Prediction Of Recovery Performance Of Oil Reservoirs Under Carbon Dioxide Flooding

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ABSTRACT

The oil and gas industry has over 40 years of continuously developing experience in recovering of the huge residual oil left in the reservoir, after primary and secondary oil recovery procedures have been exhaustively harnessed, by the use of Carbon Dioxide (CO_2) flooding Enhance Oil recovery (EOR) methods. Clearly, the technology and operational practices used by the oil and gas industry in handling and injecting CO_2 cannot be over emphasized, of which pivotal to this process is the screening criteria used in diagnosing a reservoir's potential for CO_2 flooding. The prevailing screening criteria, due to its non-robust nature possess an inherent capacity of passively qualifying reservoirs as successful or poor candidates for CO_2 EOR sequel to its vague parameters.

This study uses reservoir simulation to investigate the performance of different reservoirs to CO_2 injection. Fully compositional and pseudo-miscible black oil fluid models were tested in an inverted fivespot pattern. Detailed reservoir characterization was performed to represent the complex characteristics of the reservoir using PETREL® preprocessor. IPM-PVTp and ECLIPSE® compositional simulation model were used to evaluate the effects of various reservoir fluids and reservoir characteristics' combinations in reservoir fluids production as a function of carbon dioxide flooding. The results obtained from different permutations and combinations of 28 reservoir and fluid properties were investigated using the Design of Experiment (DOE) and Response Surface Methodology (RSM) to analyze the "key players" to the overall performance of CO_2 in EOR operations. A Meta Model for predicting the performance of using CO_2flooding was generated using the Design Expert 5.0 software based on statistical principles and the governing pattern of occurrence recorded from the investigations.

Keywords: CO_2 Flooding, Enhance Oil Recovery, Design of Experiment, Response surface Methodology, Reservoir Modeling.

Introduction

Concerns over the environmental impact of Carbon dioxide (CO_2) have led to a resurgence of interest in CO_2 injectionin oil reservoirs. The injection of CO_2 can enhance oil recovery from these reservoirs and at the same time help in mitigating the problem of increased CO_2 concentrations in the atmosphere by storing large quantities of CO_2 for a long period of time. Displacement and recovery of oil by CO_2 injection has been studied and applied in the field extensively since early 1950s. A number of attendant characteristics of the gas makes it an ace in the choice for enhanced oil recovery agent. The main advantage of CO_2 is that at most reservoir conditions it is a supercritical fluid with high solvency power to extract hydrocarbon components and displace oil miscibly.

The procedure of Carbon dioxide flooding is a capital intensive one alongside its high technicality in execution, hence the need for screening criteria which serves as a score card for investigating a reservoir's suitability for the process. These screening criteria go a long way in reducing the risk of randomly choosing a reservoir without duly certifying that they are qualified to be subjected to such capital intensive project thence reducing the uncertainty present. However, they do not duly encompass some other variables that inclusively contribute to the overall effect of a successful or impeding performance of CO_2 process as the case may be. The resultant effect of this vague encompassing criteria which presently prevail can be bolstered by recorded evidence of some field operations where low performance of CO_2 additional recovery have been recorded even with the fields conforming to the prevailing screening criteria vis-à-vis.

The affirmation of a CO2 EOR process as successful or failure as aforementioned is relative because the cost expedited in the project as a function of time is an intrinsic factor towards such conclusion. As mentioned in the preceding section, some of the parameters mentioned contribute individually to the overall process e.g. fluid gravity; others are liaised with other parameters as epitomized by saturation profile which is related to capillary, wettability and mobility ratio.

This research investigates the sole contribution of individual parameters and the effect of their aliased

interactions with other parameters inherent. A more robust platform containing contributing parameters not considered by previous researchers is investigated.

Nevertheless, sequel to the experimental investigations carried out in the course of this research, a correlation that gives an insight as to what should be expected in terms of additional production from a field upon the execution of a CO_2-EOR process, over a successful base case of none has been generated.

Design of Experiment and Response Surface Methodology

Design of Experiments (DOE) is a method of selecting simulations to maximize the information gained from each simulation and to evaluate statistically the significance of the different factors. An experimental design study is used to generate response surfaces that identify the various factors that cause changes in the responses and also predicting these variations in a simple mathematical form. The purpose of Response Surface Methodology (RSM), is to approximate a process over a region of interest, often called the operating region, Myers and Montgomery (1995). The components of the operating region include objectives, requirements, state parameters (with or without uncertainty), decision variables and constraints.

