were compared with the Guthrie and Greenberger [13] Predictive model (Equation 3) and Buckley Leverett/ Welge analysis method (Equation 4 and 5)

$$E_r = 0.2719 \log(k) + 0.25569 S_{wi} - 0.1355 \log(\mu_o) - 1.538\phi - 0.0003488h + 0.11403 \tag{3}$$

$$RF_{oil} = \frac{(S_{w(av)} - S_{wi})}{(1 - S_{wi})} \tag{4}$$

$$RF_{gas} = \frac{(S_{g(av)} - S_{gi})}{(1 - S_{gi})} \tag{5}$$

## 3. RESULTS AND DISCUSSION

The principal factors that affect each process were identified: Water-floodable Pore volume; Absolute Permeability; Capillary Pressure; Reservoir Pressure; Reservoir Depth; Fluid viscosity; hydrocarbon in Place at start of flood; Connate water saturation; Effective permeability measured at the immobile connate water saturation; Relative permeability; fluid saturation at start of flood; formation volume factor; injection rate and Pressure. The pareto chart shows that the interaction between the relative permeability to oil and oil formation volume factor BE has the highest effect. The coefficient constants shows the changes caused by the different parameters and their effects on oil recovery.

For the water-flood case; the proxy model generated is given by the equation:

$$\begin{aligned}
 RF_{oil} &= A_0 + A_1WPV + A_2K + A_3Pr + A_4Swc + A_5\mu_o + A_6\mu_w \\
 &+ A_7K_{ro(swr)} + A_8S_o + A_9B_o \\
 &+ A_{10}I_w
 \end{aligned}
 \tag{6}$$

For the gas injection under conditions of miscible flooding in non-dipping reservoirs; the proxy model generated is given by the equation:

$$\begin{aligned}
 RF_{gas} &= B_0 + B_1GPV + B_2B_o + B_3Ig + B_4Pinj + B_5Sgi + B_6N \\
 &+ B_7S_{oi} + B_8S_o + B_9P
 \end{aligned}
 \tag{7}$$

Where the constants are as shown in Table 1.

From Table 2 it can be seen that Buckley Leverett/ Welge Analysis over-estimates recovery factor; this is because it considers recovery factor as a function of displacement efficiency only, areal and volumetric efficiencies are not accounted for. It can also be seen that the recovery factor and cumulative oil Produced follow the same trend in all cases; at high viscosities and water saturation, there is a close correlation between the recovery factor using Guthrie and Greenberger Water-Flood Predictive model and Buckley-Leverett/ Welge's Analysis. It can also be observed that all cases apart from Case 1, 2 and 7, the cumulative oil produced in MMSTB calculated, predicted and obtained are close for the other cases.

From Table 3, it can be observed that Buckley Leverett/ Welge's Analysis predicts high recoveries; as stated earlier; recovery factor is a function of displacement efficiency only, though the Cumulative Oil Produced follows the same trend as the other cases; it can also be seen that

there is a close correlation between the recovery factors and Cumulative Oil Produced.

These key parameters such as reservoir heterogeneity, dip, mobility ratio of the CO<sub>2</sub> to oil, injection rate, volume of CO<sub>2</sub> available affect performance of the recovery process and the nature of the reservoir fluids [14]. Proxy models were generated for the primary recovery and water flood oil recovery from the simulation results and Monte Carlo simulation was run using the proxy equations [15]. New statistical proxy model was developed by Jaber et al., [16] which showed how to improve recovery of oil from a carbon dioxide-water alternating gas flooding operation in a heterogenous reservoir. Four parameters were used in the proxy modeling as a function for incremental recovery of oil. A grid-based smart proxy model was developed for water flooding improvement under difference scenarios of production and injection through experimental design and data mining processes. A training of sequential neural network model was used to construct the proxy model [17].

Figs. 1 and 2 shows the recovery factors in fraction against the different cases under consideration for both water flooding and gas injection. Buckley Leverett method stands out in the gas injection but was not very distinct in the water flooding scenario.

Fig. 3 shows the Pareto chart that indicates the main factors that affect oil originally in Place (OOIP), the relative permeability to oil and oil formation volume factor stands out clearly to affect the recovery process.

