Enhanced Gas Condensate Recovery by Injection of Produced Hydrocarbon Gas

Anthony Ogbaegbe Chikwe, Valentine Igwe, Chukwuebuka Francis Dike*, Federal University of Technology Owerri, Owerri, Nigeria; **Gift Aghaulor,** Covenant University, Otta, Nigeria; **Jude Emeka Odo,** Federal University of Technology Owerri, Owerri, Nigeria

Abstract

Natural gas has become an increasingly favored energy source, meeting more than a quarter of the global energy demand. Among natural gas resources, gas condensate is distinct in that it exhibits liquid separation as pressure diminishes over the reservoir's lifespan, a phenomenon that can markedly influence reservoir productivity. To counteract this and rejuvenate well productivity, chemical and mechanical interventions are implemented. While these methods can yield some measure of success, there is a pressing need for more proactive measures that can preemptively address this issue and reduce operational interruptions. Currently, a significant challenge within the oil industry pertains to attaining high hydrocarbon recovery in gas condensate fields, predominantly due to pressure complications and the presence of active aquifers within these reservoirs. This research investigates various enhanced oil recovery (EOR) methodologies, with a particular emphasis on the enhanced recovery from gas condensate reservoirs through the injection of produced hydrocarbon gas. An alternative methodology was developed and verified, demonstrating efficacy and computational efficiency. Utilizing an inverted five-spot model in a gas condensate reservoir simulation, independent parameters were established, encompassing bottom-hole pressure for production wells and gas injection rate for injection wells. Through the application of a Box-Behnken experimental design, a spectrum of parameter combinations was generated to conduct simulation experiments, yielding outcomes such as cumulative oil production and cumulative gas production. Subsequently, response surface models were constructed using response surface methodology, revealing a dependable correlation between cumulative oil production and cumulative gas production with independent parameters. To ascertain the optimal solution, a multi-objective genetic algorithm was utilized, with the aim of maximizing cumulative oil production and minimizing cumulative gas production. The analysis yielded a singular optimal solution, representing the optimal set of operating conditions for enhanced gas condensate recovery. The findings indicate that the amalgamation of proxy models and optimization algorithms can substantially assist in identifying optimal operating conditions during gas condensate reservoir simulation. This approach not only reduces computational expenses and time demands but also enhances the efficacy of gas condensate recovery.

Introduction

The global demand for fossil fuels is experiencing significant growth (Kerunwa et al. 2024) due to population growth and development. In Nigeria, the power sector has been unbundled, and the country is facing energy poverty compounded by low oil prices and volatility. To reduce costs and increase productivity, oil companies are seeking ways to address these challenges. Nigeria possesses substantial proven reserves of natural gas, estimated at 180 trillion standard cubic feet, ranking it ninth globally and the largest in Africa (Central Intelligence Agency 2014). The natural gas in Nigeria can be categorized as associated or non-associated (Elehinafe et al. 2022), with a relatively equal distribution ratio between the two. Associated gas refers to gas found together with

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*Corresponding author: dike.chukwuebuka@futo.edu.ng

oil in a reservoir, while non-associated gas refers to gas found in reservoirs without oil. Gas condensate reservoirs are valuable sources of hydrocarbons, consisting of a mixture of natural gas and liquid condensate. Optimizing the recovery of gas condensate is crucial for economic reasons, leading to increased interest in enhanced recovery techniques. One such method gaining attention is the injection of produced hydrocarbon gas, which offers potential benefits in terms of improved recovery and reservoir performance. Gas condensate reservoirs represent new challenges for the petroleum industry, and it is important to approach them with caution, as applying conventional gas/oil system knowledge without careful examination may lead to incorrect conclusions and practices. This study focuses on enhanced recovery from gas condensate reservoirs through the injection of produced hydrocarbon gas. It covers various aspects, including gas condensate properties, composition, condensate banking, economic considerations, mitigation strategies, challenges, and future directions. Understanding how condensate accumulation impacts productivity and liquid phase composition configuration is crucial for optimizing production strategies, mitigating the effects of condensate accumulation and enhancing the overall retrieval of gas and condensate.

Gas Condensate

In a gas condensate reservoir, the initial state of the reservoir fluids is primarily in the form of gas phase. As the reservoir undergoes primary production and the pressure within the reservoir decreases, the gas undergoes a phase change, and liquid condensate starts to accumulate. This accumulation is particularly significant in areas such as fractures and the well bottom hole, especially when the in-situ reservoir pressure falls below the dew-point pressure. At this point, the gas starts to condense into liquid form, forming what is known as condensate.

However, the condensate does not immediately flow; instead, it accumulates until it reaches a critical saturation level. Generally, three distinct zones can be identified from the wellbore to the reservoir boundary, each with varying concentrations of condensate and gas phases.