Description, Application of Equipment & Processes and Model Development

One of the concerns pertaining to the reservoir fluid model is selecting the simulator that best represents CO_2displacement process. Compositional simulation and pseudo-miscible black oil models have been widely used to reproduce CO_2 displacement processes. ECLIPSE® compositional simulator and the black oil finite-difference simulator IMEX were used in this study.

A total of 104 reservoir-to-fluid designs to bolster the effect of the contributing factors to the overall performance of CO_2 were investigated.The design entailed building a 30 by 30 by 20 grid cells in the X, Y and Z axis respectively of 100 by 100 by 25ft resulting to 18000 cells. The model has a constant porosity of 25% and a water saturation end point of 10% across all the regions. All the cells are active with no faults. However, the models are hypothetical models built to the Niger delta geologic representation possessing rock and petrophysical properties obtainable in the region. A total of 24 different crudes from shell Nigeria fields in the Niger Delta were obtained and characterized using proprietary fluid models of IPM 5.0 and ECLIPSE PVT*i*® to reproduce fluid performance in the simulator. Other designed parameters are discussed:

(A) Reservoir Depth: To generate a robust scenario, the analysis is carried out on three different depths: 5000ft, 10,000ft and 15,000ft. This serves as a guide in obtaining the formation pressure, equation 1, at various reservoir depths which controls CO_2injection pressure to avoid exceeding formation parting pressure and this has a direct translation on the choice of injection rate of the CO_2

$$p_f = 0.052\rho h \qquad (1)$$

(B) Reservoir Dip: On accentuation of the global placements of reservoirs, the attendant contributions of formation dips are incorporated. The dip of the reservoir further supports gravity drainage and aggravates the effect of gravity override on introduction of gas into the reservoir. In this research, five different angles of dip:0°, 5°, 15°, 30° and 40° were incorporated

(C) Modeling Reservoir Permeability: The reservoir permeability for this research is dividedinto two groups: (a) Homogeneous permeability distribution: where all the permeabilities of cells in the in the X and Y directions are similar; and the Z axis permeability is constant all through the reservoir (b) Heterogeneous permeability distribution: In this case, the permeability distribution differs across the reservoir in both the horizontal and vertical direction.

(D) Modeling Reservoir Heterogeneity: CO_2 EOR is more sensitive to reservoir heterogeneity than oil recovery by water injection alone, and therefore this is an important issue to consider if CO_2 flood is regarded as the optimum recovery mechanism.Heterogeneity by means of stratification may strongly influence the water-gas displacement process. The ratio of viscous to gravity forces is the prime variable for determining the efficiency of WAG injection and controls the vertical conformance and displacement efficiency of the flood.

Designing the Heterogeneity

Given the aforementioned, although the concept of heterogeneity has not been captured by prevailing screening criteria that are obtainable in the industry, its effect cannot be over emphasized. In the bid to incorporate this effect, Schlumberger's PETREL® pre-processor is used to build seven different heterogeneity profiles.In doing this a normal distribution profile is used to populate the permeability in the X, Y and Z axis of the 18000 cells as shown in Table A.1.

A permutational selection of each of these cases is done and imported into ECLIPSE®compositional simulator with the corresponding angle of dip included prior to importing the fluid.

(E) Modeling the Reservoir Fluid: In compositional simulation, the computational time is proportional to the number of components considered in the fluids model. Therefore it is necessary to evaluate the effect of

the number of components in the EOS tuning, this is done considering that the sample fluid will be having swelling information characterized for up to C_{30}+ component.

EOS Tuning Process for C_{7+}

PVT simulation model for EOS tuning process is performed using the Peng-Robinson EOS. First, a model with no regression of any parameters (Initial curve) is run. Then a second model by changing plus fraction critical properties and binary interaction coefficients between CO_2 and the plus fraction (Final curve) is generated and regressed until a close representation of the final curve to initial is recorded, Figure B.1

The three guiding parameters that were incorporated and satisfied when lumping the C_{7+} components of the fluids are:

First Constraint:

The sum of the mole fractions of the individual pseudo components must be equal to the mole fractions of C_{7+}.

$$\sum_{i=7}^{N^+} Z_i = Z_{Ci} \qquad (2)$$

Second Constraint:

The sum of the product of the mole fractions and the molecular weight of the individual pseudo-components must be equal to the mole fraction and the molecular weight of C_{7+}.

$$\sum_{i=7}^{N^+} ZiM_{WI} = Z_{Ci}M_{WC_{7+}} \qquad (3)$$

Third Constraint:

The sum of the product of the mole fraction and molecular weight divided by the specific gravity of each individual component is equal to that of C_{7+}.

$$\sum_{i=7}^{N^+} \frac{Z_i M_{wi}}{\gamma_i} = \frac{Z_{Ci} M_{wi}}{\gamma_i} \qquad (4)$$

Where:

i = number of carbon atoms

N^+ = last hydrocarbon in the C_{7+} with n carbon atoms.

