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A response surface model for assessing the impact of well placement and/or well injection/production control optimization approaches on foam injection performance in heterogeneous oil reservoirs

Onyebuchi Ivan Nwanwe*, Nkemakolam Chinedu Izuwa, Nnaemeka Princewill Ohia, Anthony Kerunwa

Department of Petroleum Engineering, Federal University of Technology Owerri, Nigeria

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Abstract

Optimization of well locations and/or well injection/production controls by the trial-and-error method has proven to be computationally expensive and time-consuming since numerous reservoir simulation studies need to be conducted to arrive at an optimum solution. A computationally inexpensive approach that combines response surface models and optimization algorithms in the optimization process is presented. A two-dimensional heterogeneous reservoir model with an injector and a producer was developed in this study with a reservoir simulator. Seven independent parameters namely bottom-hole pressure of the producer, gas injection rate, surfactant concentration, location of the producer and injector in i and j directions respectively were used. Using the minimum and maximum values of the independent parameters, Box-Behnken Design Method was used to generate fifty-six simulation runs, which were used as input in conducting reservoir simulations to arrive at an output. The input and output datasets were analyzed using experimental design software to generate a response surface model showing the relationship between cumulative oil produced and the seven independent parameters. The model was validated using statistical error analysis, the results of which show the accuracy and reliability of the model in navigating the design space. A comparison was made between cumulative oil produced obtained from the three optimization approaches. Results showed that a coupled well placement and well injection/production control optimization approach resulted in a higher value of cumulative oil produced. This work shows that considering a coupled well placement and well injection/production control optimization approach is preferable during field development planning and can be implemented using proxy models and optimization algorithms.

1. Introduction

1.1. Background of the Study

Gas flooding as an enhanced oil recovery technique still suffers a lot of setbacks such as viscous fingering, selective channeling through zones of high permeability, and gravity override of gas [1]

*Corresponding author at: Department of Petroleum Engineering, Federal University of Technology Owerri, Nigeria
Email address: onyebuchi.nwanwe@futo.edu.ng

caused by large differences in viscosity and density between the displacing and the displaced fluids [2]. The result is poor volumetric sweep efficiency and early gas breakthrough. These operational challenges observed from gas injection strategies can be fully addressed using Foam injection and have resulted in the use of foam injection as an alternative to gas flooding during enhanced oil recovery.

Foam enhanced oil recovery like any other EOR method can only be implemented after waterflooding has been conducted. The development of waterflooded heterogeneous oil reservoirs by this approach is usually faced with the need to ensure that field oil recovery and net present value are maximized, and investment and operational costs are minimized. Reservoir simulation can be used to achieve these objectives since it predicts field performance and ultimate recovery for various field development scenarios using reservoir simulation models. Some of the variables considered during reservoir or oilfield development are the number and type of well, well locations, and well injection/production controls. Well injection/production controls considered during foam injection are bottom-hole pressure of production well, gas injection rate, and surfactant concentration and were adopted in this study.

Previous research focused on using direct optimization approaches in determining either optimal well locations, well injection/production controls, or joint well placement and well injection/production controls in making field development decisions. MATLAB and Eclipse 300 reservoir simulator were integrated to develop software for optimizing waterflooding in a 2-dimensional synthetic reservoir [3]. The program carried out several ensemble-based optimization procedures, including robust optimization, mean-variance optimization, and conditional value at risk optimization.

Awotunde (2014) presented a joint optimization approach for determining the optimal location of wells, well rates, well type, and the number of wells [4]. The search interval of the well controls was separated into three parts: one for the region where the well is an injector, another for the region where there is no well, and a third for the region where the well is a producer. A differential evolution (DE) optimization algorithm was used for this study. This approach was able to effectively identify optimum well locations, optimum well controls, optimum well type and the optimum number of wells. To simultaneously optimize well locations and well control parameters, Li et al. (2012) used a simultaneous perturbation and stochastic approximation (SPSA) approach because of its robustness in minimizing errors during the calculation of the cost function. The authors used a channeled layer of the SPE10 model and the three-dimensional PUNQ-S3 reservoir in conducting several numerical experiments to illustrate the performance improvement that can be achieved by the simultaneous optimization of well placement and well control using SPSA [5].

All the past work presented used an approach that involved optimizing a reservoir simulation model by creating an interface between an optimizer (optimization algorithm) and a reservoir simulator (black box). The optimization algorithm automatically runs the simulator to determine the optimum operating parameters that will maximize or minimize specific objective functions. This is a proven approach for optimizing petroleum reservoir and production processes. The only challenge of using this method is the computational complexity, time-consuming factor, the computational expensive cost for the reservoir simulator, and derivative-free approximations associated with it [6]. Application of proxy models in well placement and/or well injection/production control optimization during petroleum production operations becomes necessary as it aids in addressing the challenges observed with direct optimization.

The focus of this study is on determining optimal well locations and well injection/production controls during foam injection. The coupled proxy-GA will be used to investigate the impact of various optimization approaches which include well placement, well injection/production control, and a coupled well placement and well injection/production control optimization approach on oil recovery performance during foam injection.

1.2. Problem Statement

Well placement optimization problems are usually formulated by assuming fixed well injection/production control settings while well injection/production control optimization problems are formulated by assuming fixed well locations. Solving these two problems separately can result in suboptimal solutions which are unfavorable in terms of achieving maximum field oil recovery. A solution to this problem is to consider the two scenarios simultaneously as a coupled well placement and well injection/production control optimization problem. However, optimization of well placement and/or well injection/production control parameters using the trial and error method is a challenge. This is because it involves conducting an infinite number of full-field numerical reservoir simulations to determine the optimum well locations and well injection/production control parameter values that will maximize field oil recovery. This approach is computationally expensive and time-consuming. Numerous studies have been conducted in the past couple of years by different researchers in the area of well placement and/or well control optimization [5, 7-11]. The researchers focused on determining the optimal location and/or controls placed on the wells using different optimization algorithms, such that the algorithm provides input to the reservoir simulator which runs to determine injected and produced fluid volumes required for calculating the objective function. Based on the optimization strategy, a new set of input data is generated for the reservoir simulator to perform the process again. This process continues till a set of parameters that gives the highest maximum or lowest minimum value of the objective function as desired is determined. This method is computationally complex, expensive, and time-consuming. This challenge is addressed in this study by developing a response surface model of the reservoir simulation model which when coupled to an optimization algorithm, can reliably and accurately determine an optimum solution in less time.

1.3. Objectives of the Study

The main objective of this study is to develop a reservoir simulation proxy model using the design of experiments and response surface methodology and use it to investigate the impact of well placement, well control, or a coupled well placement and well control optimization approach on foam injection performance. The specific objectives of this study are

a) Develop a proxy model using design of experiments and response surface methodology which shows the relationship between an objective function (cumulative oil produced) and well placement and well control parameters.

b) Use Genetic algorithm in MATLAB Global optimization toolbox in well placement, well control and a coupled well placement and well control optimization study with the developed proxy model as the fitness function.

c) Compare the cumulative oil produced obtained from each scenario to determine and recommend the best optimization approach to be utilized during the development of green and mature petroleum reservoirs.

2. Literature Review

2.1. Oil Recovery Processes

Oil recovery processes are subdivided into primary, secondary, and tertiary recovery processes [12], and production from a typical petroleum reservoir is usually based on these stages taking place chronologically. Reservoir production by primary oil recovery entails the use of a distinct form of energy in pushing the reservoir fluids to the surface [13], and less than 30% of original oil in place is recovered by primary oil recovery processes which are through natural flow and artificial lift [14]. Secondary oil recovery methods such as waterflooding and gas injection are usually implemented to drive more oil from the reservoir towards the production wells when primary oil recovery processes are no longer feasible. An immiscible gas injection process is not as effective as a waterflood process, causing secondary recovery to be used almost synonymously to waterflooding [12]. The common use of waterflooding as a secondary recovery method is because water is inexpensive and readily available in large volumes and is effective in increasing oil recovery. Significant quantities of crude oil remain bypassed in the reservoir after primary and secondary recovery processes have been implemented [14] which can be recovered using enhanced oil recovery (EOR) methods.

