Application of Proxy Models for Estimation of Cumulative Recovery Volume from a Heavy Oil Reservoir

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Abstract

Steam flooding as a popular method for heavy oil recovery is associated with high cost and uncertainty issues. These issues are usually analyzed through various simulations and experiments which are usually time consuming and computationally expensive. Hence, in this study a response surface model as proxy model was developed to estimate the cumulative recovery volume (CRV) from a heterogeneous reservoir undergoing a steam flooding process. A five inverted spot steam flooding pattern for the heavy oil reservoir was developed, followed by a Box-Behnken experimental design considering steam and reservoir parameters, was used for data generation. Hence, with steam injection rates, steam temperature, steam quality, bottom-hole flowing pressures of the producer wells as the input parameters, a reduced quadratic response surface model was developed to predict the CRV. With the developed model as the objective function, the maximization of the CRV was achieved while determining the optimal values for the parameters used. The study proved successful as the adjusted and predicted R^2 values were recorded as 97.59% and 95.85%, respectively. Also, up to 19% increase in CRV was achieved after the optimization process. This research, therefore, demonstrates the feasibility of using proxy models to analyse and estimate CRV of a steam flooding reservoir while benefiting from the computational advantages they provide. This approach has potential applications in the oil and gas industry, as it can help reduce uncertainty and the associated high costs of heavy oil recovery.

Introduction

There is an increasing demand for fossil energy in the world as human population and mechanization increases (Al Adasani and Bai 2011). According to the International Energy Agency (IEA) forecast for 2008-2035 outlook, there will be a primary energy demand rate of around 300 MMBOE/D and crude oil is predicted to escalate to almost 100 MMBOE/D by 2035 (Evans et al. 2021). This has therefore fostered the need for the exploration and exploitation of various unconventional energy sources. The extraction of crude oil from the subsurface generally follows three stages, namely, the primary, secondary and enhanced oil recovery (tertiary) stages. Sponsored by the natural drive mechanism of the reservoir, the oil is being produced in the primary recovery stage, and this usually results to roughly 10% of oil supposed to be produced from the formation. In secondary recovery, specialized fluids are injected into the reservoir, through a displacing technique, can extract 20-40% of original oil in place. Then the last production stage involving the production of heavy crude oil unlike primary and secondary uses specialized techniques for 30%-60% of heavy oil production (Alawode and Falode 2021; Muzzafaruddin 2019; Mokheimer et al. 2019).

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One of the most popular and efficient ways of enhanced oil recovery is the thermal recovery method (Hama et al. 2014). The idea here is that heat is used to increase the temperature of the formation thereby lowering the viscosity of the heavy oil contained in this formation, permitting the oil to easily flow towards the production well. Most times this method can involve different steam injection techniques (Chaalal 2018). Thermal recovery method can involve any of these techniques, including steam flooding, steam assisted gravity drainage (SAGD), in-situ combustion, cyclic steam injection etc. Amongst these techniques is the steam flooding thermal EOR method, which is being investigated in this research. Steam flooding is a type of thermal EOR method that uses an injection-to-production configuration for heavy oil production. Steam is pumped into the reservoir from the injector well(s), As shown in **Figure 1**, the pumped steam heats up the formation around the wellbore, eventually forming a steam zone that grows with continuous steam injection while reducing formation fluid viscosity and increasing oil mobility.

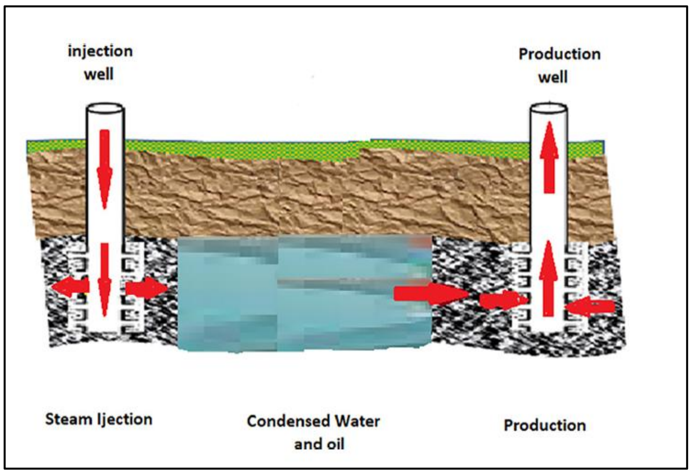


Figure 1—A typical illustration of a steam flooding process (Modified from Mokheimer et al. 2019).