- Mobile gas and mobile condensate region: This zone is located near the wellbore and consists of both gas and condensate that can freely move within the formation.
- Transition zone: This zone encompasses both mobile gas and immobile oil. It acts as a transition area between the mobile gas and condensate region and the gas phase zone without condensate dropout.
- Gas phase zone: This zone is characterized by the absence of condensate dropout and primarily contains gas (Penuela and Civian 2000).

The existence of trapped condensate in the reservoir has a notable consequence of leaving a substantial volume of high-quality oil unrecovered. This trapped condensate impedes the flow of gas towards the wellbore, causing a decline in gas production. These observations have been corroborated by various studies conducted by researchers such as Moses and Donohoe (1987), Li and Firoozabadi (2000), Pope et al. (2000). Their findings provide valuable insights into the impact of trapped condensate on oil and gas production in gas condensate reservoirs.

Figure 1 depicts a gas field in a retrograde state where the temperature exceeds the critical point temperature. The curved lines on the diagram represent the transitions between different phases of the fluid as it moves from the reservoir (indicated by the vertical green line), undergoes cooling while ascending through the wellbore, and eventually reaches the separator. Retrograde condensation in a gas condensate reservoir starts near the wellbore and gradually spreads outward in a radial pattern as the pressure decreases.

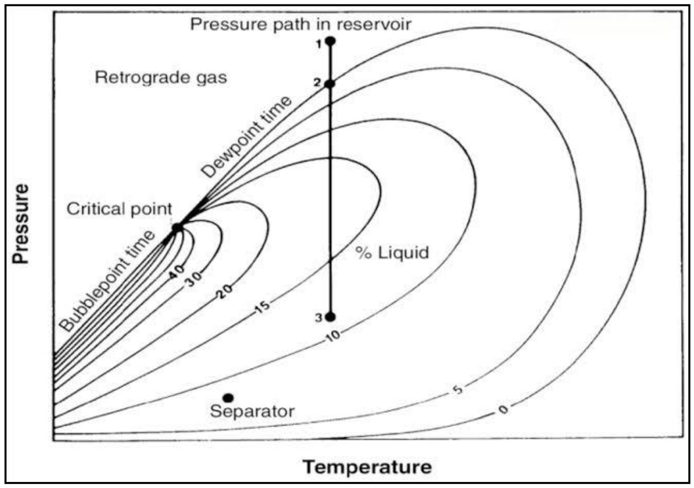


Figure 1—Phase diagram of a retrograde-condensate gas (McCain 1990).

Materials and Methods

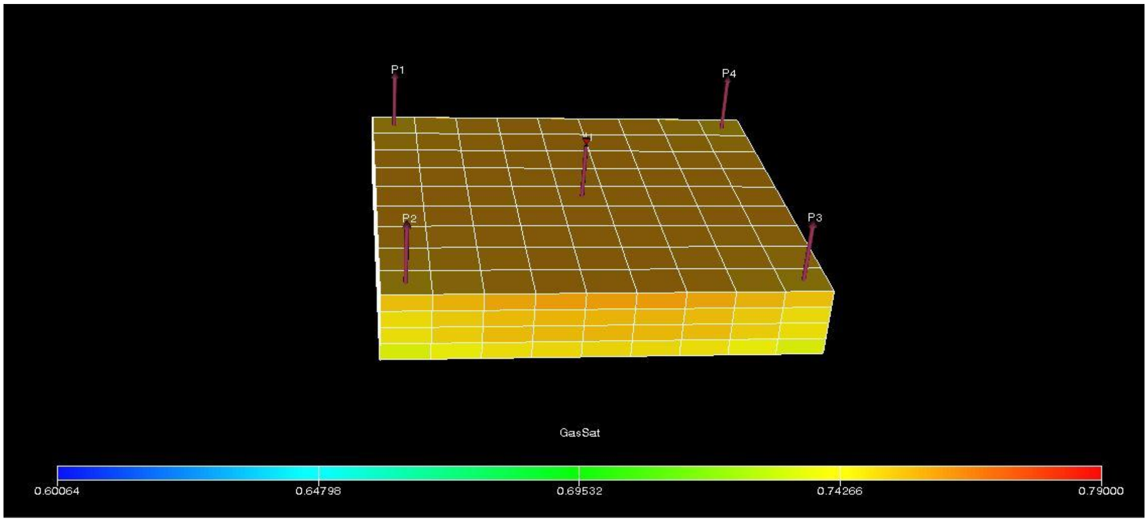
Materials. The materials utilized for this study are a typical gas condensate simulation model, design expert software and eclipse reservoir simulator. The reservoir simulation model is a representative of a real field reservoir while Eclipse reservoir simulator was used to run the reservoir simulation models to evaluate different hydrocarbon gas injection scenarios. Design expert software was used to generate parameter realization for conducting reservoir simulation runs. The reservoir simulation model consists of 9×9×4 grid blocks in the X, Y, and Z directions respectively. The dimensions in the x and y directions is 50 m while each layer in the z direction has dimensions of 10 m. The depth of the top of the reservoir is 2,070 m. The oil water contact and gas oil contacts for a gas condensate reservoir are the same and were set to be equal to 2,110 m. The net pay thickness of the reservoir is 40 m. An inverted five spot was modelled in the gas condensate reservoir such that an injection well was placed at the center while 4 producers were placed at the edges of the reservoir as shown in **Figure 2**.