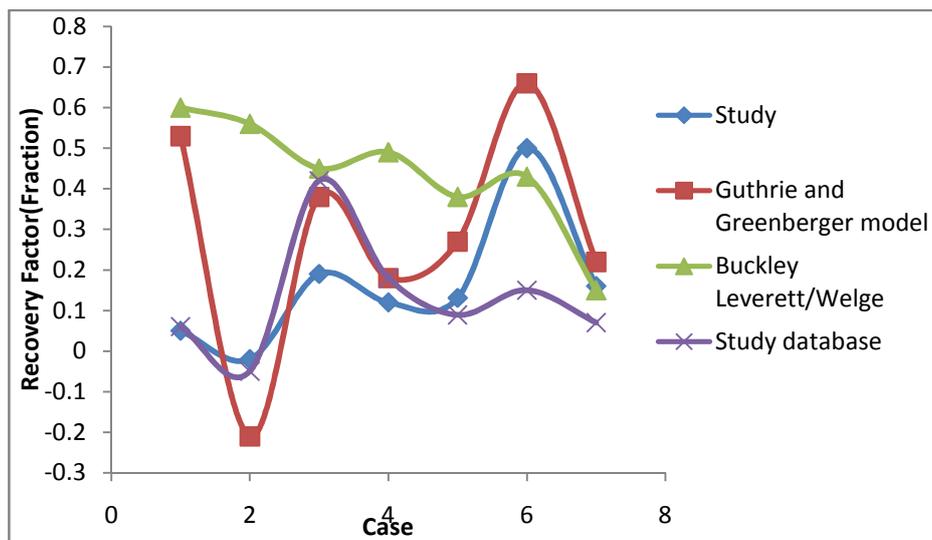


Fig. 1. Plot of recovery factor (fraction) versus case studies (water-flooding)

**Table 1. Showing the constants and values for the proxy model**

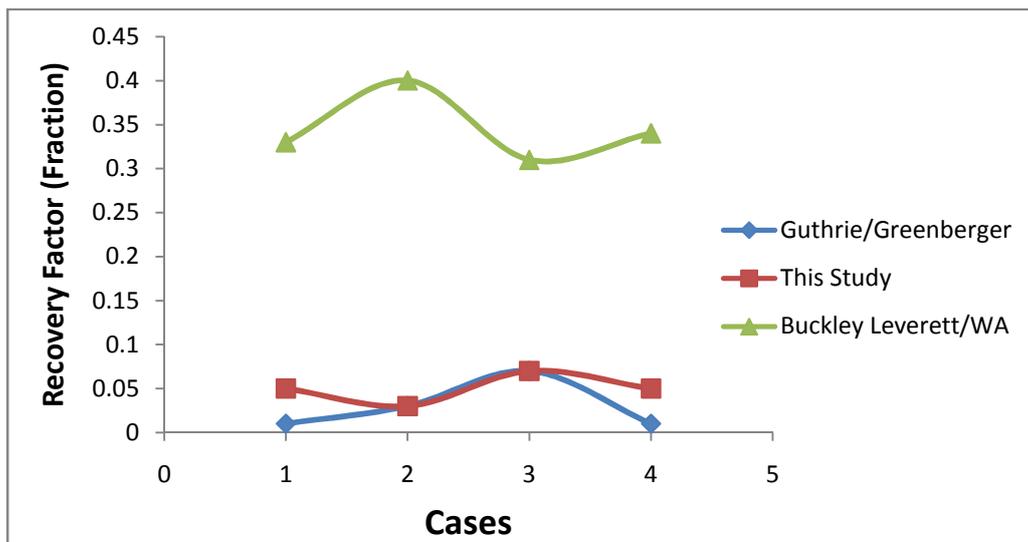
Constant	Value	Constant	Value
A <sub>0</sub>	-0.8051	B <sub>0</sub>	0.18565
A <sub>1</sub>	2.6519E-07	B <sub>1</sub>	-9.1385E-07
A <sub>2</sub>	-3.171E-06	B <sub>2</sub>	0.0434
A <sub>3</sub>	1.5834E-06	B <sub>3</sub>	-0.00061
A <sub>4</sub>	-0.01943	B <sub>4</sub>	4.497E-06
A <sub>5</sub>	0.000217	B <sub>5</sub>	3.566
A <sub>6</sub>	0.0005	B <sub>6</sub>	-2.234E-06
A <sub>7</sub>	0.00649	B <sub>7</sub>	-0.1320
A <sub>8</sub>	1.493	B <sub>8</sub>	-1.2471
A <sub>9</sub>	0.0139	B <sub>9</sub>	-3.8694E-07
A <sub>10</sub>	-2.34E-08		