Research has shown that low salinity waterflooding (LSWF) which is a newly developed enhanced oil recovery method for sandstone and carbonate formations can result in higher oil recovery in comparison with in-situ brine or high salinity water injection into oil reservoirs [15]. Approaches used in previous studies for low salinity waterflooding which include either dilution of formation or seawater or tuning of ionic composition of seawater both of which are proven to increase oil recovery have been studied [16]. Both approaches were combined to generate water referred to as ion-tuned water that was used for LSWF [16]. Results from their study for the combined scenario showed an increase in oil recovery when compared to cases when the aforementioned approaches are considered individually. A classification of enhanced oil recovery methods which include Gas Injection EOR, Chemical EOR, Thermal EOR, and other EOR methods was presented [14]. Fluids injected into a reservoir for EOR purposes supplement the natural energy of the reservoir to displace oil to the production wells, interact with the rock-oil system to create favorable conditions for oil recovery by lowering interfacial tension, oil swelling, and reduction in oil viscosity, and wettability modifications [12].

Chemical recovery processes are proven EOR processes that have significantly contributed to global daily production depicted by their capability in recovering oil bypassed in the reservoir [17]. The authors highlighted that chemical EOR methods involve the injection of specially formulated chemicals such as alkaline, surfactants, and polymers which aims at increasing the potency of the injection fluid. These chemicals can be used as singles or in various combinations such as surfactant-polymer flooding, alkaline-polymer flooding, alkaline-surfactant flooding, and alkaline-surfactant-polymer flooding [18]. Surfactants are usually recommended for enhanced oil recovery and function in reducing interfacial tension, wettability alteration, lower capillary forces, facilitating oil mobilization, and enhancing oil recovery [19]. Surfactants can be classified as ionic, non-ionic, cationic, and amphoteric surfactants. Kumar et al. (2016) reported the wide use of ionic and non-ionic surfactants in chemical EOR as they are capable of influencing surface and interfacial properties of reservoir rock and fluids. The creation of ion pairs between the cationic heads of the surfactant molecules and the adsorbed acidic components of the crude oil on the carbonate surface results in the efficiency of cationic surfactants in wettability change from oil-wet to water wet, according to research [20].

According to the classification presented by Chen (2007) and Massarweh and Abushaikha (2020), it can be inferred that foam EOR is a special form of Chemical EOR since it is formed by a combination of a surfactant solution and a gas [14, 21].

2.2. Overview of Foam Injection

Foam has been recognized as a fluid with unique rheological properties as it profoundly affects the flow patterns of non-wetting fluids in porous media [22]. Foam can improve the sweep efficiency of injected gas by reducing the effects of low gas viscosity and reservoir layering [23]. The author also highlighted two main processes that occur during foam enhanced oil recovery: Plugging and Mobility control. The plugging process plugs layers swept or invaded by gas near the injection well while the mobility control process reduces gas mobility throughout the gas-swept regions.

The presence of a foaming agent reduces the mobility of the displacing fluid (gas) causing favorable mobility ratios to be achieved with foam, which has the overall effect of achieving a uniform sweep of oil to the production wells. This results in an improvement in oil recovery [24]. The authors also highlighted that the presence of surfactant reduces interfacial tensions between the displaced fluid (oil) and the rock as it reduces the capillary pressure between oil and the rock.

Studies on the simulation of foam flow in porous media have been conducted over the past couple of decades by different researchers. The two fundamental approaches for modeling foam flow in porous media are population balance (PB) models and local equilibrium (LE) models [1]. Most reservoir simulators like Eclipse, CMG-STARS and UTCHEM use local equilibrium models in simulating foam flow in porous media [1] because they are simpler to use, require fewer parameters, and numerical difficulties encountered with population balance models are avoided [25].

Four methods for injecting foam into porous media for enhanced oil recovery are presented in the literature [1, 2]. These include Co-injection of gas and aqueous surfactant solution, and this involves the simultaneous injection of both fluid components from a single well into the reservoir; Surfactant-alternating-gas (SAG) in which surfactant and gas are injected as separate slugs from a single well into the reservoir; Dissolving surfactants in supercritical Carbondioxide such that as they come in contact with water in the reservoir, foam is formed; and Injecting surfactant solution and gas into different layers of the reservoir. In this case, surfactant solution is injected into the upper layer of the reservoir while gas is injected into the lower layer. Co-injection of gas and surfactant and surfactant alternating gas injection methods were considered the two main methods for the injection of foam into porous media [26]. The author reported that the surfactant alternating gas (SAG) injection method is more favorable at the field scale because improved injectivity is achieved when gas and surfactant are injected alternately, and also because of reduced risk of corrosion and risks related to material compatibility. In this paper, foam injection into the presented heterogeneous reservoir model is by co-injection of gas and surfactant.

Pilot studies in the Kern River Field and the South Belridge Field involving foam injection for two years and one year respectively showed a major increase in incremental oil recovery [27].

Sunmonu and Onyekonwu (2013) conducted a simulation study that investigated the possibility of increasing Nigeria's oil production by using foam enhanced oil recovery method [28]. A significant increase in oil recovery was observed for foam injection in comparison with gas and waterflooding. Also, a significant reduction in gas-oil ratio and gas production was observed with foam flooding and this is attributed to a reduction in gas mobility in the presence of foam. According to Adebanjo and Olusegun (2015), enhanced oil recovery methods such as CO2 injection, polymer flooding, and foam flooding can be considered as effective enhanced oil recovery methods for Nigeria's petroleum industry. The authors evaluated the application of foam injection in unconsolidated sands in the Niger Delta with the aim of determining its economic viability for oil reservoirs in the region. Their results showed an increase in total field oil production by foam injection in comparison with gas flooding [29].

2.3. Overview of Proxy Modeling

Proxy models are mathematically or statistically specified functions that reproduce or approximate the output of a full-field reservoir simulation model given a set of input parameters [30]. The polynomial regression model, multivariate kriging model, thin-plate splines model, and artificial neural network model are all examples of proxy models used in reservoir modeling [30]. Proxy models can serve as an alternative to reservoir simulation models and can aid in overcoming the challenges observed by running numerous full-field numerical reservoir simulations to arrive at an optimum solution [31]. The authors also presented the advantages of using proxy models in place of full-scale reservoir simulation models which are: runs in a short amount of time, takes into account a practical, less expensive, and appropriate estimate of the real reaction to improving computer efficiency, identifies the most important factors and their interactions with the answer, enables a more in-depth examination of the response's combined impact of all independent factors.

Combining proxy models and optimization algorithms can make optimization of engineering systems fast, easy, and computationally inexpensive. Proxy models have been used by numerous authors to study petroleum engineering systems. The applications of proxy modeling in various aspects of petroleum engineering were reported to include sensitivity analysis, aided history matching, field development planning, risk analysis, optimization, and reservoir characterization [31].

The time taken to run a full reservoir simulation study is a fraction of the time taken by a proxy model, and in reservoir simulation studies, proxy models are used in uncertainty and optimization studies [32]. The results from a proxy model does not necessarily give a 100% match of the numerical simulation model results but a minimal range of error between actual or simulated and model calculated or predicted results is obtained [33]. Wide application of design of experiments in uncertainty analysis in reservoir simulation studies have been reported [34]. The author highlighted the use of this method by numerous authors in determining the effect of different reservoir rock and fluid parameters on factors such as fluid in-place volumes, oil recovery, and net present value.

Design of experiments method was used to minimize the number of simulation runs required to carry out uncertainty analysis [35]. The authors studied the impact of uncertain parameters on oil reservoir production profile. The authors also carried out an uncertainty analysis on the Dena Field with 10 factors at 3 levels. One parameter at a time (OPAT) method was used to determine the most influential parameters on reservoir behavior. A three-level full factorial design which resulted in 81 runs and an inscribed central composite design which resulted in 28 simulation runs was used on the determined influential parameters to carry out the uncertainty analysis.