However, while EOR methods especially the thermal techniques have proven to be efficient, initial assessment of the feasibility of the chosen technique must be ascertained before field scale application (Matthew et al. 2023). The feasibility study must consider the risk, economic viability (realizable oil volume by the process) and optimal parameters for optimal production from such reservoirs. The industry, on this regard, has always relied on building and evaluating reservoir numerical simulation model to carry out these studies. However, the complexity of these numerical simulations makes conducting a full experimental run time-consuming. Additionally, there are significant storage constraints, and often, the simulations lack the flexibility needed to perform sensitivity studies. These studies are essential for assessing the impact of one parameter on another and identifying optimal parameters for achieving optimal production (Ma and Leung 2020; Yu et al. 2021). To mitigate these gaps, an innovative approach, known as proxy models have proven to be successful and have been utilized in providing excellent solutions. The proxy model, also known as the surrogate model, is simply a representation of a complex numerical simulation that is useful in higher levels of reservoir study such as uncertainty analysis, risk analysis, and production optimization (Bahrami et al. 2022; Silva et al. 2020). This approach has since been applied in various areas with significant results. Aboaba et al. (2020) implemented smart proxy models in in computational fluid dynamics (CFD) simulation and thereby reduced the computational cost that would have been associated with the CFD simulations. Similarly, by leveraging an optimized least-squares support vector machine (LSSVM) as an adaptive proxy model, Qiao et al. (2022) were able to handle efficiently production optimization problems. While surrogate models have been applied in these aforementioned areas, Yu et al. (2021) leveraged artificial neural networks as a suitable data-driven proxy model for forecasting the cumulative oil production during a steam-assisted gravity drainage process. While, Matthew et al. (2023) combined proxy models and NSGA-II (Non-dominated Sorting Genetic Algorithm II) to determine the optimal values for water injection rates and half-cycle lengths to maximize the oil recovery and CO_2 stored in the reservoir. These various applications of proxy models therefore make the use of proxy models suitable for application for problems having similar challenging constraints.

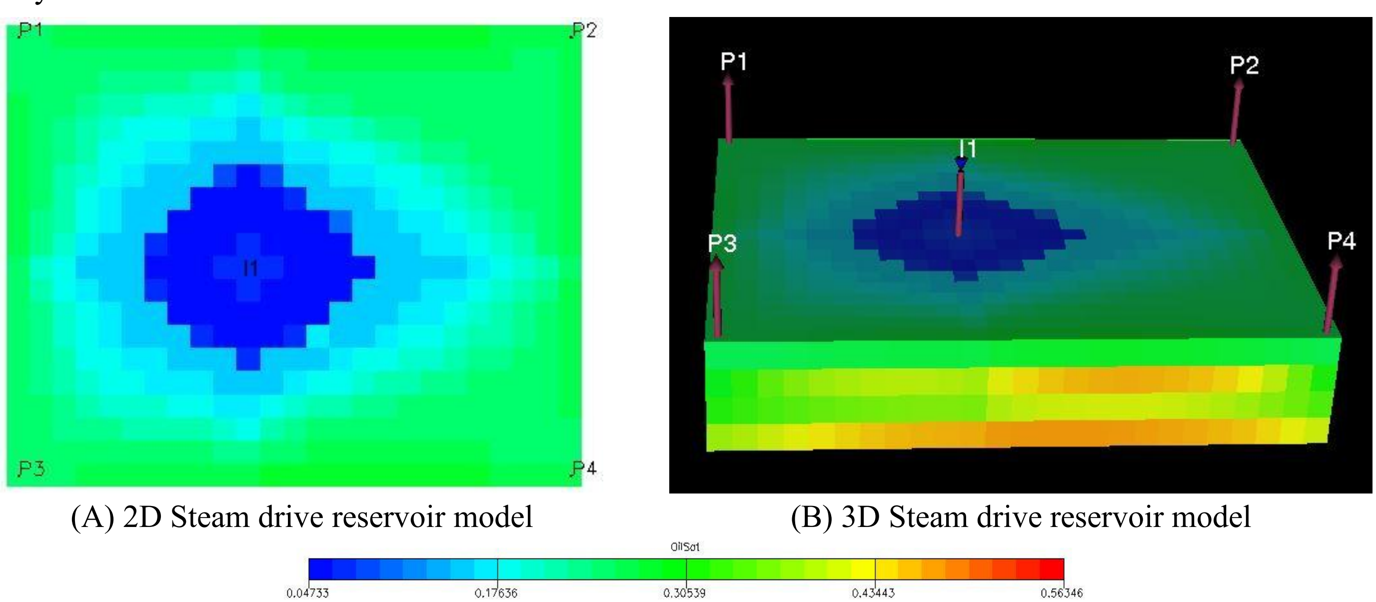
Hence in this study, a quadratic response surface proxy model was developed to estimate the cumulative recovery volume from a heterogeneous heavy oil reservoir undergoing a steam flooding process. With the developed model, further investigative studies provided optimal values for the selected parameters, including steam injection rates, steam temperature, steam quality, bottom-hole flowing pressure to maximize production from this process. Several areas covered in this study can be summarized as follows.