By lumping the heavy component (C_{7+}), the total number of components of the reservoir fluid is reduced to 12components. This 12-component mixture is used to tune the EOS to match data. The ECLIPSE®compositional simulator suggests some parameters to be changed in an initial regression.A total of 21 parameters were tweaked including critical pressure (Pc), critical temperature (Tc), critical volume (Vc), molecular weight (MW) of the heavy pseudo-components.

(F) Temperature Analysis: Temperature and pressure alongside the composition of the fluid is what determines the position of the reservoir in both the 2-phase diagram and most importantly, the ternary diagram. The evolved gas from the solution (which in any case is a function of the nature of our fluid) is also a function of the temperature; this can be verified by the amount of gas that is observed as we tend towards the right in the 2-phase envelope.

An erroneous computation abounds if we assume the region has a uniform temperature globally. Thus for the three depths investigated, the temperatures are investigated, equation 5.

Tg=1.67 °F/100ft (5)

(G) Minimum Miscibility Pressure: In this study, MMP for the twenty four fluids investigated were estimated from the MUNGAN correlation (2005). This formula is used to determine MMP based on reservoir temperature and molecular weight (MW) of the pentanes and heavier fractions of the reservoir oil (C5+), without considering the mole fractions of methane. The correlation is as shown in equation 6.

$$MMP = 15.988 * T^{(0.774206+0.0011039)*MWC^{5+}} \qquad (6)$$

Where:

T = Temperature in °F

MW C_{5+} =The molecular weight of pentane and heavier hydrocarbons in the reservoir's oil.

The molecular weight of the pentanes and heavier fractions of the oil have been derived from the IPM 5.0 - PVT*P*®software where fluid data are imputed and constrained to the reservoir temperature, pressure and the estimated fluid's saturation pressure.

(H) Reservoir Voidage Rate: For this research, a bench mark of 70% of the initial rate is set and used as the calling factor for the entire process. The wells have been completed using smart well technology and set to call-up the gas injection process once production rate declines below 70% of the initial value. The initial rate for the field is set to 100,000 BOPD, once the production falls below 70,000 BOPD, for the entire field, the injection process is called to action.

However, the rate of injection is a direct function of the voidage rate. This connotes the rate at which the reservoir is emptied of its fluid from the pore spaces. From material balance, the voidage rate is computed as follows:

$$dv/_{dt} = q_o(B_t + (R_s - R_p)B_g \qquad (7)$$

Where:

$dv/_{dt}$= Reservoir voidage rate, RM^3/Day

q_o= Oil production rate at start of CO2 injection, (SM^3/Day)

B_t= Two phase formation volume factor, (RM^3 / SM^3)

R_s= Solution gas ratio (SM^3/ SM^3)
R_p= Produced gas oil ratio (SM^3 / SM^3)
B_g= Gas formation volume factor (RM^3 / SM^3)

(I) Injection Rate: injection rate is a direct function of a number of parameters.

Rate of injection= f(voidage rate, fluid type, reservoir interconnectivity, reservoir geometry-dip, reservoir porosity and formation maximum allowable pressure)

After the voidage rate is obtained for a given period where the injection is to be commenced, we inject CO_2 at this period to enhance recovery. Thus an injection rate that corresponds to the calculated voidage rate is adopted. However we are injecting CO_2 from the surface to replace the void spaces created from our production. Hence, the surface equivalence of the voidage rate is obtained and worked with. The injection rate is therefore calculated thus:

$$Q_{inj.rate} = \frac{Void.Rate}{B_{g.co2\,@P_{fi}}} \quad (8)$$

Where:
$Q_{inj.rate}$ = Injection rate, SM^3/Day
$Void.Rate$ = Reservoir Voidage Rate, RM^3/Day
$B_{g.co2\,@P_{fi}}$ = CO_2 formation volume factor at various Formation pressures (P_{fi}), RM^3/SM^3