Experimental design method was used in selecting a development plan for the Agbami field [36]. This approach helped obtain maximum information with minimal computational effort. The authors used the Plackett-Burman design method in screening the parameters that significantly impacted the desired response. This was followed by using the D-optimal design technique in generating observations of the desired response. A comparison was made between a space-filling Maxmin Latin Hypercube sampling architecture with quadratic polynomial, kriging, multivariate adaptive regression spline (MARS), the Box-Behnken design with a quadratic polynomial response, and additivity and variance stabilizing (AVAS) [32]. The best strategy for fitting the model to data was the Box-Behnken experimental design method with a quadratic polynomial.

Proxy models were constructed with design of experiment for the integrated optimization of an oil field [37]. The seven most important parameters on the goal functions (response) were selected from 16 parameters using a two-level Plackett-Burman design of experiment approach. For the three goal functions (net present value (NPV), cumulative oil produced (COP), and cumulative water produced (CWP), the proxy model was built using a three-level Box-Behnken experimental design approach. The authors employed multi-objective optimization to find the set of parameter values that maximized NPV and COP while minimizing CWP. Proxy models were developed for estimating oil recovery under waterflood and gas flood scenarios using experimental design methodologies [38]. The model was designed to evaluate and rank potential waterflooding or gas injection reservoirs. The generated proxy models were shown to be strong and may be employed during an initial screening research for water and gas flood candidates, according to the findings of their study.

Proxy models of the PUNQ-S3 reservoir model were developed with DOE and RSM, and used in multi-objective optimizations for history matching the PUNQ-S3 reservoir [39]. The use of design of experiments in reservoir studies focuses on aspects in which the effects of one or more factors on a system or process are being investigated. This approach aids reservoir engineers to determine and adjust the most influential factors such that the reservoir is at optimum condition while ensuring maximum petroleum production. Uniform and Box-Behnken design methods and response surface methodology were used in developing proxy models for predicting the performance of water drive reservoirs [40]. The proxy models showed the relationship between recovery factor and cumulative water produced with seven independent parameters. The authors used the metaheuristic bat algorithm in determining the set of parameters that maximized the recovery factor and minimized cumulative water production which was used to calculate undiscounted net present value. The ideal number of wells and their matching locations, the optimum individual well production rate, perforation thickness, and tube head pressure are all factors to consider. To improve determination of injection well location for waterflooding in heterogeneous reservoirs, a data-driven modeling technique involving the use of artificial neural networks were utilized by the researchers to forecast fluid output as a function of heterogeneity and injection well placement [41].

3. Materials and Method

3.1. Materials

The Materials used in this study are a reservoir simulator, experimental design software, and global Optimization toolbox in MATLAB.

a) The reservoir simulator was used in developing a synthetic heterogeneous reservoir model and in running simulations based on realizations generated with the experimental design software

b) The experimental design software was used to generate parameter realizations for running simulations with the reservoir simulator. Using input parameter realizations and responses from reservoir simulation, the proxy model is developed.

c) Global Optimization Toolbox was used to determine the optimum set of parameters of the proxy model that maximized the objective function. Genetic Algorithm was used in this study.

3.2. Method

A simple synthetic heterogeneous reservoir model developed with a reservoir simulator. The reservoir model consists of 48 x 48 x 1 grid blocks with dimensions of 300 x 300 x 100 ft in the X, Y and Z directions respectively. The reservoir model consists of 2,304 grid blocks and the dimensions of the reservoir model in the X, Y, and Z directions are 14400 x 14400 x 100 ft respectively. Tables 1 shows the rock and fluid properties used in reservoir model development. Two wells: one producer and one injector were used in this study. Figure 1 shows an illustration of a two-dimensional (2D) heterogeneous reservoir model with the injection well (INJ1) and production well (PROD1) placed as shown.

Table 1. Reservoir Model Parameters

Property	Value
API Gravity	45°API
Gas Gravity	0.06054
Water Density	64.79 Ibm/ft^3
Datum Depth	8400 ft.
Pressure at Datum Depth	4800 psia
Reservoir Thickness	200 ft.
Depth of Oil Water Contact	8600 ft.
Depth of Gas Oil Contact	8400 ft.
Permeability Range	30.01 to 961.79 md

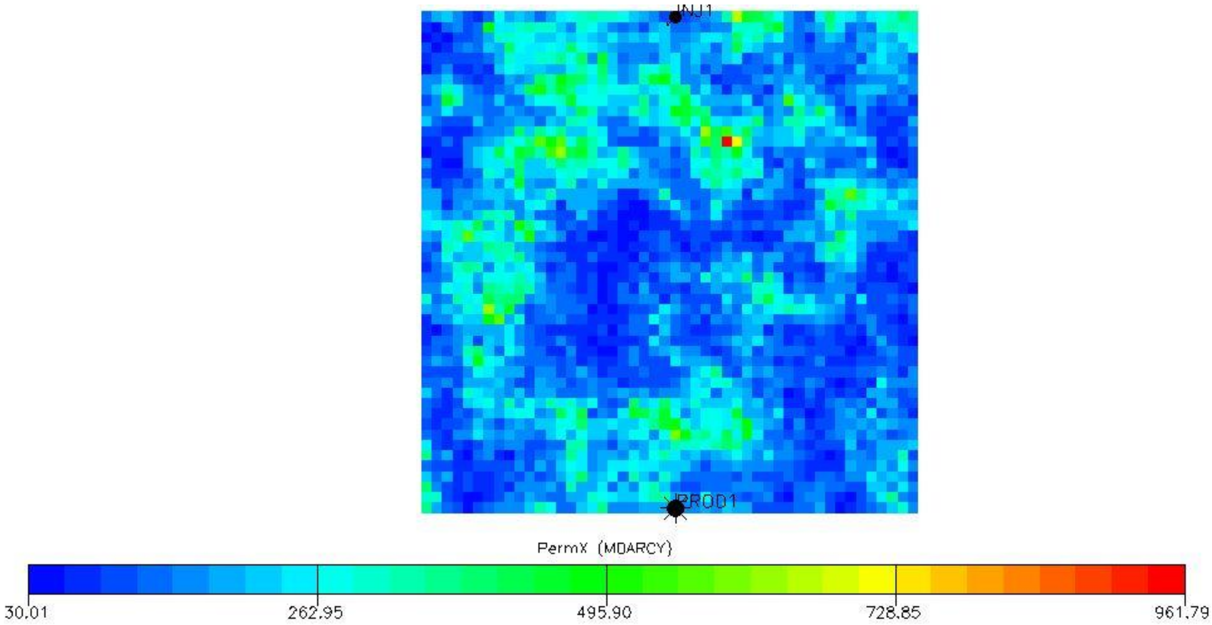

Figure 1. Synthetic Heterogeneous Reservoir Model

3.2.1. Parameter Ranges for Development of Response Surface Model

In this study, the response surface model was developed by considering well locations and controls placed on wells, and was in the form of a quadratic polynomial model. This model was then used in combination with genetic algorithm in determining the optimum parameters that will maximize cumulative oil produced for each of well placement, well control and a coupled well placement optimization and comparisons made. Table 1 shows the range for well placement and well control variables considered in this study as independent variables.

Table 2. Parameter Ranges for the well placement and well control optimization problem

Parameter	Symbol	Minimum value	Maximum value	unit
BHP of Producer	X1	500	4500	Psia
Gas injection rate for Injector	X2	1000	100000	MSCF/day
Surfactant concentration for Injector	X3	0.1	3	Ib/STB
Location of Producer in the i direction	X4	1	48	-
Location of Producer in the j direction	X5	1	48	-
Location of Injector in the i direction	X6	1	48	-
Location of Injector in the j direction	X7	1	48	-

3.2.2. Generation of Parameter realizations for running Reservoir Simulations

To build parameter realizations for executing reservoir simulations with the Eclipse 100 reservoir simulator and to determine the link between response functions and other independent variables, the Box Behnken design approach was used referred to as a rotatable second-order design based on three-level incomplete factorial designs. The Box–Behnken design unique organization allows the number of design points to grow at the same pace as the number of polynomial coefficients. The number of experimental runs that can be obtained using Box-Behnken experimental design method is given by Equation 1 [42].

$$N = k^2 + k + c_p \tag{1}$$

where N is the number of runs, k is the number of factors and c_p is the replicate number of the central point.

