Estimation of Oil Recovery for Hydrocarbon Injection EOR Method using a Newly-Developed Predictive Model

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Abstract. Application of predictive model in enhanced oil recovery has been mainly to obtain an estimate of production performance. The advantage of a predictive model over reservoir simulation are the computational speed and its significantly lower cost. A predictive model is able to provide results instantly, comparing to the whole process of reservoir simulation. However, it should be noted that predictive model is not a substitute for reservoir simulation, but rather as a starting approach for field development planning purposes. Hydrocarbon injection is an EOR method which incorporates the injection of hydrocarbon gas to increase oil production. Presently, there has been little to none predictive models developed to estimate oil production for hydrocarbon injection method. In this study, a predictive model of the hydrocarbon injection method is presented. The predictive model was developed using commercial software CMG. Based on an inverted 5-spot reservoir model, thousands of reservoir simulation cases with different parameter values were conducted as a sensitivity analysis. Cumulative oil production result was captured from each simulation case to build the predictive model. Polynomial regression and neural network predictive models were built. The neural network model fitted the simulation data better than the regression model. R-square value for both predictive models exceeded 90%. This predictive model can be confidently used to estimate cumulative oil production as long as the input parameter values are within the parameter intervals of the model.

1. Introduction

In reservoir simulation, predictive model has been mainly used for the purpose of sensitivity analysis, risk analysis, history matching, production forecasting and production optimization [1]. The advantage of predictive model over reservoir simulation are the computational speed and its significantly lower cost. A predictive model is able to provide results instantly, comparing to the whole process of reservoir simulation which incorporates screening, modelling, history matching, field development planning, and running the simulation. However, its purpose is by no means as a substitute for reservoir simulation, but rather as a starting approach to provide an assisting insight on designing a development plan for the specified method to be applied [2].
Hydrocarbon injection is an enhanced oil recovery (EOR) method which involves the injection of hydrocarbon gas to increase oil production. Its displacement mechanism can be either miscible or immiscible, depending on the minimum miscibility pressure (MMP) and hydrocarbon components [3]. In the present, there has been little to none predictive models developed to estimate oil production for hydrocarbon injection method. Morteza [4] developed a predictive model to estimate oil production rate based on vapor extraction transport and Cronin [5] developed a predictive model to estimate oil recovery based on diffusion-dominated transport. Both models were limited to tight reservoirs.

In this study, a new predictive model was developed to estimate cumulative oil production of hydrocarbon injection method based on reservoir simulation data. The model was capable to be used in different reservoir conditions due to a wide range of input parameter values. Polynomial regression and neural network model were built and compared to observe which model best fitted the simulation data.

2. Methodology

The predictive model for hydrocarbon injection was developed based on reservoir simulation result data using commercial software Computer Modelling Group (CMG)\textsuperscript{TM}. The design steps were as follows: Creating a synthetic reservoir model, conducting sensitivity analysis, and developing the predictive model.

2.1. Synthetic Reservoir Model

The reservoir model was a bounded, homogeneous inverted 5-spot model with cartesian grid (Figure 1). It had a injection-production well ratio of 1:1. There were 5 vertical layers in the model. The perforations for injection well were located in the 2 top layers and the perforations for production wells were located in the 3 bottom layers.

![Figure 1. Synthetic Inverted 5-spot Reservoir Model](image1)

Compositional fluid models were built using CMG WINPROP\textsuperscript{TM}. The model consisted of light components (C\textsubscript{1}-C\textsubscript{3}), medium components (C\textsubscript{4}-C\textsubscript{6}), heavy components (C\textsubscript{7+}) and impurities (N\textsubscript{2}, CO\textsubscript{2}). The fluid model had an API degree values ranged from 15 to 45 degrees. This variation of API was achieved by modifying the percentages of each component. The phase envelope of these fluid models is shown in Figure 2. Relative permeability was built using Corey’s equation by varying endpoint saturation variables [6]. The model covered oil-water and gas-liquid system as well as both sandstone and carbonate rock type.

