Advanced ML and AI Approaches for Proxy-based Optimization of CO2-Enhanced Oil Recovery in Heterogeneous Clastic Reservoirs

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Abstract

Constructing a simpler model to represent a complex reservoir simulation that will be employed to define the optimum future development plans have been achieved through the use of different simulation techniques that include EOS-compositional reservoir simulation, Proxy Modeling as well as Design of Experiments. A sector of the main pay of the sandstone reservoir in the South Rumaila, located in Southern Iraq, was used to implement this integrated workflow. Once reliable history matching was achieved, the key five operational decision parameters were optimized for their optimum level to achieve ideal flow response factor. These key parameters govern the production and the injection processes in the studied reservoir. A low-discrepancy and consistent procedure was used to generate several hundred simulation runs or experiments to build a proxy-based optimization approach by adopting the Latin Hypercube Sampling with the five decision parameters. At the end of the forecast case, the optimum cumulative produced oil resulted in achieving 4.6039 MMMSTB of oil production compared with 4.39 MMMSTB of oil production that was produced from the base scenario of the GAGD technique assessment of original decision parameters' conditions.

Lastly, four machine learning (ML) and Artificial Intelligence (AI) algorithms were considered as proxy metamodels to serve as an alternative to the complex compositional reservoir simulation: Second-Degree Polynomial Equation (QM), Fuzzy Logic-Genetic Algorithm (FUzzy-GEnetic), Multivariate Additive Regression Splines (MARS), and Generalized Boosted Modeling (GBM). The cross validation of the Adjusted R^2_{adj} along with the Root Mean Square Error were the base to conclude the optimum proxy metamodel which provides the lowest mismatch of the proxy- and simulator-based model considering the cumulative produced oil as response by CO2-GAGD technique. Consequently, GBM was determined to be the best shorten alternative metamodel for the GAGD process evaluation and prediction scenarios.

Keywords: `Proxy Metamodeling`, Design of Experiments, Cross-validation, Gravity Drainage, Enhanced Oil Recovery, Clastic Oil Reservoirs

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1. Introduction

Energy consumption worldwide is vastly increasing annually due to the technology revolution and the population significant incrimination. Discoveries of new oil fields have become rare in the last decade. Therefore, boosting oil production by utilizing all available technological methods including Enhanced Oil Recovery methods (EOR) is inevitable. Specifically, Enhanced oil recovery is becoming more important than ever, as finding new sources are becoming more cost and time consuming, especially when the oil price is facing huge reduction. Gas flooding is considered one of the most promising technologies used in EOR projects. Gas flooding is being implemented through the Continuous Gas Injection (CGI) or Water Alternating Gas (WAG) methods. However, the Gas Assisted Gravity Drainage (GAGD) technique is lately implemented to advance the volume of the recovered oil in both secondary and tertiary stages for immiscible/miscible gas injection methods (Rao , 2012). Consequently, it was proposed to boost the volume of the recovered oil in the main pay of Zubair formation in Rumaila oil field which is located in southern Iraq. That field was selected because it is a mature oil field that has been producing for more than 60 years and waterflooding is no longer effective to increase the recovered of oil.

Elevating oil recovery by implementing the gas flooding is a crucial task in the field development through Enhanced Oil Recovery (EOR) projects, especially when conducted in real oil fields. There are many limitations that impact the reservoir production through the CO2-EOR processes. These parameters can be operational or controllable by field operators, such as the well production and injection constraints. Some other factors are uncontrollable, such as the geological properties. These operational factors need to be optimized to identify the optimal solution of the reservoir flow response. It is indispensable to define the ideal limits of the operational parameters which govern the effectiveness of the Enhanced Oil Recovery method. These factors are primarily comprised of operational constraints with the injection and production wells in a certain reservoir. More specifically, the manner in which the production constraints are defined to regulate the volume of produced and the injected volumes in the reservoir; consequently, it provides a major influence on the reservoir flow response. Therefore, the enhancement of these parameters can achieve ideal reservoir performance with the time relative to reservoir cumulative oil production as well as Net Present Value (NPV) (White and Royer , 2003).