From Equation 1, and considering 7 parameters, a total of 56 simulation runs as depicted in Table 2 were generated. Each of the generated datasets were used to conduct different reservoir simulations to arrive at corresponding responses or outputs referred to as cumulative oil produced. The input and output data are analyzed using Design Expert Software to develop a proxy model in which the cumulative oil produced is presented as a function of 7 independent parameters as depicted in Equation 2.

$$COP = f(X1, X2, X3, X4, X5, X6, X7) \tag{2}$$

3.2.3. Optimization

Optimization is an important tool in decision science and in the analysis of physical systems whose use requires the identification of an objective function such as profit, time, or any quantity that can be represented by a single number. The goal of optimization is to find optimum values of a set of independent variables that can maximize or minimize specific objective functions.

The developed model has both well placement and well control parameters as independent variables of the form shown in Equation 2. The proxy model will be coded in MATLAB and genetic algorithm used in optimization studies in which three optimization approaches will be investigated: well injection/production control optimization, well placement optimization, and a coupled well placement and well injection/production control optimization approach.

a) The well injection/production control optimization approach was evaluated by fixing the injector and producer well locations on grid (1, 1) and grid (48, 48) respectively. In this case, the well locations did not change while the well injection/production control parameters for the model which are the bottom-hole pressure of the production well (X1), the gas injection rate (X2), and the surfactant concentration (X3) changed between the minimum and maximum values presented in Table 1.

b) For the well placement optimization approach, the well injection/production control parameters which are bottom-hole pressure of the producer (X1), gas injection rate (X2), and surfactant concentration (X3) were fixed at 2500 psia, 50500 Mscf/day, and 1.55 IB/STB respectively while the well locations change between 1 and 48 both in the i and j directions for the injector and producer. The well location for the producer (X4 and X5) and injector (X6 and X7) are presented as coordinates in i and j direction respectively as shown in Table 1.

c) For the coupled well placement and well control optimization approach, the well locations and well injection/production controls are not fixed, they change during optimization with genetic algorithm between the minimum and maximum values for each variable.

4. Results and Discussion

4.1. Results

4.1.1. Conducting Reservoir Simulations from parameter realizations

Using the data ranges for each scenario shown in Table 1, parameter realizations for running reservoir simulations were generated using Box Behnken design method. For 7 variables, a total of 56 simulation runs were conducted to determine cumulative oil produced for each run. Each simulation was conducted for 3660 days and the cumulative oil produced for each run are presented in Table 3.

Table 3. Parameter Realizations and Responses from Simulation

Run	A:X1 PSIA	B:X2 MSCF/Day	C:X3 IB/STB	D:X4	E:X5	F:X6	G:X7	COP MMSTB
1	2500	1000	1.55	25	48	25	1	34.1096
2	4500	50500	0.1	25	1	25	25	36.0231

3	2500	1000	1.55	25	1	25	48	29.9037
4	2500	50500	3	1	25	25	1	58.479
5	4500	50500	1.55	25	25	48	1	45.2476
6	2500	100000	1.55	25	1	25	48	89.1215
7	500	1000	1.55	48	25	25	25	42.2253
8	4500	50500	0.1	25	48	25	25	35.2632
9	2500	100000	1.55	25	48	25	48	9.05635
10	2500	50500	1.55	48	48	1	25	59.4241
11	4500	100000	1.55	48	25	25	25	33.4108
12	2500	1000	0.1	25	25	1	25	37.542
13	4500	1000	1.55	1	25	25	25	3.03754
14	2500	100000	1.55	25	48	25	1	98.7802
15	2500	1000	3	25	25	48	25	37.6494
16	2500	1000	1.55	25	1	25	1	27.2037
17	2500	50500	0.1	48	25	25	1	50.8907
18	2500	100000	0.1	25	25	1	25	68.3015
19	500	50500	3	25	1	25	25	62.319
20	2500	100000	0.1	25	25	48	25	56.4466
21	500	50500	1.55	25	25	48	48	73.7247
22	2500	50500	0.1	48	25	25	48	48.3666
23	500	50500	0.1	25	1	25	25	59.8491
24	500	100000	1.55	1	25	25	25	57.5282
25	2500	50500	1.55	1	48	1	25	32.403
26	500	100000	1.55	48	25	25	25	47.042
27	2500	50500	1.55	48	1	48	25	38.0516
28	2500	50500	1.55	1	48	48	25	64.1986
29	2500	50500	3	1	25	25	48	54.0981
30	2500	50500	0.1	1	25	25	48	51.1992
31	500	50500	1.55	25	25	1	48	80.3668
32	4500	50500	1.55	25	25	48	48	40.2163
33	2500	50500	0.1	1	25	25	1	54.9441
34	2500	50500	1.55	1	1	1	25	32.228
35	2500	50500	1.55	48	48	48	25	26.9367
36	2500	50500	3	48	25	25	48	50.7093
37	2500	1000	3	25	25	1	25	37.6502
38	500	50500	1.55	25	25	48	1	79.7806
39	2500	50500	3	48	25	25	1	54.0189
40	4500	1000	1.55	48	25	25	25	3.01493
41	500	50500	1.55	25	25	1	1	85.1036
42	4500	50500	3	25	48	25	25	36.8214
43	2500	50500	1.55	48	1	1	25	71.931
44	2500	1000	1.55	25	48	25	48	31.7031
45	500	50500	0.1	25	48	25	25	56.7827
46	4500	100000	1.55	1	25	25	25	40.5907
47	2500	100000	1.55	25	1	25	1	4.2026
48	4500	50500	1.55	25	25	1	1	48.2522
49	2500	100000	3	25	25	1	25	68.6802
50	2500	50500	1.55	1	1	48	25	54.2584
51	500	50500	3	25	48	25	25	58.22
52	4500	50500	1.55	25	25	1	48	44.3887
53	4500	50500	3	25	1	25	25	37.7262
54	2500	1000	0.1	25	25	48	25	37.5059
55	500	1000	1.55	1	25	25	25	43.3086
56	2500	100000	3	25	25	48	25	56.3731

4.1.2. Development of Proxy model

The input and output data for each scenario shown in Table 3 were analyzed using the experimental design Software to generate a proxy model (response surface model) showing the relationship between cumulative oil produced and the stated seven (7) independent parameters. Table 4 shows the analysis of variance for the proxy model.

Table 4. Analysis of Variance for Response Surface Model

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	22307.66	36	619.66	461.47	< 0.0001	significant
A-X1	2484.27	1	2484.27	1850.08	< 0.0001	
B-X2	1733.32	1	1733.32	1290.84	< 0.0001	
C-X3	3.76	1	3.76	2.80	0.1108	
D-X4	16.40	1	16.40	12.22	0.0024	
E-X5	12.58	1	12.58	9.37	0.0064	
F-X6	109.22	1	109.22	81.34	< 0.0001	
G-X7	38.75	1	38.75	28.86	< 0.0001	
AB	299.06	1	299.06	222.71	< 0.0001	
AD	2.38	1	2.38	1.78	0.1985	
AE	3.78	1	3.78	2.82	0.1097	
AF	2.87	1	2.87	2.13	0.1604	
BC	0.0004	1	0.0004	0.0003	0.9871	
BD	34.66	1	34.66	25.81	< 0.0001	
BE	4.35	1	4.35	3.24	0.0879	
BF	72.75	1	72.75	54.18	< 0.0001	
BG	3.14	1	3.14	2.34	0.1429	
CD	0.1159	1	0.1159	0.0863	0.7721	
DE	141.84	1	141.84	105.63	< 0.0001	
DF	1809.24	1	1809.24	1347.38	< 0.0001	
EF	15.45	1	15.45	11.51	0.0031	
EG	4045.36	1	4045.36	3012.66	< 0.0001	
A^2	274.09	1	274.09	204.12	< 0.0001	
B^2	1955.45	1	1955.45	1456.26	< 0.0001	
C^2	45.47	1	45.47	33.86	< 0.0001	
D^2	922.23	1	922.23	686.80	< 0.0001	
E^2	776.71	1	776.71	578.43	< 0.0001	
F^2	32.82	1	32.82	24.44	< 0.0001	
BEG	3592.73	1	3592.73	2675.58	< 0.0001	
DEF	8.77	1	8.77	6.53	0.0194	
A^2D	1.02	1	1.02	0.7586	0.3946	
AB^2	59.31	1	59.31	44.17	< 0.0001	
AE^2	153.38	1	153.38	114.22	< 0.0001	
B^2E	79.02	1	79.02	58.85	< 0.0001	
BC^2	22.77	1	22.77	16.96	0.0006	
CD^2	5.36	1	5.36	3.99	0.0602	
DE^2	38.15	1	38.15	28.41	< 0.0001	
Residual	25.51	19	1.34			
Cor Total	22333.17	55				