1. The complex numerical simulation to model a steam flooding pattern with five inverted spots for a heavy oil reservoir was first developed.
2. The study utilized a Box-Behnken experimental design, considering steam injection rates, steam temperature, steam quality, and bottom-hole flowing pressure of the producing wells.
3. After creating and validating the proxy model, further uncertainty studies were conducted to evaluate the behaviour of input parameters and optimize the objective function.

The paper comprises multiple sections. Section 1 provides an overview of the background and research objectives. Section 2 outlines the materials and methods employed to attain these objectives. Section 3 is dedicated to presenting the results and discussing the comprehensive findings of the study. The final section encompasses the conclusions and recommendations derived from our research.

Materials and Methods

Steam Flooding Reservoir Simulation Model. In proxy model design, defining the actual complex system of interest must first be accomplished. This system otherwise referred (Aboaba et al. 2020), involves a space and time simulation usually generated with a simulator with defined input and output sections. Hence, in this study a reservoir simulation was developed for a five inverted spot steam flooding pattern for 10 years time step, using Eclipse 2019 edition. The developed heterogeneous mode with dimensions of $2500 \times 2000 \times 2500$ (ft), has a porosity of 30%, with varying permeabilities ranging from 500,000 to 1000,000 mD across the formations. The model is made up of a single injector well located at the center, from which steam is pumped in and four producer wells as can be depicted in **Figure 2**. However, it is worthy to note that all the reservoir, well configuration and PVT data were obtained from SPE 2 model (SPE 2010), with slight modifications to our study.



(A) 2D Steam drive reservoir model (B) 3D Steam drive reservoir model

Figure 2—Steam flooding reservoir simulation model.

Data Generation. In building a proxy model, data is of uttermost importance as the algorithm will leverage on it to produce a suitable proxy model. Hence, the data generation for this study took several steps which are summarized as seen in **Figure 3**. Firstly, a Box-Behnken experimental design was utilized to develop experimental runs considering various reservoir and steam flooding parameters. Box-Behnken Design (BBD) is a type of design pattern for response surface modelling specifically for fitting a second-order (quadratic) model.