Methods. The Method comprises of development of input & output data, development of polynomial regression model, and validation & optimization of polynomial regression models.

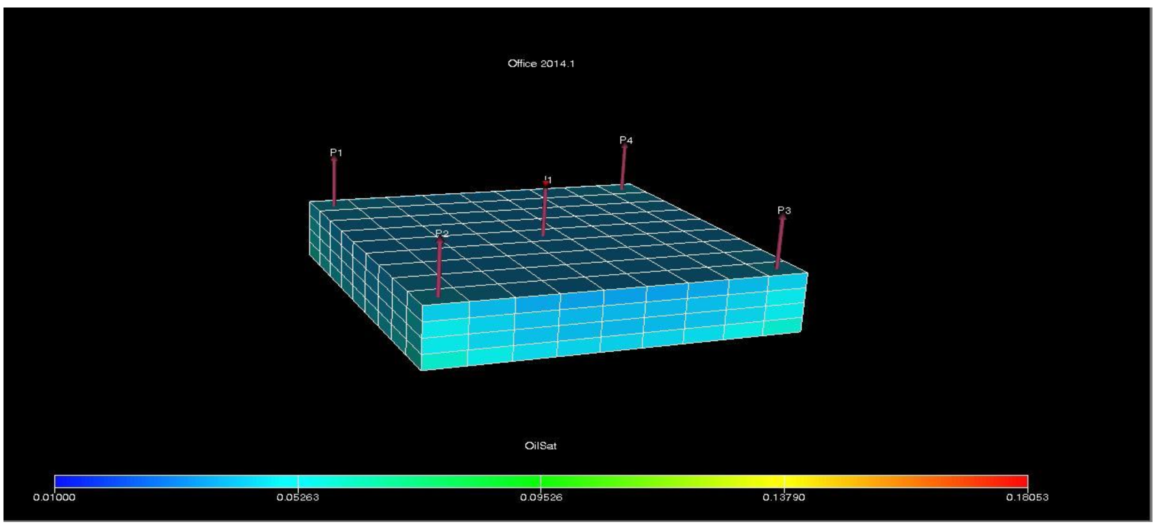
Development of Input and Output Data. The input data was developed using the Box-Behnken design approach in the Design Expert Software. The Box-Behnken method entailed the generation of parameter realization based on introduced minimum and maximum value depicted in **Table 1**. These generated input data from Design Expert Software was introduced into Eclipse Simulator Software for Simulation. The result of the eclipse simulation run yielded cumulative oi production and cumulative gas injection and cumulative gas production depicted in **Table 2**

Table 1—Minimum and Maximum values of input data.

Factor	Name	Units	Min.	Max.	Mean	Std. Dev.
Bottom-hole pressure of P1	X1	Bar	20.00	45.00	32.50	7.45
Bottom-hole pressure of P2	X2	Bar	20.00	45.00	32.50	7.45
Bottom-hole pressure of P3	X3	Bar	20.00	45.00	32.50	7.45
Bottom-hole pressure of P4	X4	Bar	20.00	45.00	32.50	7.45
Gas injection rate of I1	X5	M3/day	100.00	1000.00	550.00	268.33



(a) Gas saturation



(b)Oil saturation

Figure 2—3D modeling of an inverted five spot.

Development of Polynomial Regression Model. The developed input and output datasets were entered into Design Expert software from which analysis of variance (ANOVA) was conducted to determine the parameters that were significant to the model.

Validation and Optimization of Polynomial Regression Models. The models were validated using cross plots and statistical error evaluation, while the optimization was carried out using polynomial regression models. The polynomial regression models were coded in a MATLAB script file so that an optimization algorithm within MATLAB's global optimization toolbox can be used to run the models. The models were run using multi-objective genetic algorithm because two objective functions represented by two polynomial regression models were considered.

Table 2—Input and output data obtained BBD and reservoir simulation.