Results from Analysis of Variance (ANOVA) show that a majority of the model terms are significant because their p-values are less than 0.05. However, model terms that have a p-value greater than 0.1 which are considered to be insignificant are allowed in the reduced cubic model because they support hierarchy. Based on the significant model terms and those allowed to support the hierarchy obtained from ANOVA, a reduced cubic model in which cumulative oil produced is a function of well placement and well injection/production control parameters was developed and is presented in Equation 3.

$$
\begin{aligned}
COP = {} & -3.70992 + -0.000859842 \ast X1 + 0.000751982 \ast X2 + 7.79259 \ast X3 + 1.9691 \\
& \ast X4 + 2.02727 \ast X5 + 0.38541 \ast X6 + 0.0114161 \ast X7 + -1.76207e-08 \\
& \ast X1 \ast X2 + 3.84574e-05 \ast X1 \ast X4 + -0.000260269 \ast X1 \ast X5 + 1.2734e \\
& -05 \ast X1 \ast X6 + -6.14675e-05 \ast X2 \ast X3 + -1.78917e-06 \ast X2 \ast X4 \\
& + 1.28733e-05 \ast X2 \ast X5 + -2.59241e-06 \ast X2 \ast X6 + 1.84547e-05 \\
& \ast X2 \ast X7 + -0.0649173 \ast X3 \ast X4 + -0.0173153 \ast X4 \ast X5 + -0.025251 \\
& \ast X4 \ast X6 + 0.00449203 \ast X5 \ast X6 + -0.00156415 \ast X5 \ast X7 + -1.33221e \\
& -06 \ast X1\text{^}2 + -9.98709e-09 \ast X2\text{^}2 + -2.13688 \ast X3\text{^}2 + -0.0213978 \\
& \ast X4\text{^}2 + -0.0377149 \ast X5\text{^}2 + 0.00367041 \ast X6\text{^}2 + -7.75223e-07 \ast X2 \\
& \ast X5 \ast X7 + -8.06562e-05 \ast X4 \ast X5 \ast X6 + -5.36861e-09 \ast X1\text{^}2 \ast X4 \\
& + 7.85933e-13 \ast X1 \ast X2\text{^}2 + 5.61018e-06 \ast X1 \ast X5\text{^}2 + 6.6865e-11 \\
& \ast X2\text{^}2 \ast X5 + 1.98583e-05 \ast X2 \ast X3\text{^}2 + 0.00125275 \ast X3 \ast X4\text{^}2 \\
& + 0.000238113 \ast X4 \ast X5\text{^}2
\end{aligned}
\tag{3}
$$

The model (Equation 3) was used to carry out optimization studies with emphasis on making comparisons between cumulative oil produced obtained during each of well placement, well control, and a coupled well placement and well injection/production control optimization which is effective and computationally inexpensive.

4.1.3. Validation of Proxy model

The proxy model was validated using the coefficient of determination, R^2 obtained from a plot of actual versus predicted cumulative oil produced. Also, actual and predicted cumulative oil produced versus simulation runs were plotted on the same axis to determine if the actual and predicted results were in close agreement with each other.

Root mean Square Error (RMSE) and Average Absolute Percentage Error (AAPE) were calculated using Equations 4 and 5, and were found to be 0.675 and 2.239 % respectively.

$$
RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_{sim} - Y_{pred}\right)^2}{n}} \tag{4}
$$

$$
AAPE = \frac{1}{N}\sum_{i=1}^{N}\left(\sqrt{\left(\left(\frac{Y_{sim} - Y_{pred}}{Y_{sim}}\right)^2\right)}\right) \ast 100\ \% \tag{5}
$$

A plot of actual vs. predicted cumulative oil produced, and actual and predicted versus simulation runs are shown in Figures 2 and 3 respectively.

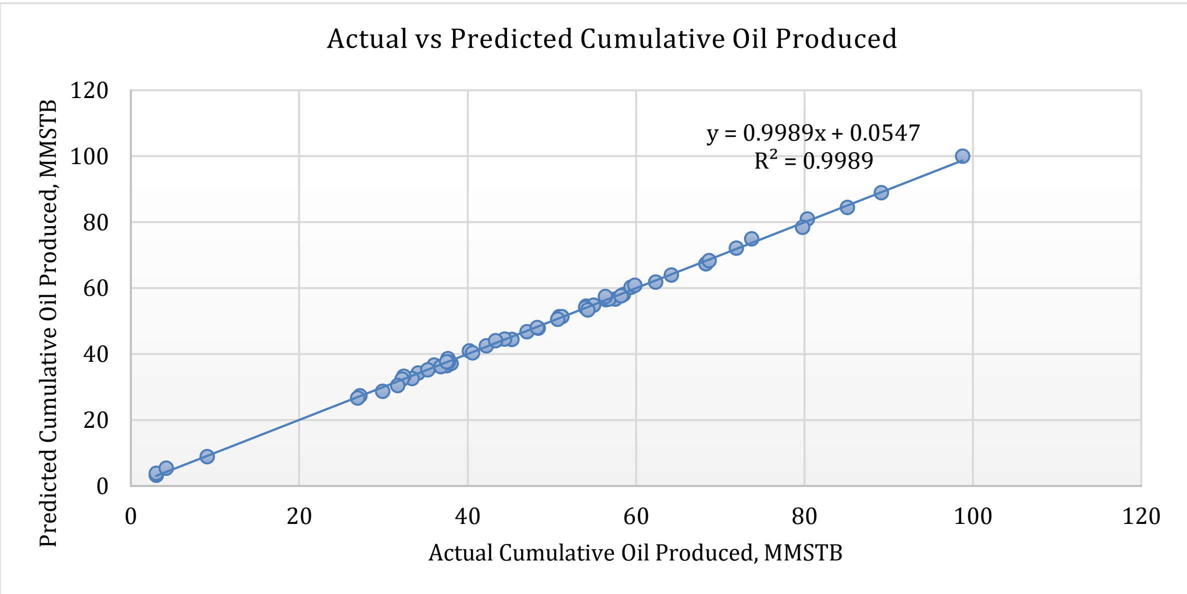

Figure 2. Plot of Actual versus Predicted Cumulative Oil Produced depicting R^2 value