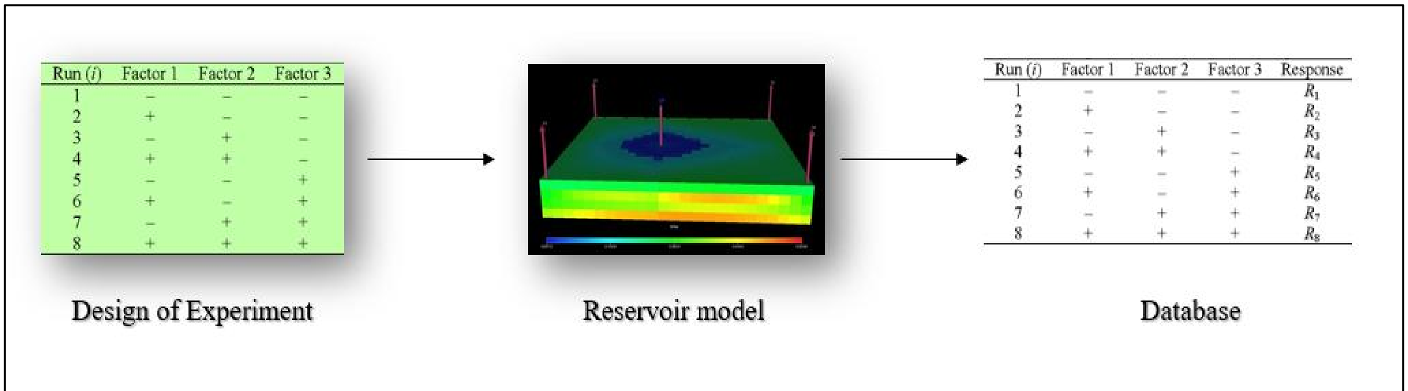


Figure 3—Steps for generating data for proxy model development.

BBD proves beneficial as it eliminates the need to test points at the extremes of the cubic region resulting from two-level factorial combinations. This is particularly advantageous, given that such points are either prohibitively expensive or impossible to test due to physical constraints in experimentation (Ahmad et al. 2020; Ferreira et al. 2007). Next, with the generated experimental runs fed into the reservoir model, the output was then collected for each row or experimental run. While this process may seem time consuming, a Python automation script was developed to handle this process within few minutes. **Table 1** shows the various controllable reservoir parameters considered for the model development.

Table 1—Reservoir and Steam flooding parameters for proxy model development.

S/N	Parameters	Identifiers	Units	Min	Max
1.	Bottom-hole pressure for Well 1	X_1	psi	500	2000
2.	Bottom-hole pressure for Well 2	X_2	psi	500	2000
3.	Bottom-hole pressure for Well 3	X_3	psi	500	2000
4.	Bottom-hole pressure for Well 4	X_4	psi	500	2000
5.	Steam injection rate	X_5	Cc/day	1000	10000
6.	Steam quality	X_6	-	0.1	1
7.	Steam temperature	X_7	ºC	100	200

Proxy Model. A quadratic proxy model serves as a pivotal tool in approximating complex relationships between variables within a system. In this study, the quadratic proxy model was constructed using DesignExpert-13 software, a robust statistical tool known for its capabilities in experimental design and analysis. Generally, quadratic equation takes the general form as,

$$f(x) = ax^2 + bx + c \text{ ,} \quad (1)$$

where a, b, and c are coefficients, and x represents the independent variable.

This equation encapsulates a nonlinear relationship wherein the variable x is squared, thus allowing for the representation of curvature in the relationship between variables. The quadratic model was selected as the proxy model in this study because of both its performance, simplicity and interpretability. Additionally, quadratic model provides flexibility by accommodating curvature and nonlinearity in the data, allowing for the representation of complex relationships and often yields accurate predictions within the range of observed data points, making it valuable for interpolation tasks (Shacham et al. 2007).

Objective Function. An objective function serves as a cornerstone in optimization tasks, encapsulating the desired outcome or criteria to be maximized or minimized. In our study, the objective function encapsulates the fundamental goals or performance metrics that we aim to optimize. Maximizing the objective function is crucial as it enables us to enhance specific aspects of the system under investigation, leading to improved efficiency, performance, or effectiveness. By maximizing the objective function, we seek to achieve the optimal configuration or set of parameters that yield the most desirable outcomes (Bhaskar et al. 2017; Minhas et al. 2021). In cases where the goal is to maximize the objective function, hence, the general equation for such optimization process can be expressed in the equation below;

$$y = \max[\![f(x_1, x_2, \ldots, x_n)]\!], \quad (2)$$

where y represent the output value from the optimization process, while $f(\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_\mathrm{n})$, represents the objective function to be maximized while $\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_\mathrm{n}$ represents the variables or parameters under consideration within the system.

Similarly, in our case study, the proxy model developed for the estimation of the cumulative volume of oil recoverable from the steam flooding process becomes the objective function to be maximized, while determining the optimal parameters for the reservoir parameters.