**Table 2. Results obtained using case studies (water- flooding) recovery factor (fraction)**

Case	Study	Guthrie and Greenberger model	Buckley Leverett/Welge Analysis	Study database
1	0.05	0.53	0.6	0.06
2	-0.02	-0.21	0.56	-0.05
3	0.19	0.38	0.45	0.42
4	0.12	0.18	0.49	0.18
5	0.131	0.27	0.38	0.089
6	0.5	0.66	0.43	0.15
7	0.16	0.22	0.15	0.07

**Table 3. Results obtained using case studies for gas injection (recovery factor)**

Case	This Study	Guthrie and Greenberger	Buckley Leverett/Welge Analysis
1	0.05	0.01	0.33
2	0.03	0.03	0.4
3	0.07	0.07	0.31
4	0.05	0.01	0.34



**Fig. 2. Plot of recovery factor (fraction) versus case studies (gas injection)**

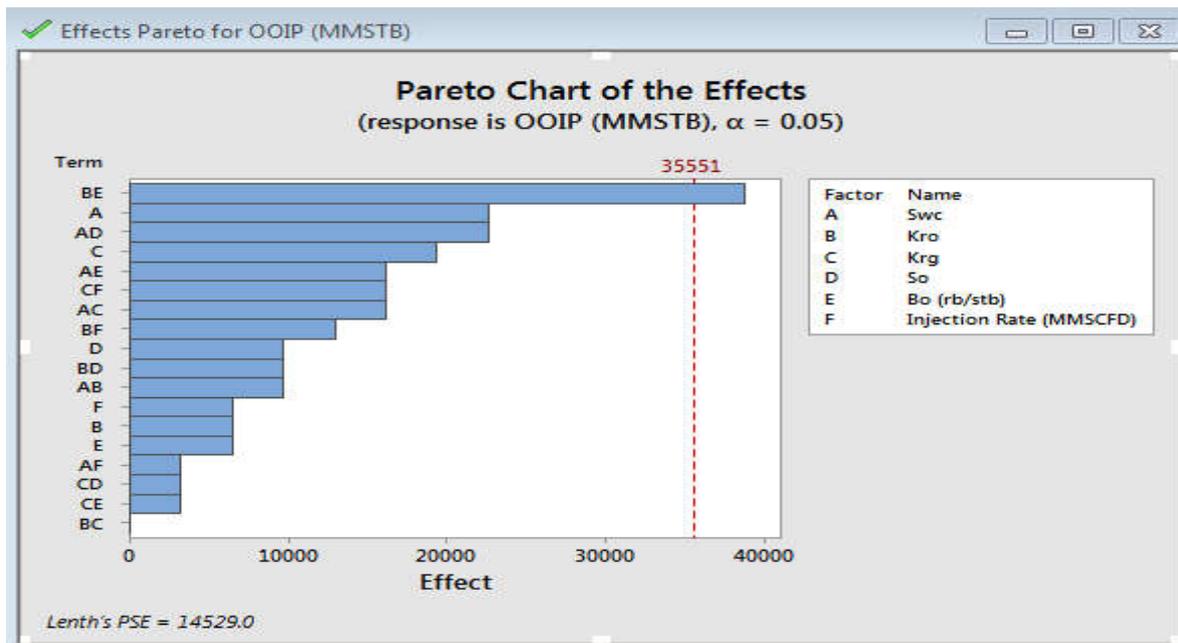


Fig. 3. Pareto chart for OOIP

#### 4. CONCLUSION

Recovery factor of any improved oil recovery process can be expressed as a function of reservoir rocks and fluid properties; this function can be used to predict recoveries before extensive simulations are done. Design of Experiment and Response Surface Methodology can be used with a high degree of accuracy to predict oil recovery factors.

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#### COMPETING INTERESTS

Authors have declared that no competing interests exist.

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