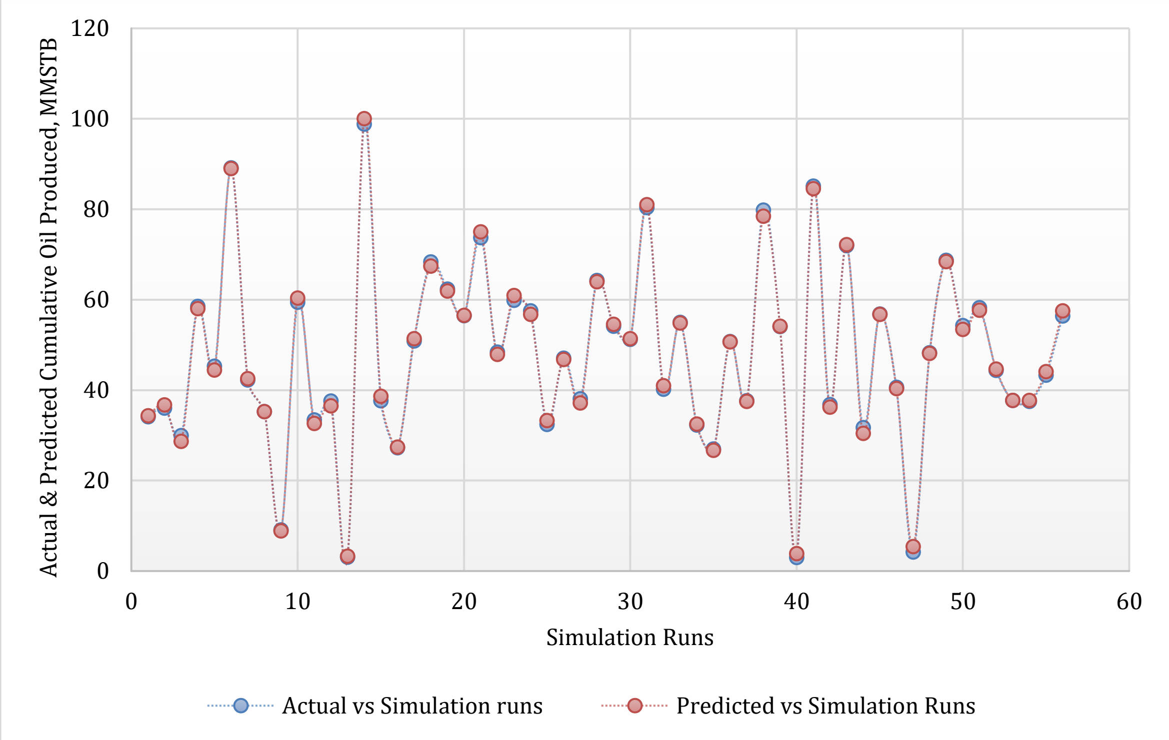

Figure 3. Actual and Predicted Cumulative Oil Produced vs Simulation Runs

4.1.4. Determination of Optimum well locations and/or well control parameters with Genetic algorithm

Genetic algorithm was used to determine from the developed proxy model shown in Equation 3 the following:

a) The optimum well locations with well control settings fixed at the midpoints of the minimum and maximum values that maximized the cumulative oil produced

b) The optimum controls placed on wells with the well locations fixed at grid (1, 1) and (48, 48) for the injector and producer respectively that maximized the cumulative oil produced. The well control variables X1, X2, and X3 changed between the minimum and maximum values of each variable as stated in Table 1.

c) The optimum well locations and controls placed on all wells that maximized cumulative oil produced. The well locations and controls placed on the wells (X1 to X7) changed simultaneously.

Results from the optimization study for the three scenarios are shown in Table 5 and illustrated in Figure 5.

Table 5. Well Placement, Well Control and a coupled well placement and well control optimization results

	Optimum Well Placement and/or well injection/production Control Variables for each case							
Optimization Approach	X1 PSIA	X2 MSCF/day	X3 IB/STB	X4	X5	X6	X7	COP MMSTB
Well Control Optimization	1253.045	81943.545	2.623	1	1	48	48	87.573
Well Placement Optimization	2500	50500	1.55	46	1	1	48	92.998
Well Placement and Well Control Optimization	984.355	71478.8	2.116	45	1	1	48	106.172

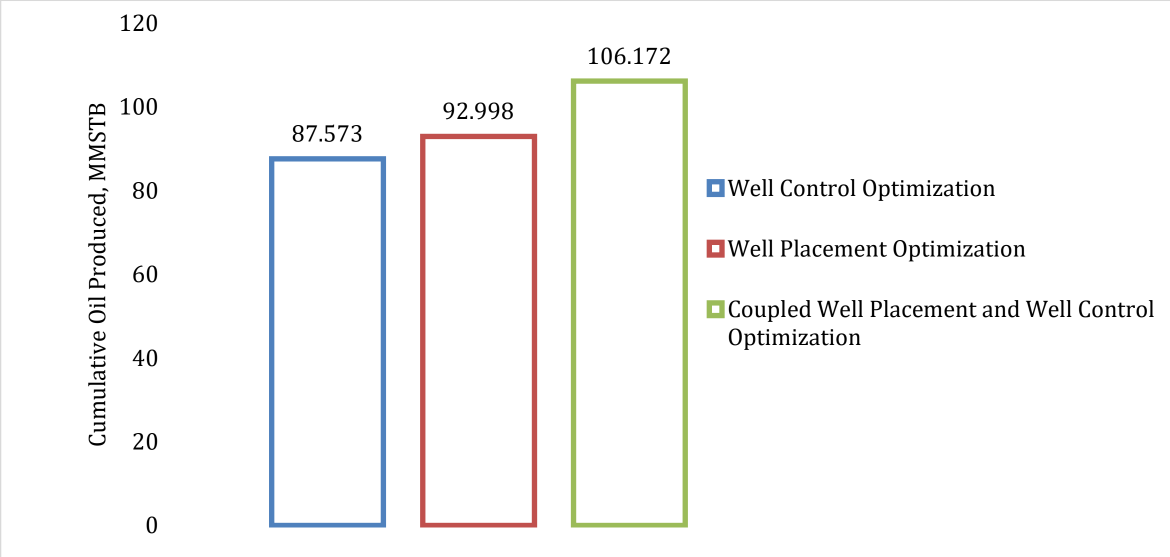

Figure 4. Comparison of Cumulative Oil Produced for different Optimization Approaches

4.1.5. Comparison between Optimization and Simulation Results

The optimum input parameters obtained for each case were used as input data to the reservoir simulation model to ascertain if results obtained from both scenarios are in agreement with each other. Table 6 and Figure 7 shows a comparison of cumulative oil produced from optimization and simulation using the optimum input parameter values presented in Table 3.

Table 6. Cumulative Oil Produced obtained from simulation and Optimization using optimum parameter values

Optimization Approach	**Cumulative Oil Produced, MMSTB**		
	Optimization	**Simulation**	**Error**
Well Control	87.573	77.33	0.1325
Well Placement	92.998	73.66	0.2625
Well Placement and Well Control	106.172	102.39	0.0369

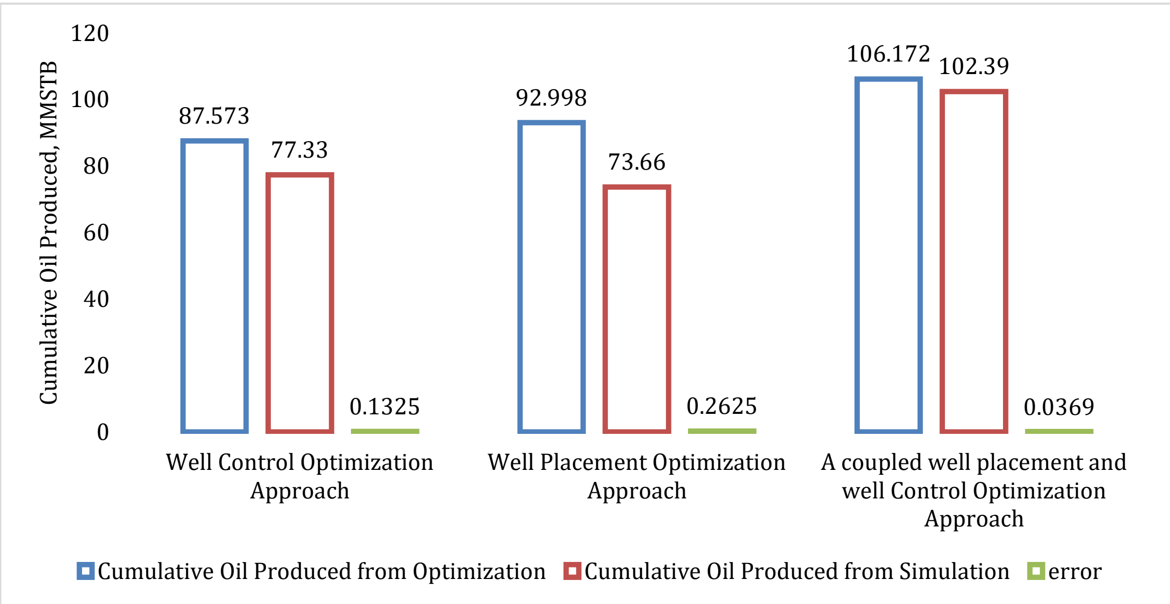

Figure 5. Comparison between Cumulative Oil Produced obtained from Simulation and Optimization studies

4.2. Discussion of Results

Determining optimum well locations and/or well injection/production controls that will maximize field oil recovery is a computationally expensive and time-consuming process which is the challenge being addressed in this paper. Response surface methodology was used to develop a proxy model (equation 3) in which cumulative oil produced (dependent variable) is a function of well placement and well injection/production control (independent) variables.