Results and Discussions

Proxy Model Result and Interpretation. Proxy models in reservoir engineering are known for their usefulness in approximating relationships within complex reservoir simulation models. In this research, the developed model is a reduced quadratic model which is defined as thus,

$$\log_{10} CRV = 0.0688692{X_6}^2 + 2.56296 \times 10^{-9}{X_5}^2 - 9.9533 \times 10^{-9}{X_4}^2 - 6.33966 \times 10^{-9}{X_1}^2 - 2.61898 \times 10^{-6}X_5X_6 + 1.58417 \times 10^{-9}X_4X_5 + 1.744 \times 10^{-9}X_3X_5 - 3.90065 \times 10^{-5}X_7 - 0.0831905X_6 - 4.30134 \times 10^{-5}X_5 + 1.37941 \times 10^{-5}X_4 - 1.2208 \times 10^{-5}X_3 + 1.41117 \times 10^{-5}X_1 + 7.02342 \quad (3)$$

From **Eq. 3**, we can observe that the output is in logarithmic values, hence to obtain the actual values, we need to take exponential of both sides, thereby resulting to a final model as shown in **Eq. 4**,

$$CRV = e^{[\![\log_{10} CRV]\!]} \quad (4)$$

Hence, by providing the combination of reservoir and steam flooding parameters, such as the bottom-hole well pressure, steam temperature, and the steam quality values for **Eq. 4**, the cumulative recoverable volume can be accurately estimated.

Statistical Evaluation of Developed Model. The ANOVA table, as shown in **Table 2** presents a rigorous examination of the model's performance and the individual predictors. The overall model exhibits remarkable significance ($p<0.0001$), signifying that it effectively predicts the variable. The high R^2 value of 0.9816 further reinforces this, indicating that approximately 98% of the variance in the dependent variable can be attributed to our model. Moreover, the R^2 score is in reasonable agreement with the adjusted R^2, that is the difference is less than 0.2. From the table also, its worthy to note that the alphabets A, C, D, E, F and G represent X_1, X_3, X_4, X_5, X_6 and X_7, respectively. Hence, among the predictors, A, E, F, E^2, and F^2 emerged as key contributors due to their substantial F-values and low p-values ($p<0.0001$). These variables significantly enhance our model's predictive power. However, it is essential to consider that C, D, and G exhibit p-values greater than 0.05, rendering them statistically insignificant at the 95% confidence level selected in this study.

Table 2—Analysis of Variance (ANOVA) for CRV.

Source	**Sum of Squares**	**Df**	**Mean Square**	**F-value**	**p-value**	
Model	0.1141	13	0.0088	172.30	< 0.0001	significant
A-X1	0.0000	1	0.0000	0.8001	0.3762	
C-X3	0.0001	1	0.0001	1.81	0.1853	
D-X4	0.0001	1	0.0001	1.50	0.2280	
E-X5	0.0712	1	0.0712	1397.20	< 0.0001	
F-X6	0.0023	1	0.0023	45.51	< 0.0001	
G-X7	0.0001	1	0.0001	1.79	0.1879	
CE	0.0003	1	0.0003	5.44	0.0245	
DE	0.0002	1	0.0002	4.49	0.0401	
EF	0.0002	1	0.0002	4.42	0.0416	
A^2	0.0002	1	0.0002	3.00	0.0908	
D^2	0.0004	1	0.0004	7.38	0.0095	
E^2	0.0323	1	0.0323	634.59	< 0.0001	
F^2	0.0023	1	0.0023	45.82	< 0.0001	
Residual	0.0021	42	0.0001			
Cor Total	0.1162	55				
SD=0.0071	Mean=6.87	*CV%=0.1039	PRESS=0.0048	R^2=0.9816	Adj R^2=0.9759	Adeq. Precision=39.0244

* CV is coefficient of variation and PRESS is predicted residual error of sum of squares.