Run	A:X1	B:X2	C:X3	D:X4	E:X5	R1-CGP	R2-COP	R3-CGI
1	32.5	32.5	32.5	32.5	550	413.905	59.8002	1.825
2	20	45	32.5	32.5	550	452.963	66.4864	10.0375
3	32.5	32.5	32.5	32.5	550	433.875	63.188	10.0375
4	32.5	32.5	20	20	550	453.017	66.6856	10.0375
5	32.5	32.5	20	32.5	100	452.204	66.3689	1.825
6	20	32.5	32.5	20	550	453.016	66.6909	10.0375
7	20	32.5	32.5	32.5	1000	453.773	66.5757	18.25
8	32.5	32.5	32.5	20	100	452.204	66.3689	1.825
9	45	45	32.5	32.5	550	433.874	63.1921	10.0375
10	32.5	20	32.5	45	550	452.963	66.4896	10.0375
11	20	32.5	32.5	45	550	452.963	66.4828	10.0375
12	45	32.5	45	32.5	550	433.874	63.1908	10.0375
13	45	32.5	32.5	20	550	452.963	66.4827	10.0375
14	20	32.5	32.5	32.5	100	452.204	66.3688	1.825
15	32.5	45	32.5	20	550	452.963	66.4895	10.0375
16	45	32.5	32.5	32.5	100	433.06	63.0101	1.825
17	20	32.5	45	32.5	550	452.963	66.4895	10.0375
18	32.5	32.5	32.5	20	1000	453.773	66.5757	18.25
19	45	20	32.5	32.5	550	452.963	66.4864	10.0375
20	45	32.5	20	32.5	550	452.963	66.4896	10.0375
21	32.5	45	45	32.5	550	433.874	63.1941	10.0375
22	32.5	32.5	45	32.5	100	433.06	63.0101	1.825
23	32.5	45	32.5	32.5	100	433.06	63.01	1.825
24	32.5	32.5	32.5	45	100	433.06	63.01	1.825
25	32.5	32.5	32.5	45	1000	434.689	63.3832	18.25
26	32.5	32.5	20	32.5	1000	453.773	66.5757	18.25
27	32.5	45	32.5	32.5	1000	434.689	63.3832	18.25
28	32.5	20	32.5	32.5	100	452.204	66.3689	1.825
29	32.5	20	20	32.5	550	453.016	66.6909	10.0375
30	32.5	32.5	20	45	550	452.963	66.4864	10.0375
31	32.5	32.5	45	32.5	1000	434.689	63.3832	18.25
32	32.5	32.5	32.5	32.5	550	433.875	63.188	10.0375
33	32.5	32.5	45	45	550	433.874	63.1921	10.0375
34	32.5	20	32.5	20	550	453.017	66.6804	10.0375
35	32.5	20	45	32.5	550	452.963	66.4828	10.0375
36	20	32.5	20	32.5	550	453.017	66.6804	10.0375
37	32.5	20	32.5	32.5	1000	453.773	66.5757	18.25
38	32.5	32.5	32.5	32.5	550	433.875	63.188	10.0375
39	32.5	45	32.5	45	550	433.874	63.1908	10.0375
40	32.5	32.5	32.5	32.5	550	433.875	63.188	10.0375
41	45	32.5	32.5	32.5	1000	434.689	63.3832	18.25
42	45	32.5	32.5	45	550	433.874	63.1941	10.0375
43	20	20	32.5	32.5	550	453.017	66.6856	10.0375
44	32.5	32.5	32.5	32.5	550	433.875	63.188	10.0375
45	32.5	32.5	45	20	550	452.963	66.4863	10.0375
46	32.5	45	20	32.5	550	452.963	66.4828	10.0375

Result and Discussion

Analysis of Variance. **Tables 3** to **5** present the ANOVA results for cumulative gas production, cumulative oil production, and cumulative gas injection, respectively. It is deducible that the models and their corresponding terms are statistically significant. Consequently, the model is deemed accurate and suitable for predictive purposes. **Eqs. 1** to **3** illustrate polynomial regression models delineating the correlations between cumulative gas production, cumulative oil production, and cumulative gas injection with the independent variables, (such as gas injection rate and bottom-hole pressure, respectively.

Table 3—ANOVA for cumulative gas production.

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	4353.92	16	272.12	13.03	< 0.0001	significant
A-X1	571.88	1	571.88	27.39	< 0.0001	
B-X2	571.88	1	571.88	27.39	< 0.0001	
C-X3	571.88	1	571.88	27.39	< 0.0001	
D-X4	571.88	1	571.88	27.39	< 0.0001	
E-X5	10.23	1	10.23	0.4898	0.4896	
AB	90.58	1	90.58	4.34	0.0462	
AC	90.58	1	90.58	4.34	0.0462	
AD	90.59	1	90.59	4.34	0.0462	
BC	90.59	1	90.59	4.34	0.0462	
BD	90.58	1	90.58	4.34	0.0462	
CD	90.58	1	90.58	4.34	0.0462	
A^2	680.27	1	680.27	32.58	< 0.0001	
B^2	680.27	1	680.27	32.58	< 0.0001	
C^2	680.27	1	680.27	32.58	< 0.0001	
D^2	680.27	1	680.27	32.58	< 0.0001	
E^2	143.60	1	143.60	6.88	0.0138	
Residual	605.54	29	20.88			
Lack of Fit	273.20	24	11.38	0.1713	0.9988	not significant
Pure Error	332.34	5	66.47			
Cor Total	4959.46	45				

Table 1—ANOVA for cumulative oil production.