Proxy modeling and the Design of Experiments (DoE), also noun as Designed Experiments, are statistical techniques which are integrated to build a Response Surface Methodology (RSM) as a uncomplicated substitute or metamodel for the convoluted models to assess the several constructed experiments in the enhancement approach instead of evaluating the same simulator (Lee et al. , 2003). The proxy modeling optimization has not been found in the literature when it comes to the CO2-GAGD technique. However, the proxy model has been implemented in different reservoir studies and EOR modeling, such as oil production optimization (Badru and Kabir , 2003, Zangl et al. , 2006), waterflooding processes (Guyaguler et al. , 2000, Haghighat Sefat et al. , 2014), gasflooding processes (Ampomah et al. , 2016), steam injection (Fedutenko et al. , 2013a,b, Vanegas Prada and Cunha , 2008, Yang et al. , 2011), chemical flooding (Zerpa et al. , 2007), and history matching (Zubarev , 2009, Goodwin , 2015, He et al. , 2016). The DoE concepts generate various computer trials (realizations) for the subject by connecting the levels for every parameter. These experiments are evaluated to compute the response factor. The created experiments and response factor are taken account of the statistical modeling to generate a relationship, which characterizes the proxy or surrogate model. Many DoE approaches have been used in various reservoir simulation studies to build the proxy models. The most common DoE approaches are fractional factorial design (Vanegas Prada and Cunha , 2008), Central composite (CC) designs (Yeten et al. , 2005), D-optimality also noun as D optimal design (Zerpa et al. , 2007), and Latin Hypercube Design (Zubarev , 2009). There are many successful examples of using the proxy models in the literature of reservoir studies, for instance, the second degree polynomial equation (Avansi , 2009, Hassani et al. , 2011, Fedutenko et al. , 2013b, White and Royer , 2003), kriging algorithms (Fedutenko et al. , 2013b, Osterloh , 2008, Zubarev , 2009), and artificial neural networks algorithm (Zangl et al. , 2006, Zubarev , 2009, Vo Thanh et al. , 2020).

In this paper, the Designed Experiments and proxy modeling have been combined to for optimizing the volume of the recovered oil through the Gas Assisted Gravity Drainage (GAGD) technique in the heterogeneous Zubair formation main pay in south Rumaila field. To apply the optimization procedure, a compositional reservoir model was built to assess the reservoir production by the CO2-GAGD flooding during 10 years of future reservoir production. Then, the proxy model was enhanced by adjusting the operational decision parameters that impact CO2 flooding by the GAGD technique by the Design of Experiments (DoE). More specifically, the Design of Experiments and Proxy Modeling were incorporated in the purpose of generating a simplified surrogate approach (metamodel) to the compositional reservoir model for the improvement of the operational decision parameters that impact the GAGD technique. Four ML and AI algorithms were utilized as proxy metamodels for the full compositional reservoir model: polynomial proxy model, Fuzzy Logic-Genetic Algorithm, Multivariate Additive Regression Splines and Generalized Boosted Modeling. The cross-validation with variance calculations were then used to validate these four proxy models. To best of the knowledge, Fuzzy Logic-Genetic Algorithm as well as Generalized Boosted Modeling approaches have never been used before as proxy models in the reservoir simulation studies, especially in the gas injection workflows. In addition, the presented workflow of integrating Design of Experiments with Fuzzy Logic-Genetic Algorithm along with Generalized Boosted Modeling proxy models has never been adopted on CO_2 EOR studies yet, particularly the Gravity Drainage-based CO2-EOR Process.

2. Gas-Assisted Gravity Drainage Process

Natural separation of reservoir fluids is imperative to boost the recovery of bypassed oil by the CO2 Assisted Gravity Drainage (GAGD) technique by supplying gravity steady oil sweep. The GAGD technique was patented to improved oil recovery in different production stages including secondary and tertiary for both immiscible and miscible gas injection practices (Rao , 2012). The GAGD process is achieved by placing horizontal production wells at lower part of the target reservoir. Then, immiscible or miscible gas injection process in a gravity-stable state by the vertical injectors in the top of reservoir is initiated (Rao et al. , 2004). Because of the gravity segregation occurring from the various fluid densities at reservoir conditions, the accumulation of the injected gas will be at the top of reservoir to generate a gas cap. This process will supply gravity stable oil sweep that moves the hydrocarbon to the bottom of the reservoir towards horizontal production wells which help to achieve improved sweep performance and optimum oil recovery.

Mostly, the CO2 gas is favored for GAGD process as it provides optimum volumetric sweep performance with ideal microscopic displacement efficiency, particularly when it is used in miscible injection processes. Furthermore, the ideal volumetric sweep performance enhances retarding CO2 arrival in production wells (Rao , 2012). Slowing down or diminishing the arrival of the injected gas minimizes concurrent gas-liquid flow, and later enhances gas injection to sustain the reservoir pressure.

3. Field Description

The subject oil field was first discovered in the end 1953 in south of Iraq. The field is approximately 50 km to the west of Basrah city and located 30 km to the west of the Zubair field (Al-Ansari , 1993). The field length is 100 km with 12 to 14 km width and located 3 km below sea level. Reservoir flanks are dipping with angles that do not exceed 3 o degrees while the crest only dips with 1^o degree. South Rumaila oil field was found to be comprised of several oil bearing reservoirs intervals. The main prolific oil reservoir is Zubair that is characterized by the Late Berriasian Albian cycle while its sediments goes back to the Lower Cretaceous age. The thickness of Zubair reservoir ranges from 280 m to 400 m and the sand to shale ratio depicts that Zubair formation involves five members which are rich of organic contents (Al-Obaidi , 2009). These five key members called as: upper shale, upper sandstone, middle shale, lower sand, and lower shale where the main producing interval were found to be the upper sandstone member (Mohammed et al. , 2010). According to Al-Ansari (1993), Zubair formation is a conventional reservoir that does not contain any complicated geological structures and figures such as faults or fractures (Al-Ansari , 1993). Four key sectors were defined in South Rumaila field which are called Janubia, Rumaila, Shamiya, and Qurainat. Rumaila sector and only minor regions of Shamiya and Janubia sectors will be studied in this research. The selection of these parts was decided depending on the gathered reservoir data and the capability to characterize the major parts of the reservoir, where the wells are producing and water injection activities are performed, shown in Figure 1.