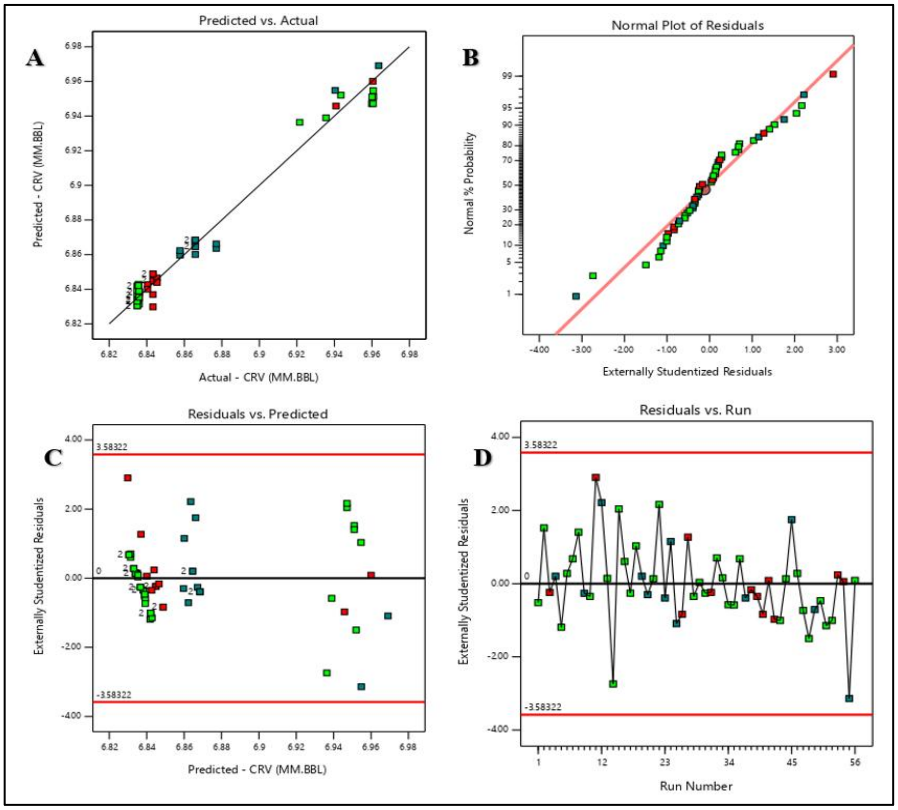


Figure 4—(A) Plot of actual vs. predicted response of surface; (B) Normal probability plot to residuals of CRV data; (C) The plot of residuals vs. predicted response of CRV data; (D) The plot of residuals vs. run of CRV data.

Figure 4(A) compares the predicted and actual values of CRV (MM.BBL) and hence, it can be observed that the data points are scattered around the diagonal line, which represents good prediction with approximately 98% accuracy. Points close to the diagonal line indicate accurate predictions, while deviations from the line specifically in red and green colors account for the 2% error in prediction. Additionally, the normal probability plot as shown in **Figure 4(B)** indicates that the residuals follow a normal distribution, thus follow the straight line and "S-shaped" curve, suggests that the transformation of the response will provide a better analysis. **Figure 4(C),** however, presents the plot of the residuals versus the ascending predicted response values, which is a random scatter depicting expanding variance, suggesting need for response transformation. Lastly, **Figure 4(D)** shows the plot of the residuals versus the experimental run order. The scatter of residuals appears random and is evenly distributed around the mean residual value. This suggests that the residuals are not influenced by the order in which the runs were conducted, indicating their independence from the run sequence.

Sensitivity Analysis. In an attempt to study the effect of the factors (reservoir and steam flooding parameters) considered in this study, a sensitivity study was carried out using the perturbation functionality of the Design Expert software. The effect of these factors on our response, the cumulative recoverable volume can be seen in **Figure 5**.

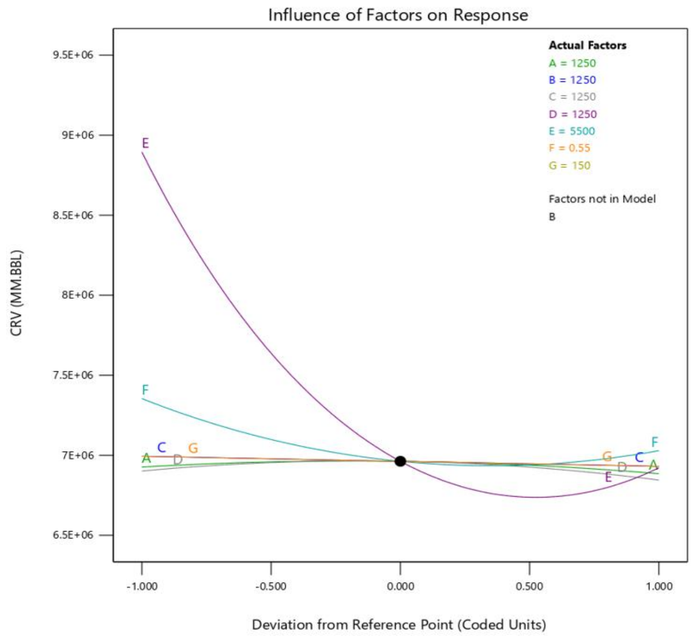


Figure 5—The effect of these factors on our response surface.