![Figure 2. Phase Envelope of Compositional Fluid Models Used for Predictive Model Development](image2)

The flowing bottom hole pressure for the production wells were set equal to reservoir pressure. This was done intentionally to ensure that hydrocarbon injection was the only cause of incremental production. The operating parameter was the gas injection rate. Enriched gas, composed by light components (C\textsubscript{1}-C\textsubscript{3}) was the injected fluid. Production and injection were done continuously for 15 years. The operating constraint was producing gas-oil ratio (GOR), in which the simulation will be stopped when producing GOR reaches 100 MSCF/STB. This compositional reservoir model was simulated using commercial simulator CMG GEM\textsuperscript{TM}. 
2.2. Sensitivity Analysis

Sensitivity analysis was conducted using CMG CMOST™. Latin Hypercube Method was used to create a numerous simulation experiment cases by varying the values of 20 input variables. The range of values of input variables were based on field implementation data and EOR screening criteria by Aladasani and Taber [7][8]. Table 1 shows the input variables in this study with their range of values.

A sampling control was conducted before running the simulation. This was attempted to avoid unrealistic experiment cases which resulted in reservoir models that physically should not exist in nature. Combinations of input parameters needed to be controlled were oil density, reservoir temperature, reservoir pressure, permeability, rock-fluid properties, porosity, and drainage area.

After sampling control, 4022 simulation experiment cases were ready to be simulated using a reservoir simulator. The cumulative oil production from each simulation result was captured as a response variable. The effect of each input variable to the response was calculated in CMG CMOST™ to build the predictive model.

| No | Parameter                                | Unit  | Min | Max  |
|----|------------------------------------------|-------|-----|------|
| 1  | Pattern Area                             | Acre  | 5   | 30   |
| 2  | Net Pay Thickness                        | ft    | 10  | 250  |
| 3  | Porosity                                 | %     | 8   | 26   |
| 4  | Lateral Permeability                     | mD    | 10  | 1250 |
| 5  | Kv/Kh Ratio                              | Fraction | 0.1 | 0.3   |
| 6  | Oil Density                              | °API  | 15  | 45   |
| 7  | Reservoir Temperature                    | °F    | 100 | 300  |
| 8  | Reservoir Top Depth                      | ft    | 3000| 15000|
| 9  | Reservoir Pressure                       | psia  | 500 | 5000 |
| 10 | Initial Water Saturation                 | Fraction | 0.1 | 0.95 |
| 11 | Connate Water Saturation                 | Fraction | 0.125 | 0.4 |
| 12 | Residual Oil Saturation (Water-Oil Table)| Fraction | 0.1 | 0.45 |
| 13 | Connate Gas Saturation                   | Fraction | 0   | 0.1  |
| 14 | Residual Oil Saturation (Gas-Liquid Table)| Fraction | 0.05 | 0.2  |
| 15 | Corey Exponent for Kro and Krl           | Fraction | 1  | 4    |
| 16 | Corey Exponent for Krw and Krg           | Fraction | 1   | 4    |
| 17 | Kro at Connate Water Saturation          | Fraction | 0.35 | 1   |
| 18 | Krw at Irreducible Oil Saturation        | Fraction | 0.35 | 1   |
| 19 | Krg at Connate Liquid Saturation         | Fraction | 0.35 | 1   |
| 20 | Gas Injection Rate                       | MMSCFD | 0.05 | 5    |

2.3. Predictive Model Development

Polynomial regression and neural network model were both developed in CMG CMOST™. From 4022 simulation data, 80% of the result was treated as training data and the remaining 20% was treated as testing data. Polynomial regression (PR) method is a form of analysis to determine the relationship between input variables and response variable as a polynomial equation. In this model, the cumulative oil production was represented as a reduced quadratic function of 20 input parameters.

Neural network predictive model was also built, incorporating all input variables. The model was a multilayer neural network model, consisting of an input layer, several hidden layers and an output layer. Each layer had a weighting table which represents the effect of each neuron to the next layer.

Both models were evaluated by their R-square value to see which model fitted the simulation data better. A scatter plot of actual vs predicted data was also presented to visualize the performance of the model. A good, representative model will have both its training and testing data points located close to a 45-degree line ($y = x$) and yield a high R-square value.
3. Result and Discussion

Cumulative oil production (Np) was represented as a function of 20 input parameters. The polynomial equation can be found in Appendix A. The training and testing R-square values of this model are 0.972 and 0.968 respectively, which is considered a high R-square value. Actual vs predicted plot is shown in Figure 3.