(I) The Hydrocarbon Pore Volume Injected (HCPV) and Fractional Pore Volume (FPV): Although a corresponding injection rate is calculated as a function of voidage rate of the reservoir at the start of injection, the HCPV introduced can be a function of the formation maximum allowable pressure, availability of CO_2 or economics. The total investigated time for this research is 25years; the time to commencement of CO_2 injection is obtained and subsequently netted out from the total investigated time of 25years so that the remaining years is applied as the effective time of injection as illustrated below:

$$HCPV = Q_{Inj.Rate} * t_{eff} \quad (9)$$
$$t_{eff} = 25*365 - t_{initial} \quad (10)$$

Where:
$Q_{inj.rate}$ = CO_2 injection rate, SM^3/Day
t_{eff} = Time of effective CO_2 injection, Day
$t_{initial}$ = Time before inception of CO_2 injection, Day

More so, the fractional pore volume is the ratio of the total volume of CO_2 injected at time t= t_{eff}, to the total pore volume of the reservoir. Calculated as:

$$FPV = \frac{HCPV}{RSPV} \quad (11)$$

Where:
FPV= Fractional Pore Volume, ratio
$HCPV$= Hydrocarbon Pore Volume, RM^3
$RSPV$= Reservoir Pore Volume, RM^3

(J) CO_2 Mobility Ratio: Because the viscosity of CO_2 at reservoir conditions is much lower than that of most oils, viscous instability will limit the sweep efficiency of the displacement and, therefore, oil recovery, Campbell (1985). Mobility ratio, which is the ratio of the mobility of the CO_2 in the reservoir to that of oil, is computed using the property curve (wettability, capillary & relative permeability) as a function of saturation. The viscosity function is obtained from the LBK correlation at each point as a function of pressure for both the gas and reservoir oil.

$$M = \frac{k_{rco2}/u_{co2}}{K_{rowg}/u_o} \quad (12)$$

Where:
M = Mobility ratio of CO_2 to oil
k_{rco2} = Relative permeability of rock to CO_2
K_{rowg} = Relative permeability of rock to oil in the presence of water and gas
u_{co2} = Viscosity of CO_2, cp
u_o = Viscosity of oil, cp

Model Development

In this research, a dedicated RSM and its supporting DOE methodologies are introduced to construct response surfaces as proxies of a simulator when input factors of the simulator, such as heterogeneity and mobility ratios amongst others, cause strong non-linear effects. These methodologies are used to generate RS of arbitrary shapes by iteratively interpolating on a multi-level grid in the experimental space, which allows the local subdivision of the parameter domain. New partitions and interpolation points are added adaptively in the selected parameters regions if local errors of the constructed response surfaces exceed a pre-selected threshold. The art of these methodologies consists of:

- Splitting the whole domain into sub-domain of multiple scale levels, where the components of a RS can be accurately modeled with 'thin plate' spline interpolants. The resultant RS is obtained by combining its global and local components.
- Achieving adequate RS accuracy with the minimum number of simulation runs.

The Placket Burman Design

In view of optimal handling of data analysis, a 'fold over' that doubles the number of runs in a way that increases the resolution of highly aliased Plackett-Burman designs and standard fractional factorials is explored.

Identifying the Main Contributors

Let us begin the analysis by investigating the main effects of the 28 parameters to be examined on a response (R). By averaging the highs and the lows, the difference or contrast is examined. This contrast is the effect of a factor.

Mathematically, the calculation of an effect is expressed as follows:

$$Effect = \frac{\sum Y_+}{n_+} - \frac{\sum Y_-}{n_-} \quad (13)$$

Where:
N= Number of data points collected at each level
Y= Associated responses

The half-normal probability curve is used to identify the sensitivities of the factors along with their interactions.Half probability plot is used to take the absolute value of the effect as shown in figure B.2.

Modeling Responses with Predictive Equations

This is a good place to provide details on the model tested in the analysis of variance, ANOVA. The model is a mathematical equation used to predict a given response.

$$Y = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 \quad (14)$$

Where:
Y= The predicted response
β= Model coefficients

For statistical purposes, this model is kept in the coded form of: -1 for low and +1 for high. For model in coded form, the value of the intercept (β_o) represents the average of all the actual responses. The uncoded models are used to generate predicted values. To verify the authenticity of the generated metamodel, factor levels from the designs are entered to generate predicted response. This predicted value is compared with the actual (observed) value from Eclipse simulator to measure the discrepancy, in any case, called the residual.