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	133.73	16	8.36	14.60	< 0.0001	significant
A-X1	18.13	1	18.13	31.66	< 0.0001	
B-X2	18.13	1	18.13	31.66	< 0.0001	
C-X3	18.13	1	18.13	31.66	< 0.0001	
D-X4	18.13	1	18.13	31.66	< 0.0001	
E-X5	0.3364	1	0.3364	0.5875	0.4496	
AB	2.39	1	2.39	4.18	0.0500	
AC	2.41	1	2.41	4.22	0.0491	
AD	2.37	1	2.37	4.14	0.0510	
BC	2.37	1	2.37	4.14	0.0510	
BD	2.41	1	2.41	4.22	0.0491	
CD	2.39	1	2.39	4.18	0.0500	
A^2	20.82	1	20.82	36.36	< 0.0001	
B^2	20.82	1	20.82	36.36	< 0.0001	
C^2	20.82	1	20.82	36.36	< 0.0001	
D^2	20.82	1	20.82	36.36	< 0.0001	
E^2	3.88	1	3.88	6.77	0.0144	
Residual	16.61	29	0.5726			
Lack of Fit	7.04	24	0.2934	0.1534	0.9994	not significant
Pure Error	9.56	5	1.91			
Cor Total	150.34	45				

Table 5—ANOVA for cumulative gas injection.

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	1079.90	6	179.98	107.66	< 0.0001	significant
A-X1	0.0000	1	0.0000	0.0000	1.0000	
B-X2	0.0000	1	0.0000	0.0000	1.0000	
C-X3	0.0000	1	0.0000	0.0000	1.0000	
D-X4	0.0000	1	0.0000	0.0000	1.0000	
E-X5	1079.12	1	1079.12	645.52	< 0.0001	
A^2	0.7820	1	0.7820	0.4678	0.4981	
Residual	65.20	39	1.67			
Lack of Fit	8.99	34	0.2645	0.0235	1.0000	not significant
Pure Error	56.20	5	11.24			
Cor Total	1145.10	45				

$$\mathrm{CGP} = 543.521 + -1.18159 * \mathrm{X1} + -1.1816 * \mathrm{X2} + -1.1816 * \mathrm{X3} + -1.1816 * \mathrm{X4} + -0.0202577 * \mathrm{X5} + -0.030456 * \mathrm{X1} * \mathrm{X2} + -0.0304548 * \mathrm{X1} * \mathrm{X3} + -0.0304574 * \mathrm{X1} * \mathrm{X3} + -0.0304573 * \mathrm{X2} * \mathrm{X3} + -0.0304548 * \mathrm{X2} * \mathrm{X4} + -0.0304559 * \mathrm{X3} * \mathrm{X4} + 0.0565043 * \mathrm{X1}^2 + 0.0565043 * \mathrm{X2}^2 + 0.0565043 * \mathrm{X3}^2 + 0.0565043 * \mathrm{X4}^2 + 2.00312\mathrm{e} - 05 * \mathrm{X5}^2 \quad \text{,.............................(1)}$$

$$\mathrm{COP} = 84.9002 + -0.244973 * \mathrm{X1} + -0.244975 * \mathrm{X2} + -0.244974 * \mathrm{X3} + -0.244976 * \mathrm{X4} + -0.0032982 * \mathrm{X5} + -0.00495211 * \mathrm{X1} * \mathrm{X2} + -0.00497278 * \mathrm{X1} * \mathrm{X3} + -0.00492893 * \mathrm{X1} * \mathrm{X4} + -0.00492904 * \mathrm{X2} * \mathrm{X3} + -0.00497267 * \mathrm{X2} * \mathrm{X4} + -0.00495202 * \mathrm{X3} * \mathrm{X4} + 0.00988563 * \mathrm{X1}^2 + 0.00988566 * \mathrm{X2}^2 + 0.00988566 * \mathrm{X3}^2 + 0.00988559 * \mathrm{X4}^2 + 3.29129\mathrm{e} - 06 * \mathrm{X5}^2 \quad \text{,........................(2)}$$

$$CGI = 1.5768 + -0.11388 * X1 + 9.48346e - 17 * X2 + -5.19117e - 18 * X3 + -3.24107e - 19 * X4 + 0.01825 * X5 + 0.001752 * X1^2 \quad \text{,.............................(3)}$$

Polynomial Regression Model. The validation process of the models was rigorously conducted through the utilization of cross plots and a comprehensive statistical error analysis. **Figures 3** through **5** present detailed cross plots that correspond to cumulative gas production, cumulative oil production, and cumulative gas injection, respectively. In Figure 3, it is evident that the predicted cumulative gas production achieved an impressive regression value of 87.81% when compared to the actual cumulative gas production data. This indicates a strong correlation between the predicted and actual values, underscoring the accuracy of the model in this aspect.