Neural network predictive model showed an even promising result. With the training and testing R-square values of 0.996 and 0.991, it fitted the simulation data better than the polynomial regression model. The multilayer neural network model had an architecture of 1 input layer with 20 neurons (input parameters), 3 hidden layers with 8-6-4 neurons configuration and 1 output layer with 1 neuron (cumulative oil production). The weight table of the neural network can be found in Appendix B. Actual vs predicted plot for this model is shown in Figure 4.

![Figure 3. Actual vs Predicted Plot for the Polynomial Regression Model](image1)

![Figure 4. Actual vs Predicted Plot for the Neural Network Model](image2)

Both models provided a good prediction of cumulative oil production with high R-square value as shown in Table 2. The actual vs predicted plots also agreed with this result as the training and testing data for both models were lined up close to the 45-degree line. The blue dots represent training data sets and the green dots represent testing data sets.

As seen in Figure 3 and 4, the neural network model was relatively more accurate in estimating the result compared to the polynomial regression model. The data points of actual vs predicted plot in polynomial regression model have a wider distribution along the 45-degree line compared to the neural network model. The similar conclusion was reached on the other study regarding the application of predictive model in different data sets [9]. This was due to the nonlinearity of the simulation results, thus finding a linear trend would be highly perplexing. Neural network method was preferred in modelling such cases.

| Predictive Model                  | Training R-square | Testing R-square |
|-----------------------------------|-------------------|------------------|
| Polynomial Regression Model       | 0.972             | 0.968            |
| Neural Network Model              | 0.996             | 0.991            |

The cumulative oil production values were ranged from 1 to 5300 MSTB. Nearly all simulation results had a production period of 15 years, which means the constraint (producing GOR) set to stop the simulation was rarely met. Initial water saturation, oil density, gas injection rate and volume of the reservoir affected the cumulative oil production value more dominant than other input parameters.

The weaknesses of the developed predictive model are: (1) Applicable only when the value of input parameters fall within the range of parameters used to develop the predictive model (refer to Table 1); and (2) The only estimated result is the cumulative oil production at the end of the production period, regardless of the oil production rate profile over time. A further research is necessary to forecast the production rate profile using predictive model. As already stated beforehand, predictive model should be used solely as a starting approach for a field development plan. For example, determining feasibility of hydrocarbon injection method toward a specified reservoir, or determining an optimum value of gas injection rate to maximize oil production.
4. Conclusion
The predictive models to estimate cumulative oil production for hydrocarbon injection method had been successfully developed. Both polynomial regression and neural network model were highly with most R-squared values above 0.95. Neural network model slightly provides a better performance than polynomial regression model and is preferred to be used because simulation results data tend to be nonlinear. The developed predictive model from this study are recommended to use as a starting approach for field development planning purposes.

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Appendix A: Polynomial Regression Model of Cumulative Oil Production for Hydrocarbon Injection Method

Table 3. CMOST Parameters of Each Input Variables for Sensitivity Analysis and Predictive Model Development

| Parameter                          | CMOST Parameter       |
|------------------------------------|-----------------------|
| Pattern Area                       | Area                  |
| Net Pay Thickness                  | Thickness             |
| Porosity                           | Porosity              |
| Lateral Permeability               | Permeability _IJ      |
| Kv/Kh Ratio                        | KV_KH                 |
| Oil Density                        | API                   |
| Reservoir Temperature              | ResTemp               |
| Reservoir Top Depth                | TopDepth              |
| Reservoir Pressure                 | ResPressure           |
| Initial Water Saturation           | SWi                   |
| Connate Water Saturation           | SWcon                 |
| Residual Oil Saturation (Water-Oil Table) | SOrw                |
| Connate Gas Saturation             | SGcon                 |
| Residual Oil Saturation (Gas-Liquid Table) | SOrg                |
| Corey Exponent for Kro and Krl     | NO                    |
| Corey Exponent for Krw and Krg     | NOW                   |
| Kro at Conrate Water Saturation    | KROcw                 |
| Krw at Irreducible Oil Saturation  | KRWiro                |
| Krg at Conrate Liquid Saturation   | KRGcl                 |
| Gas Injection Rate                 | InjRate               |