Developing the Right Transform

It is common for the standard deviation and the mean response to exhibit a "power law" relationship for the abnormal residual plots statistically; this situation is symbolized as follows:

$$\sigma_y \propto \mu^{\alpha} \quad (15)$$

Where:
σ= True standard deviation of response Y
μ= True mean
$\propto$= Arbitrary power for the relationship

Hence, applying this theory, the inverse transformation was adopted and tried over the sample spaces available. Tweaking the constants and lambda demonstrated a near perfect scenario for the combination with R-square and adjusted R-square equal to 1.0. This effect is further bolstered by the conformance of the models F-Value of <.0.001 limit which lies below the minimum of 0.05 for acceptability and significance of model.

The generated equation from inverse transform in terms of the actual factor is given as:

$$\frac{1}{(\text{ADD RECOV}+1000002)} = \{1.00003E-006 - 1.32294E-011*Ø - 5.38567E-011 * NTG - 1.29548E-014 * Kx + 7.03298E-015* Ky + 6.24671E-014* Kz + 1.76294E-011 *KvKh - 1.77156E-014 * HH + 2.15642E-014* VH - 1.33092E-013 * API - 1.66683E-012 * \mu o - 5.30945E-015 * MMP - 2.07089E-012*Pc + 1.62500E-014*Pi + 5.27384E-015 * Pb + 9.68585E-015* Pref + 1.12521E-017* Vr - 1.50031E-013* Dip + 7.50462E-017* D - 5.33625E-012 * Kro + 2.85318E-016*M - 1.52557E-014*Rs - 6.73741E-016* Rp + 7.74225E013*So + 1.23132E-012* HPVi - 1.16768E-017* Qi + 2.57234E-014 * T \quad (16)$$

Where:
* ADD RECOV = Additional recovery
*Ø = Porosity of the formation
* NTG = Net to gross ratio
* Kx = Horizontal permeability in the x axis
* Ky = Horizontal permeability in the y axis
* Kz = Vertical permeability
* Kv/Kh= Vertical to horizontal permeability ratio
* HH = Heterogeneity index in the horizontal direction
* VH = Heterogeneity index in the vertical direction
* API = Fluid gravity
* μo = Fluid viscosity
* MMP = Minimum miscibility pressure
* Pc = Capillary pressure
* Pi = Reservoir initial pressure
* Pb = Reservoir bubble pressure
* Pref = Reference presure for Co_2 injection
* Vr = Reservoir voidage rate at inception of CO_2 injection
* Dip = Reservoir angle of dip
* D = Formation depth
* Kro = Oil relative permeability at inception of CO_2 injection
* M = CO_2 to oil mobility ratio at inception of CO_2 injection
* Rs = Solution gas at inception of CO_2 injection
* Rp = Produced gas at inception of CO_2 injection
* So = Oil saturation at inception of CO_2 injection
* HPVi = HCPV of CO_2 introduced to the formation
* Qi = CO_2 injection rate
* T = Reservoir temperature

Model Validation

Validation of the generated model is based on comparing prediction of the meta-model developed to the predictive performance of Claridge Correlation. Moreso, the predictive trend of these two models is finally compared to that of ECLIPSE® CO_2 compositional simulation runs at different depths within the modal space.

The Claridge Correlation- Modified Koval for Inverted 5-Spot Pattern

The performance model developed here is a fractional-flow based screening model. It is based on the Koval methodKoval (1963), for predicting recovery in a secondary CO_2 – flood,to model secondary miscible flooding process modified by Claridge(1992)for aerial sweep in an inverted five –spot pattern. Koval developed the original method to model secondary unstable miscible flooding processes, in which there is no mobile water, which is similar to the process developed for this research, and the fractional flow of CO_2 and oil only dependent on the viscosity ratio of oil to CO_2.

Acomparative representation of the predictive performance exhibited by the generated meta model, Claridge Correlation and the prediction from Eclipse® compositional simulator for the various depths of 5000ft, 10000ft and 15000ft and dip of 0°, 15°, 30° and 40° is shown:

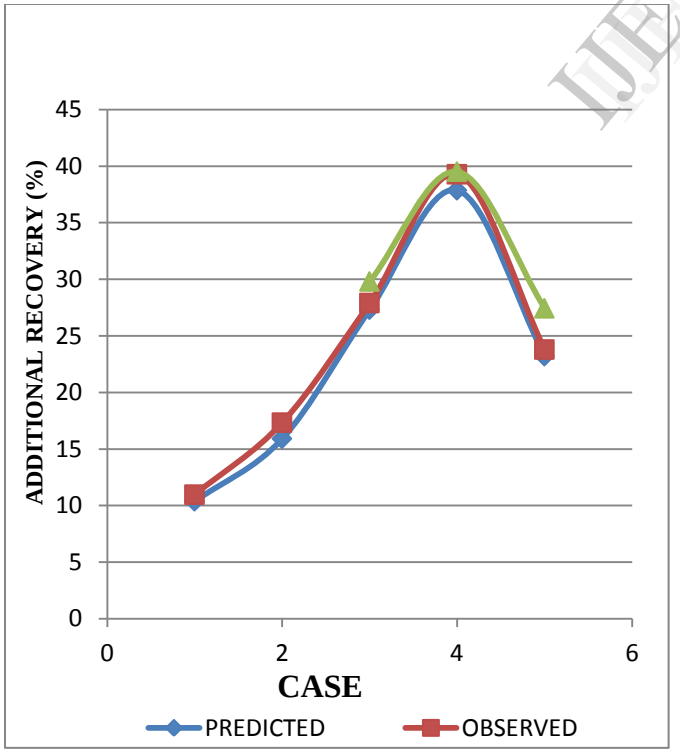

Figure 1: Models Predictions Vs ECLIPSE Observed performance @ 5000ft & 110°F

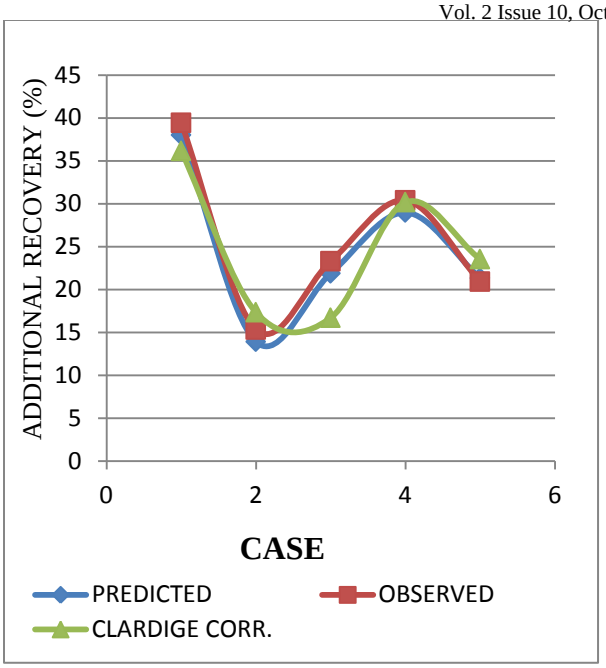

Figure 2: Models Predictions Vs ECLIPSE Observed performance @ 10000ft & 187°F

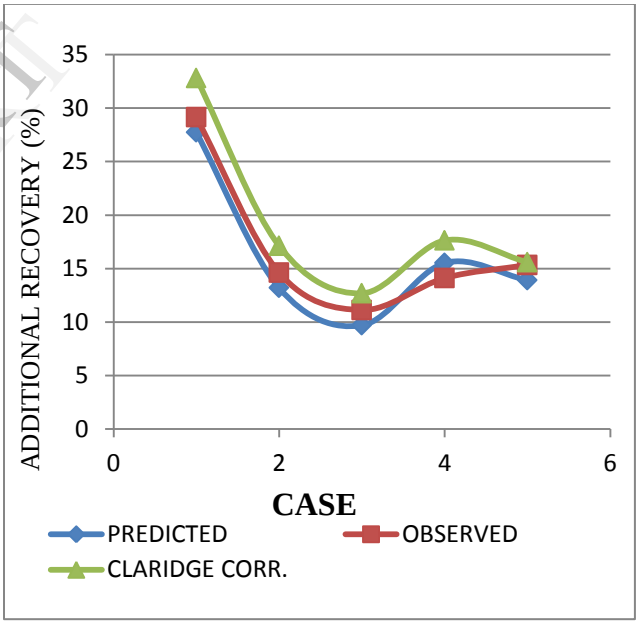

Figure 3: Models Predictions Vs ECLIPSE Observed performance @ 15000ft & 280°F

Analysis of Model Predictions

Tables 1, 2 and 3 presents the observed data from ECLIPSE® and the predicted data from the generated model and Claridge correlation as well. Columns 5 & 6 in the tables represent the discrepancies present from the various predictors to the observed values from ECLIPSE® simulator. From the tables, the average deviation is calculated using:

$$AverageDevitaion = \frac{1}{n}\sum_{i=1}^{5} |x - \bar{x}| \qquad (17)$$

Where:
n = no of runs
x = calculated difference
$\bar{x}$= mean of calculated difference

From the equation, predicted values demonstrates infinitesimal discrepancy from the observed data during the simulation. The deviations in the 5000ft, 10000ft and 15000ft are 0.399%, 0.906% and 0.586% for the generated Meta Model; this affirms the validity of the generated equation in terms of prediction. The Claridge Correlation exhibits discrepancies to the tune of 1.145%, 1.11% and 1.59% respectively.