Similarly, Figure 4 illustrates the cross plot for cumulative oil production, where the predicted values exhibited a regression of 88.91% against the actual cumulative oil production figures. This high degree of correlation further substantiates the reliability of the model in forecasting oil production trends. Moreover, Figure 5 depicts the cross plot for cumulative gas injection, revealing that the predicted values had a regression of 94.31% with respect to the actual cumulative gas injection data. This exceptionally high regression value suggests that the model is highly effective in capturing the dynamics of gas injection processes.

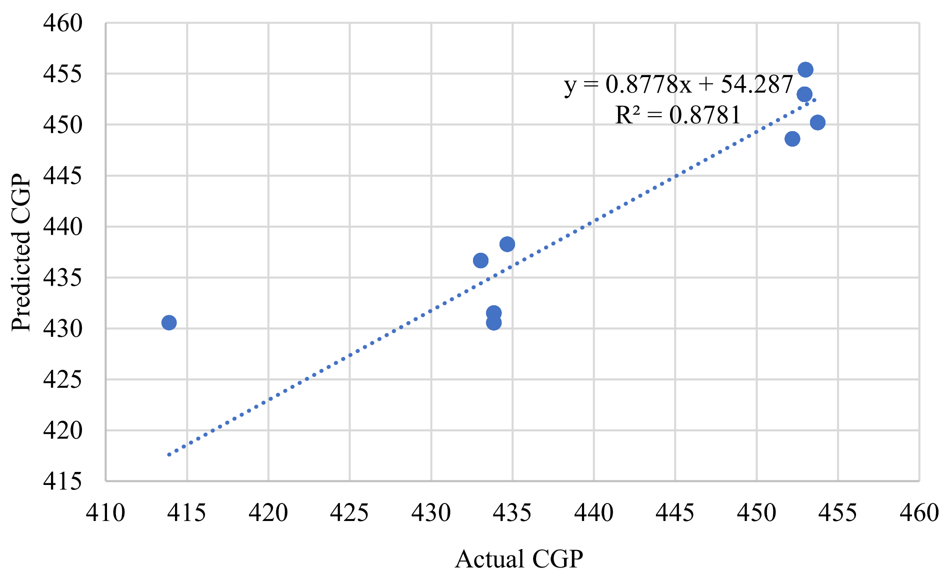


Figure 3—Cross plots for cumulative gas production.

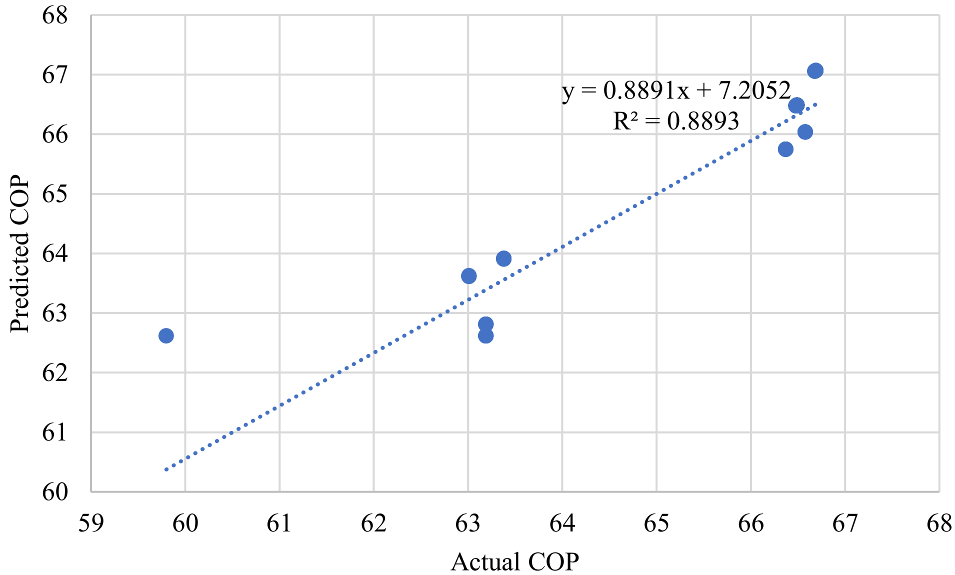


Figure 4—Cross plots for cumulative oil production.