\[
N_{pOil} = -1.93916E+06 + 5882.72*\text{Thickness} + 42933.6*\text{Area} + 2.6813*\text{TopDepth} - \\
25.0818*\text{ResPressure} - 72558.2*KV\_KH - 470.607*\text{Permeability}_IJ + 6.82274E+06*\text{Porosity} + \\
512.223*\text{ResTemp} + 1.00648E+06*\text{SWi} - 603806*\text{SWcon} + 1.41662E+06*\text{SOrw} + 988240*\text{SOrg} - \\
1.43473E+06*\text{SGcon} + 30091.3*\text{NW} - 99941.7*\text{NOW} + 478255*\text{KROcw} - 107682*\text{KRWiro} - \\
523512*\text{KRGcl} + 58178.3*\text{API} + 0.11645*\text{InjRate} + 2.046*\text{Thickness}^2 + \\
148.976*\text{Thickness}^3*\text{Area} + 0.13042*\text{Thickness}*\text{ResPressure} - 1854.97*\text{Thickness}^2*KV\_KH + \\
0.491627*\text{Thickness}^2*\text{Porosity} + 2.6043*\text{Thickness}^2*\text{ResTemp} - \\
16304.2*\text{Thickness}^2*\text{SWi} + 4769.04*\text{Thickness}^2*\text{SWcon} - 2900.97*\text{Thickness}^3*\text{SOrw} -
\]
9060.26*Thickness*SOrg + 5192.3*Thickness*SGcon + 586.753*Thickness*NW - 
726.161*Thickness*NOW + 1653.96*Thickness*KROcw - 818.556*Thickness*KRWiro - 
839.254*Thickness*KRGcl - 97.2032*Thickness*API + 0.000370516*Thickness*InjRate - 
11627.8*Area*KV_KH + 103448*Area*Porosity - 16.5316*Area*ResTemp - 87406.6*Area*SWi + 
17218.4*Area*SWcon - 19324.3*Area*SOrg - 48556.1*Area*NOW + 3052.29*Area*NW - 
3607.8*Area*NOW + 5762.42*Area*KROcw - 10878.6*Area*KRGcl - 305.58*Area*API + 
0.00238098*Area*InjRate + 0.00708762*TopDepth*Permeability_IJ - 2.1895*TopDepth*NW - 
0.0333276*ResPressure*ResPressure + 0.0343031*ResPressure*Permeability_IJ + 
0.137007*ResPressure*ResTemp - 404.606*ResPressure*SGcon + 16.3578*ResPressure*NOW + 
5.80865*ResPressure*API + 574.966*KV_KH*Permeability_IJ - 4.1171E+06*KV_KH*Porosity + 
3337.26*KV_KH*ResTemp + 18292.8*KV_KH*API - 0.109669*KV_KH*InjRate + 
0.129147*Permeability_IJ*Porosity + 443.005*Permeability_IJ*SOrg - 
53.552*Permeability_IJ*NW + 189.91*Permeability_IJ*KROcw - 5.57235E-05*Porosity*SOrg + 5.93137E-06*Porosity*SWi - 109.437*ResTemp*NW + 122.414*ResTemp*NOW - 36.5285*ResTemp*API + 
874830*SWi*SWi - 84074.4*Porosity*API + 0.388034*Porosity*InjRate - 
10.9437*ResTemp*NW + 122.414*ResTemp*NOW - 36.5285*ResTemp*API + 
874830*SWi*SWi - 65760.3*SWi*NW + 921774*SWi*KRGcl + 73578.8*SWi*API - 
0.142666*SWi*InjRate - 148482*SWcon*NW + 208572*SWcon*NOW - 16027.9*SWcon*API - 
89176.9*SOrg*NW + 345522*SOrg*NOW + 1.24463E+06*SOrg*KRGcl + 
555431*SGcon*NOW + 0.417493*SGcon*InjRate - 58391.3*NW*KROcw + 
52914.8*NW*KRWiro - 2675.2*NW*API + 0.0131557*NW*InjRate + 12286*NOW*NOW + 
1718.45*NOW*API - 0.00162349*API*InjRate - 1.94701E-08*InjRate*InjRate
Appendix B: Neural Network Model of Cumulative Oil Production for Hydrocarbon Injection Method

Figure 5. Multilayer Neural Network Model Architecture

Figure 6. Weight Table of the Neural Network Model