Table 1: Analysis of Models Precisions @ 5000ft

RUNS	PREDIC-TED	CLARIDGE CORR.	OBSER-VED	DIFF. BTW MODEL & OBSERVED	DIFF. BTW CLARIDGE CORR. & OBSERVED
1	10.3791	46.724	10.9632	0.584095792	-
2	15.9116	35.48	17.3275	1.415867637	-
3	27.3159	29.802	27.9	0.584073637	1.902
4	37.8675	39.5119	39.2834	1.415926817	0.2285
5	23.2059	27.432	23.79	0.584085276	3.642

Table 2: Analysis of Models Precisions @ 10000ft

RUNS	PREDIC-TED	CLARIDGE CORR.	OBSER-VED	DIFF. BTW MODEL & OBSERVED	DIFF. BTW CLARIDGE CORR. & OBSERVED
1	27.7371	32.81	29.153	1.415925876	3.657
2	13.2033	17.126	14.6192	1.415913736	2.50682
3	9.7033	12.6904	11.1192	1.415903825	1.5712
4	15.5259	17.6324	14.11	-1.415887313	3.5224
5	13.9141	15.59	15.33	1.415886733	0.26

Table 3: Analysis of Models Precisions @ 15000ft

RUNS	PREDIC TED	CLARIDGE CORR.	OBSER VED	DIFF. BTW MODEL& OBSERVED	DIFF. OF CLARIDGE CORR. & OBSERVED
1	38.024	36.166	39.44	1.415955007	3.274
2	13.9141	17.35	15.33	1.415886733	2.02
3	21.8841	16.71	23.3	1.415909302	6.59
4	28.9841	30.1874	30.4	1.415929408	0.213
5	21.3359	23.546	20.92	-0.415906597	2.626

Conclusion

Ultimately, it has been discovered by inference from this work that benching on the screening parameters that already exist as constraining criteria, reservoirs that have good potentials of performing favourably to CO_2 EOR may be by-passed. In like manner, false judgments may be served to other reservoirs that may comply with the vertices of the prevailing screening criteria. Moving forward, in addition to what already abounds in literature, other key players in CO_2 EOR that influence the performance of CO_2 in enhance oil recovery include: degree of heterogeneity of the reservoir, reservoir dip,mobility ratio of the CO_2 to oil, injection rate as well as volume of CO_2 introduced to the formation. An underlying factor also is the well configurations.

Finally, an interesting finding from this research is that the quantitative performance of CO_2 EOR can actually be prognosticated before execution of the process to a great precision. Prior to this research, more attention has been paid to the technical feasibility and economic viability of CO_2 EOR. The contribution of a *priori-knowledge* to the extra recovery that will be obtained if CO_2 EOR is embarked on is therefore a prudent approach towards good engineering judgment for candidate reservoirs. This research has produced a predictive correlation that centers on key players and mild contributors alike to the quantitative prediction of recovery performance of oil reservoirs under Carbon Dioxide Flooding.

Nomenclature

BOPD = Barrel of Oil Produced per day
CO_2 = Carbon Dioxide
DOE = Design of Experiment
EOR = Enhanced Oil Recovery
EOS = Equation of State
HC = Hydrocarbon
IPM = Integrated Petroleum Management
MMP = Minimum Miscibility Pressure
MW = Molecular Weight

P_{fi} = Formation Pressure
RM^3= Reservoir Cubic Meter
RSM = Response Surface Methodology
SM^3= Standard Cubic Meter
WAG = Water Alternating Gas

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Appendix

TableA.1 Design Cases of Populated Heterogeneity

Property	1	2	3	4	5	6	7
Kx (md)	100-400	250-310	80-600	200-800	150-750	90-200	300-1000
Ky(md)	100-400	250-310	80-600	200-800	150-750	90-200	300-1000
Kz(md)	10-20	5-9	12-33	2-7	1-15	3-30	2-18