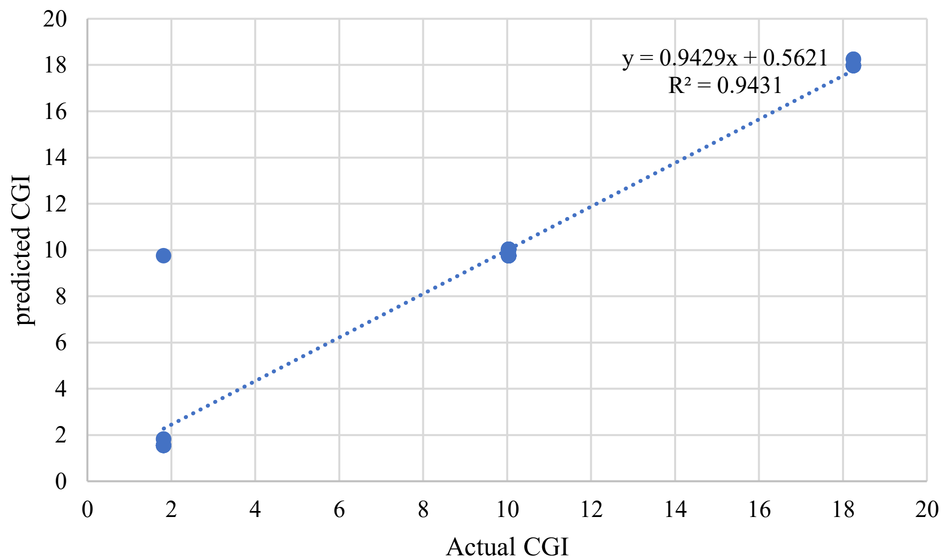


Figure 5—Cross plots for cumulative gas injection.

Collectively, these cross plots and their corresponding statistical analyses provide compelling evidence that the developed polynomial regression models are not only valid but also robust enough to be employed for predictive and optimization studies. The high regression values across all three categories-cumulative gas production, cumulative oil production, and cumulative gas injection-demonstrate the models' capability to accurately represent real-world scenarios. This validation is crucial for ensuring that any predictions or optimizations derived from these models will be based on a solid foundation of empirical data and analytical rigor. Therefore, it is reasonable to conclude that these models can be confidently utilized in further studies to enhance understanding and performance in the respective fields of gas production, oil production, and gas injection.

Optimization of Polynomial Regression Models. Table 6 showed the multi-objective optimization results. The models were run using multi-objective genetic algorithm because two objective functions represented by two polynomial regression models were considered. The optimization was geared towards get the highest cumulative oil production and the least cumulative water production. As shown in Table 6, the X_1, X_2, X_3, X_4 and X_5 values of serial number 16 recorded the highest cumulative oil production and the least cumulative water production showing the role of optimization in production capacity enhancement. **Figure 6** shows the Pareto front. As observed from the Pareto front increase in cumulative oil production yielded a reduction in cumulative gas production, and vice versa

Table 6—Multi-objective optimization results.

S/N	x1	x2	x3	x4	x5	y1	y2
1	44.99835	44.12597	44.99238	35.92743	617.1253	60.95589	407.6993
2	44.99914	44.70789	44.98837	42.14048	617.3741	60.09117	410.8003
3	44.99983	44.99617	44.99998	44.9608	618.6007	59.94088	413.5667
4	44.99923	44.06912	44.99925	36.44121	616.9327	60.8564	407.7916
5	44.99925	44.00692	44.99938	36.77325	616.8554	60.79503	407.8758
6	44.99986	44.53442	44.99991	38.65928	617.8937	60.48542	408.5261
7	44.99872	44.7249	44.9956	40.62113	618.5155	60.23432	409.6339
8	44.99922	44.74702	44.99191	43.2595	618.0383	60.01514	411.8113
9	44.99843	44.42491	44.99319	37.02922	616.9287	60.74936	407.9331
10	44.9991	44.2125	44.99207	37.99829	617.9439	60.58704	408.2783
11	44.99889	44.06207	44.99943	35.48444	617.0295	61.04561	407.6294
12	44.99877	44.28185	44.99814	40.18627	617.3646	60.28689	409.3936
13	44.99881	44.92972	44.99796	42.72717	617.6583	60.04498	411.2694
14	44.99984	44.98566	44.99992	44.14489	617.9883	59.96714	412.6583
15	44.99979	44.5243	44.98589	39.22763	617.5508	60.4049	408.8248
16	45	43.98145	45	34.39897	616.8373	61.28123	407.5679
17	44.99575	44.56349	44.99753	41.31478	617.4664	60.16476	410.1453
18	44.99801	44.93166	44.99919	41.7078	618.3014	60.1253	410.4034