A two-dimensional heterogeneous reservoir model with an injector and producer (Figure 3) was used in this study to illustrate the approach. The well locations were represented as coordinates in the i and j directions while the well injection/production control parameters consist of the bottom-hole pressure of the producer, gas injection rate at the injection well, and concentration of surfactant added to the gas being injected at the injection well. This gives a total of seven independent parameters. The Box-Behnken design method was used to generate parameter realizations based on the minimum and maximum value of each variable which was used as input in conducting reservoir simulations to obtain cumulative oil produced (Table 2). The input and output datasets were further analyzed using ANOVA from which a proxy model (Equation 3) which shows the relationship between cumulative oil produced and seven independent parameters shown in Table 1 was developed.

The developed proxy model was validated by making a plot of actual cumulative oil produced versus predicted cumulative oil produced as shown in Figure 4 which depicts a coefficient of determination R^2 of 0.9989 which is close to unity. The proxy model was also validated by plotting actual and predicted cumulative oil produced against the simulation runs (Figure 5) which shows that actual and predicted results are in close agreement with each other depicted by an overlap of actual by predicted results. Root mean squared error (RMSE) and average absolute percentage error (AAPE) were calculated using equations 4 and 5, and were also used in validating the model whose values were found to be 0.675 and 2.239 % respectively. A combination of a coefficient of determination value, R^2 of 0.9989, an overlap of actual cumulative oil produced versus simulation runs curve by predicted cumulative oil produced versus simulation runs curve, and relatively low values of RMSE and AAPE indicate that the developed model is accurate, reliable, and can be used to navigate the design space, used in sensitivity analysis, and optimization studies.

The developed proxy model was coded in a MATLAB script file and with the aid of genetic algorithm in MATLAB Global Optimization toolbox, the optimum set of parameters that maximized cumulative oil produced was determined. The developed proxy model was used in well injection/production control, well placement, and a coupled well placement and well injection/production control optimization studies and comparisons were made between the cumulative oil produced for all scenarios. Results in Figure 6 show that a coupled well placement and well injection/production control optimization approach resulted in a cumulative oil produced of 106.172 MMSTB higher than that obtained for each of well injection/production control and well placement optimization approaches. This shows that it is preferable to simultaneously consider well placement and well control variables during field development optimization. A comparison was made between cumulative oil produced obtained from simulation and optimization using the optimum input parameters and results from Table 6 and Figure 5 shows good agreement depicted by low percentage errors for all three scenarios.

5. Conclusion

The following conclusions can be drawn from the results obtained in this study

a) A computationally inexpensive, accurate and reliable approach that consumes less time is proven to be effective in well placement and/or well injection/production control optimization.

b) A reservoir simulation proxy model (response surface model) which uses cumulative oil produced (COP) as the dependent variable and well placement and/or well injection/production control as independent variables was developed using design of experiments and response surface methodology.

c) The response surface model was coupled to genetic algorithm in determining with ease and minimal computational effort, the optimum set of parameter values that will maximize the objective function.

d) It is possible to determine optimum well locations and/or optimum well injection/production controls by coupling a reservoir simulation proxy model with an optimization algorithm.

e) The developed proxy model was used in comparing the efficiency of well placement and/or well injection/production control optimization approaches on-field oil recovery during foam injection to ascertain the best optimization approach in making field development planning decisions.

f) A coupled well placement and well injection/production control optimization approach was found to be preferable in field development optimization because it resulted in a maximum value of the objective function (cumulative oil produced) as shown in this study. It can be inferred in this study that considering coupled well placement and well injection/production control optimization resulted in an improvement in foam injection performance.

6. Further Work

Further research work in this regard will focus on using a reservoir model based on real field data with more wells which will consider two or more objective functions such as Net Present Value (NPV), Payout Time (POT), and Return on Investment (ROI) in addition to cumulative oil produced in making field development decisions. In this case, a multi-objective optimization algorithm such as a multi-objective genetic algorithm or multi-objective particle swarm optimization algorithm will be used.

NOMENCLATURE

EOR	Enhanced Oil Recovery
X1	Bottomhole pressure of producer, psia
X2	Gas injection Rate, MSCF/day
X3	Surfactant Concentration, IB/STB
X4, X5	Location of Producer in the i and j direction respectively
X6, X7	Location of Injector in the i and j direction respectively
COP	Cumulative Oil produced
RMSE	Root mean squared error
AAPE	Average Absolute Percentage Error, %
$\boldsymbol{R^2}$	Coefficient of Determination

References

[1] Rossen W. R.: Numerical Challenges in Foam Simulation: A Review. in SPE Annual Technical Conference and Exhibition. (2013 of Conference). DOI: 10.2118/166232-MS

[2] Hematpur H., Mahmood S. M., Nasr N. H., Elraies K. A.: Foam flow in porous media: Concepts, models and challenges. Journal of Natural Gas Science and Engineering, **53**, 163-180 (2018). DOI: https://doi.org/10.1016/j.jngse.2018.02.017

[3] Hørsholt S., Nick H. M., Jørgensen J. B.: Oil Production Optimization of Black-Oil Models by Integration of Matlab and Eclipse E300 ∗∗This research is funded by the Danish Hydrocarbon Research and Technology Centre