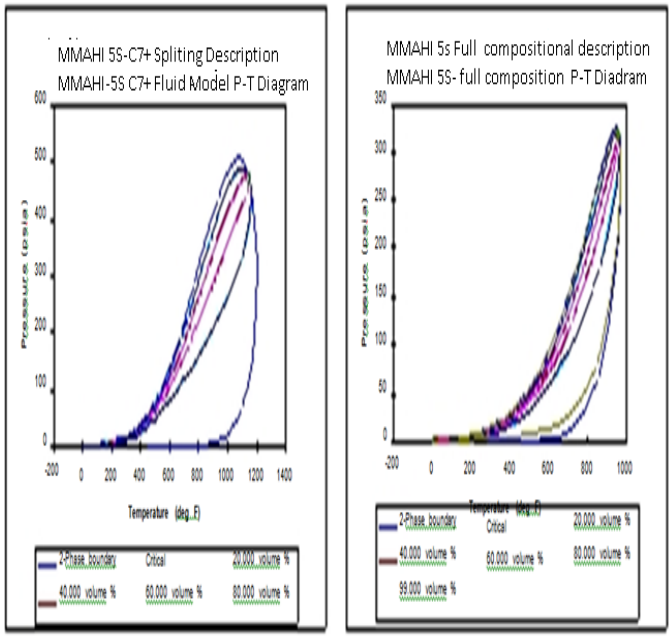

Figure B.1Descriptions of a C_{7+} and Full Fluid Compositional Model

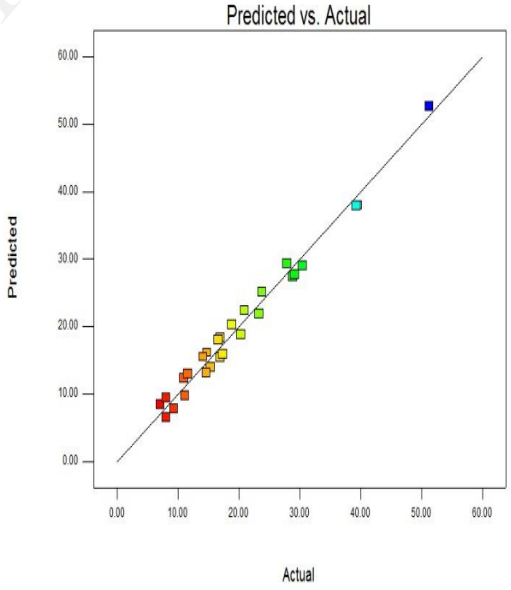

Figure B.2 Predicted Vs Actual Profile for Factors

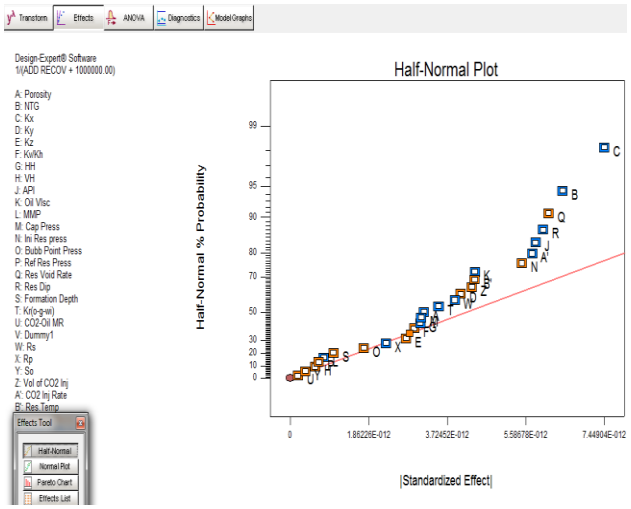

Figure B.3 Half Normal Plot for Effect of Factors in CO_2Injection

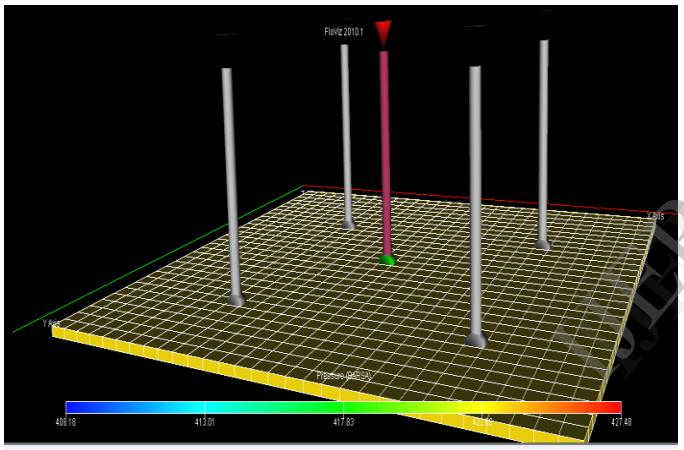

Figure B.4 Well Configurations for a Horizontal Reservoir (0° Dip)