As can be observed from **Figure 5**, as the deviation from the reference point increases, CRV sharply decreases, this shows that factor E (steam injection rate) plays a critical role in reducing CRV and hence, determining its optimal parameter can lead to significant improvements in CRV. However, factors A (BHP well_1), C (BHP well_3), and G (steam temperature) can be observed to have exhibited minimal influence as they have relatively flat lines near the reference point, hence, changes in factors A, C, and G have minimal impact on CRV. Additionally, while factors F (steam quality) and D (BHP well_4) may not be as impactful as factor E, optimizing F and D may contribute positively to CRV as they show slight inclines, indicating positive correlations with CRV.

Optimization Analysis. The numerical optimization algorithm adopted in this research follows the hill climbing technique. Firstly, the objective function (desirability function) is set to ranges from zero to outside of the limits to one at the goal. By leveraging a penalty function, a set of random points based on defined constraints are checked to see if there is a more desirable solution. Based on this approach, the solution highlighting the top 5 optimization results is shown in **Table 3**.

Table 3—Top 5 optimization results.

Number	X_1	X_2	X_3	X_4	X_5	X_6	X_7	Optimized CRV	Desirability
1	1250	0	1250	500	1000	0.1	150	9313994.303	0.959
2	1250	0	1250	500	1000	1	150	9121955.466	0.946
3	648.822	0	747.588	665.041	1418.562	0.108	114.617	9120851.876	0.946
4	1250	0	1250	2000	1000	0.1	150	9013188.917	0.938
5	500	0	500	1250	1000	0.55	150	9009920.854	0.938

From Table 3, it can be observed that the Feature B was set to zero, since it was not part of the objective function. From the result also, it can be observed that the highest cumulative recoverable volume 9,313,994.303 bbl which is approximately 19% increase as compared to the average cumulative recoverable volume from the reservoir experimental results.

Conclusions and Recommendations

In this study, we developed a quadratic response surface proxy model to estimate the cumulative recovery volume (CRV) from a heterogeneous heavy oil reservoir undergoing steam flooding. Through rigorous numerical simulations and experimentation, we addressed the challenges associated with high costs and uncertainty in heavy oil recovery processes. Our findings demonstrate the feasibility and effectiveness of using proxy models to analyse and optimize steam flooding operations, thereby potentially reducing costs and improving recovery rates in the oil and gas industry. The development of the proxy model involved the creation of a complex numerical simulation to model a steam flooding pattern with five inverted spots for the heavy oil reservoir. Utilizing a Box-Behnken experimental design, we considered key parameters such as steam injection rates, steam temperature, steam quality, and bottomhole flowing pressure of the producing wells. The resulting proxy model, validated with high adjusted and predicted R2 values, successfully predicted CRV with remarkable accuracy. Through further sensitivity studies, we evaluated the behaviour of input parameters and optimized the objective function to maximize production from the steam flooding process. Our results indicate that steam injection rate, steam quality and Bottomhole pressure for well_4 played critical role in CRV determination, while BHP well_1, BHP well_3, and steam temperature exhibited minimal influence. Following the optimization process, we observed a substantial CRV increase of up to 19%, highlighting the potential of our approach to enhance recovery outcomes.

Based on the outcomes of our study, we offer the following recommendations for future research and practical applications:

- Further research could focus on refining the proxy model by incorporating additional parameters and considering more complex reservoir conditions. This could improve the accuracy of predictions and optimize steam flooding operations even further.
- Our findings suggest that the developed proxy model has practical applications in the oil and gas industry. Field trials and implementation studies could be conducted to validate the effectiveness of the model in real-world heavy oil reservoirs.
- Evaluating the cost-effectiveness of implementing the proxy model compared to traditional simulation methods is essential. Cost-benefit analyses could provide stakeholders with valuable insights into the economic feasibility of adopting proxy models for reservoir optimization.

This research work contributes to the ongoing efforts to improve heavy oil recovery techniques by offering a practical and efficient approach for estimating CRV in steam flooding operations. By leveraging proxy models, we can mitigate uncertainty and optimize production processes, ultimately driving efficiency and reducing costs in the oil and gas industry.

Conflicting Interests

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

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