under the Advanced Water Flooding programme. IFAC-PapersOnLine, **51**, 88-93 (2018). DOI: https://doi.org/10.1016/j.ifacol.2018.06.360
[4] Awotunde A. A.: On The Joint Optimization of Well Placement and Control. in SPE Saudi Arabia Section Technical Symposium and Exhibition. (2014 of Conference). DOI: 10.2118/172206-MS
[5] Li L., Jafarpour B., Mohammad-Khaninezhad M. R.: A simultaneous perturbation stochastic approximation algorithm for coupled well placement and control optimization under geologic uncertainty. Computational Geosciences, **17**, 167-188 (2013). DOI: 10.1007/s10596-012-9323-1
[6] Alfarizi M. G., Stanko M., Bikmukhametov T.: Well control optimization in waterflooding using genetic algorithm coupled with Artificial Neural Networks. Upstream Oil and Gas Technology, **9**, 100071 (2022). DOI: https://doi.org/10.1016/j.upstre.2022.100071
[7] Afshari S., Pishvaie M. R., Aminshahidy B.: Well placement optimization using a particle swarm optimization algorithm, a novel approach. Petroleum science and technology, **32**, 170-179 (2014).
[8] Annan Boah E., Kwami Senyo Kondo O., Aidoo Borsah A., Brantson E. T.: Critical evaluation of infill well placement and optimization of well spacing using the particle swarm algorithm. Journal of Petroleum Exploration and Production Technology, **9**, 3113-3133 (2019). DOI: 10.1007/s13202-019-0710-1
[9] Bellout M. C., Echeverría Ciaurri D., Durlofsky L. J., Foss B., Kleppe J.: Joint optimization of oil well placement and controls. Computational Geosciences, **16**, 1061-1079 (2012). DOI: 10.1007/s10596-012-9303-5
[10] Kim J., Yang H., Choe J.: Robust optimization of the locations and types of multiple wells using CNN based proxy models. Journal of Petroleum Science and Engineering, **193**, 107424 (2020). DOI: https://doi.org/10.1016/j.petrol.2020.107424
[11] Montes G., Bartolome P., Udias A. L.: The Use of Genetic Algorithms in Well Placement Optimization. in SPE Latin American and Caribbean Petroleum Engineering Conference. (2001 of Conference). DOI: 10.2118/69439-MS
[12] Green D. W., Willhite G. P.: Enhanced oil recovery. Vol. 6. Henry L. Doherty Memorial Fund of AIME, Society of Petroleum Engineers ... (1998).
[13] Smith C. R., Tracy G. W., Farrar R. L.: Applied reservoir engineering. (1992).
[14] Massarweh O., Abushaikha A. S.: The use of surfactants in enhanced oil recovery: A review of recent advances. Energy Reports, **6**, 3150-3178 (2020). DOI: https://doi.org/10.1016/j.egyr.2020.11.009
[15] Katende A., Sagala F.: A critical review of low salinity water flooding: Mechanism, laboratory and field application. Journal of Molecular Liquids, **278**, 627-649 (2019). DOI: https://doi.org/10.1016/j.molliq.2019.01.037
[16] Saw R. K., Mandal A.: A mechanistic investigation of low salinity water flooding coupled with ion tuning for enhanced oil recovery. RSC Advances, **10**, 42570-42583 (2020).
[17] Duruodunzea N. O., Nwankwoa I. S., Kinatea B. B.: Numerical Approach of Evaluating the Performance of Polymer Concentration and Adsorption to Enhance Frontal Advancement During Injection. international journal of petroleum and geoscience engineering, **2021**, 1-16 (2021).
[18] Sheng J. J.:Chapter 9 - ASP Fundamentals and Field Cases Outside China, in Enhanced Oil Recovery Field Case Studies, J. J. Sheng, Editor Gulf Professional Publishing, Boston189-201 (2013)
[19] Sheng J. J.: Status of surfactant EOR technology. Petroleum, **1**, 97-105 (2015). DOI: https://doi.org/10.1016/j.petlm.2015.07.003
[20] Kumar S., Panigrahi P., Saw R. K., Mandal A.: Interfacial Interaction of Cationic Surfactants and Its Effect on Wettability Alteration of Oil-Wet Carbonate Rock. Energy & Fuels, **30**, 2846-2857 (2016). DOI: 10.1021/acs.energyfuels.6b00152
[21] Chen Z.: Reservoir simulation: mathematical techniques in oil recovery, SIAM (2007).
[22] Kovscek A. R., Radke C. J.:Fundamentals of Foam Transport in Porous Media, in Foams: Fundamentals and Applications in the Petroleum IndustryAmerican Chemical Society, Vol. 242. 115-163 (1994)
[23] Rossen W. R.:Foams in enhanced oil recovery, in Foams: Theory Measurements, and Applications (1st ed.), R. K. Prud'homme, S. A. Khan, Editors. Routledge413-464 (1996)
[24] Farajzadeh R., Andrianov A., Zitha P. L. J.: Investigation of Immiscible and Miscible Foam for Enhancing Oil Recovery. Industrial & Engineering Chemistry Research, **49**, 1910-1919 (2010). DOI: 10.1021/ie901109d
[25] Boeije C. S., Rossen W. R.: Fitting Foam-Simulation-Model Parameters to Data: I. Coinjection of Gas and Liquid. SPE Reservoir Evaluation & Engineering, **18**, 264-272 (2015). DOI: 10.2118/174544-PA
[26] Farajzadeh R., Eftekhari A. A., Hajibeygi H., Kahrobaei S., van der Meer J. M., Vincent-Bonnieu S., Rossen W. R.: Simulation of instabilities and fingering in surfactant alternating gas (SAG) foam enhanced oil recovery. Journal of Natural Gas Science and Engineering, **34**, 1191-1204 (2016). DOI: https://doi.org/10.1016/j.jngse.2016.08.008
[27] Kovscek A. R., Patzek T. W., Radke C. J.: Mechanistic Foam Flow Simulation in Heterogeneous and Multidimensional Porous Media. SPE Journal, **2**, 511-526 (1997). DOI: 10.2118/39102-PA
[28] Sunmonu R. M., Onyekonwu M.: Enhanced Oil Recovery using Foam Injection; a Mechanistic Approach. in SPE Nigeria Annual International Conference and Exhibition. (2013 of Conference). DOI: 10.2118/167589-MS

[29] Adebanjo F. O., Olusegun O.: Evaluating the application of foam injection as an enhanced oil recovery in unconsolidated sand. Journal of Petroleum and Gas Engineering, **6**, 22-37 (2015).
[30] Zubarev D. I.: Pros and Cons of Applying Proxy-Models as a Substitute for Full Reservoir Simulations. in SPE Annual Technical Conference and Exhibition. (2009 of Conference). DOI: 10.2118/124815-MS
[31] Jaber A. K., Al-Jawad S. N., Alhuraishawy A. K.: A review of proxy modeling applications in numerical reservoir simulation. Arabian Journal of Geosciences, **12**, 701 (2019). DOI: 10.1007/s12517-019-4891-1
[32] Schuetter J., Mishra k. S., Ganesh P. R., Mooney D.: Building Statistical Proxy Models for CO2 Geologic Sequestration. Energy Procedia, **63**, 3702-3714 (2014). DOI: https://doi.org/10.1016/j.egypro.2014.11.399
[33] Alenezi F., Mohaghegh S.: A data-driven smart proxy model for a comprehensive reservoir simulation. in 2016 4th Saudi International Conference on Information Technology (Big Data Analysis) (KACSTIT). (2016). DOI: 10.1109/KACSTIT.2016.7756063
[34] Gurav Y. S., Dandekar A. Y., Patil S. L., Patwardhan S. D.: Application of Design of Experiments for Well Pattern Optimization in Umiat Oil Field: A Natural Petroleum Reserve of Alaska Case Study. in SPE/IATMI Asia Pacific Oil & Gas Conference and Exhibition. (2019 of Conference). DOI: 10.2118/196495-MS
[35] Moeinikia F., Alizadeh N.: Experimental Design in reservoir simulation: an integrated solution for uncertainty analysis, a case study. Journal of Petroleum Exploration and Production Technology, **2**, 75-83 (2012). DOI: 10.1007/s13202-012-0023-0
[36] Spokes J. J., Ovuede M. A., Ginger E. P., Narahara G. M., Haga O., Gontijo J.: Application of Experimental Design in Selecting a Development Plan for the Agbami Field. in Offshore Technology Conference. (2004 of Conference). DOI: 10.4043/16994-MS
[37] Rajabi-Kochi M., Khamehchi E.: Integrated production optimization of an oil field based on constructing of a proxy model using DOE methods. Journal of Petroleum Exploration and Production Technology, **10**, 2465-2482 (2020). DOI: 10.1007/s13202-020-00887-4
[38] Olanipekun M., Akpabio J. U., Isehunwa S. O.: Development of Proxy Models for Screening Water Flood and Gas Flood Candidates. Journal of Engineering Research and Reports, **20**, 51-57 (2021). DOI: https://doi.org/10.9734/jerr/2021/v20i117246
[39] Negash B. M., Awang M., Jufar S. R., Robert A. J.: History matching of the PUNQ-S3 reservoir model using proxy modeling and multi-objective optimizations. in International Conference on Industrial Engineering Operations Management. Kuala Lumpur, Malaysia: IEOM Society International (2016).
[40] Naderi M., Khamehchi E.: Application of DOE and metaheuristic bat algorithm for well placement and individual well controls optimization. Journal of Natural Gas Science and Engineering, **46**, 47-58 (2017). DOI: https://doi.org/10.1016/j.jngse.2017.07.012
[41] Xiong X., Lee K. J.: Data-driven modeling to optimize the injection well placement for waterflooding in heterogeneous reservoirs applying artificial neural networks and reducing observation cost. Energy Exploration & Exploitation, **38**, 2413-2435 (2020). DOI: 10.1177/0144598720927470
[42] Aslan N., Cebeci Y.: Application of Box–Behnken design and response surface methodology for modeling of some Turkish coals. Fuel, **86**, 90-97 (2007). DOI: https://doi.org/10.1016/j.fuel.2006.06.010