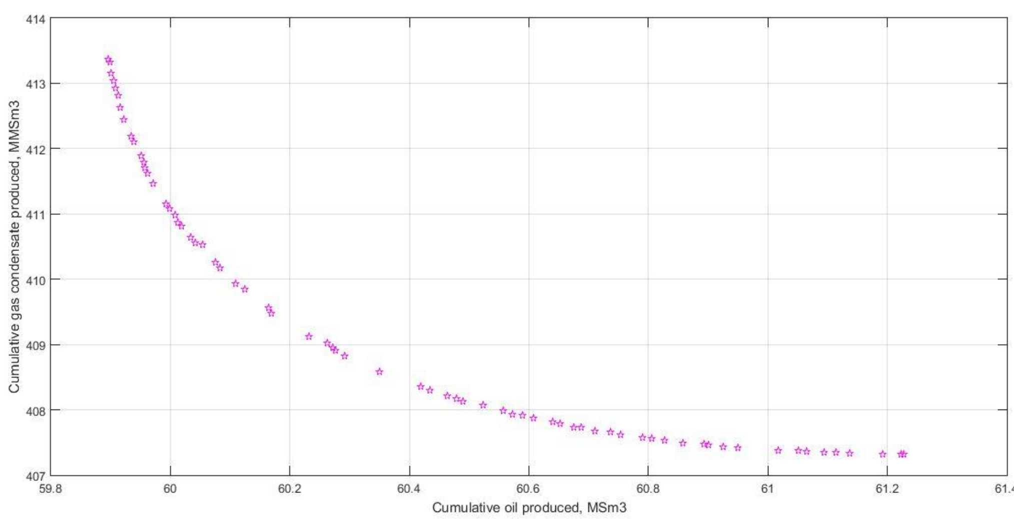


Figure 6—Pareto front showing optimal solutions.

Conclusions

This study concentrated on enhancing gas condensate recovery by identifying optimal operational parameters through the construction of surrogate models and optimization algorithms. Conventional methodologies for pinpointing optimal conditions, which typically involve trial and error or direct optimization via reservoir simulation, can be both computationally demanding and time-intensive. In contrast, the methodology employed in this study, which incorporates surrogate models and an optimization algorithm, has been shown to yield optimal outcomes with reduced computational expenditure.

Utilizing an inverted five-spot model and a comprehensive parameter set generated by a Box-Behnken experimental design, a sequence of simulation experiments was executed in this study. The resultant responses, namely cumulative oil production and cumulative gas production, were ascertained. Response surface models were constructed employing response surface methodology, and these models exhibited a satisfactory correlation between cumulative oil production, cumulative gas production, and the independent variables. Validation of the models confirmed their reliability for optimization endeavors.

A multi-objective genetic algorithm was implemented to ascertain a singular optimal solution that maximizes cumulative oil production and minimizes cumulative gas production. The identified optimal solution represents the optimal combination of bottom-hole pressure for production wells and gas injection rate for injection wells. By implementing this optimal solution, more efficient gas condensate recovery can be realized.

The project conclusively demonstrated that the amalgamation of surrogate models and optimization algorithms facilitates the determination of optimal operational parameters in gas condensate reservoir simulation. This approach diminishes computational costs and temporal demands, offering a valuable asset for reservoir engineers and operators.

Recommendation

Based on the findings and conclusions of this project, the following recommendations can be made for further studies and practical applications.

- Expand the Scope. The current study focused on an inverted five-spot model in a gas condensate reservoir. Future research can explore different reservoir geometries, injection strategies, and field development scenarios to validate the effectiveness of the proposed approach across a broader range of scenarios.
- Consider Additional Objective Functions. While the current study focused on maximizing COP and minimizing CGP as objective functions, other factors such as the economic viability, environmental impact, or resource utilization efficiency can be included as additional objectives for a more comprehensive analysis.
- Experimental Validation. Conducting laboratory experiments or pilot tests to validate the results obtained from the proxy models and optimization algorithms can further enhance the reliability and practical applicability of the approach.
- Field Application. Collaborate with industry partners to implement and field test the optimized operating conditions derived from this study. Real-world data and feedback can provide valuable insights into the effectiveness and practicality of the proposed approach.
- Integration of Advanced Technologies. Explore the integration of advanced technologies such as artificial intelligence, machine learning, or advanced data analytics techniques to improve the accuracy and efficiency of proxy models and optimization algorithms.

Conflicting Interests

The author(s) declare that they have no conflicting interests.

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Chukwuebuka Francis Dike is a Research Technologist at the Department of Petroleum Engineering, Federal University of Technology Owerri. He has research interest in Drilling Fluids Technology, Reservoir Engineering, Enhanced Oil Recovery and Flow Assurance. Dike Holds a bachelor's degree and master's degree in petroleum engineering from Federal University of Technology Owerri.