It was found that Zubair formation has two types of boundary conditions that include a no-flow boundary and an aquifer. The no-flow boundary condition was proposed to cover the northern and the southern areas of the reservoir. This assumption is acceptable as it mimics the reality since the reservoir adopted the balance production and injection rates. Moreover, the streamlines in the north of the reservoir was crossed by the isobaric lines which are perpendicular to the reservoir boundaries. Therefore, the direction of the flow in the reservoir is parallel to boundaries in the south and the north of the reservoir as shown in Figure 1. Whereas the east and the west flanks were characterized by flow boundaries that symbolize the natural water drive to mimic the effects of the existing infinite aquifer (Al-Mudhafer et al. , 2010).

South Rumaila field was first developed on primary production in 1954 while water injection was

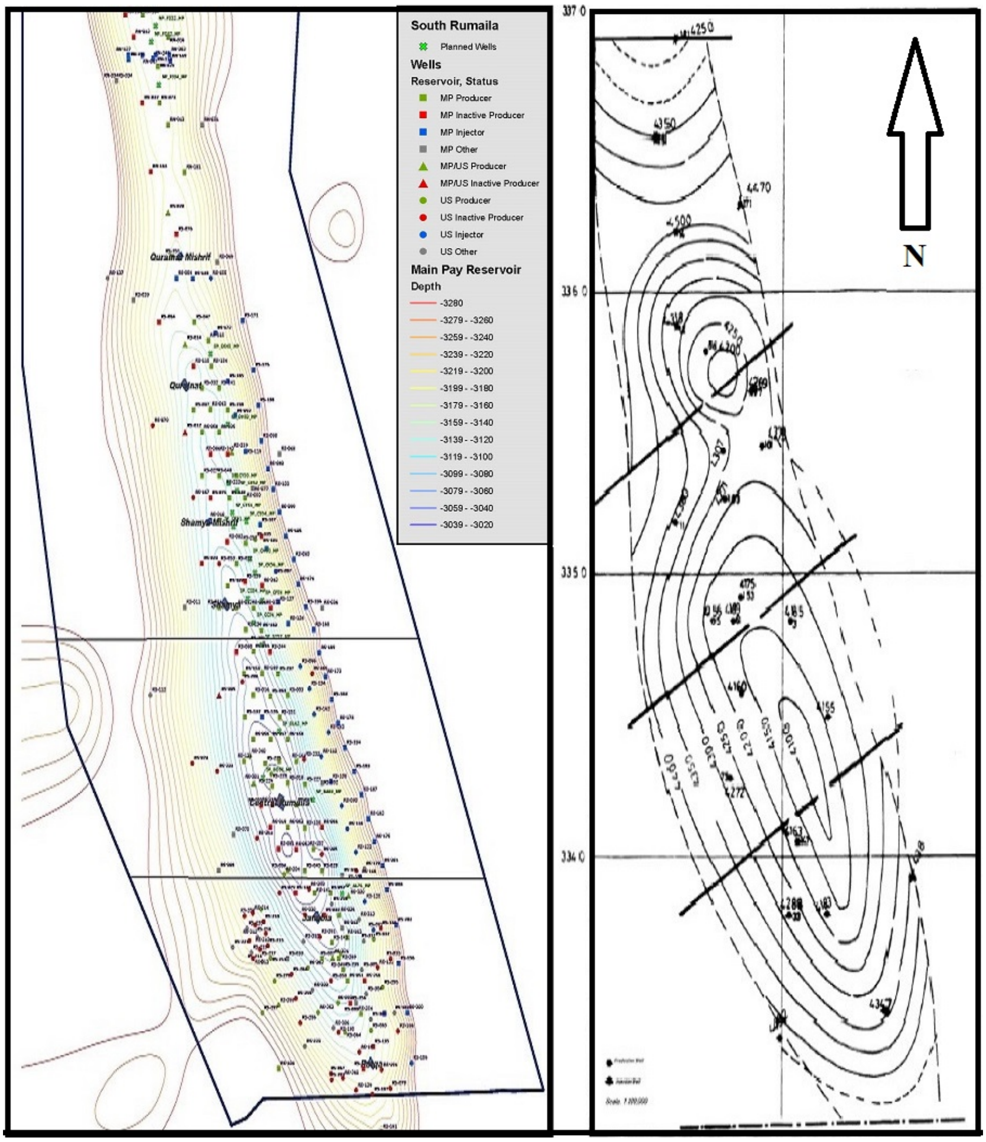

Figure 1: (Left) Sectors of the field with Well Locations. (Right) Isobaric Map of South Rumaila Oil Field, Modified from (Mohammed et al. , 2010)

commenced in 1980s to maintain the reservoir pressure and to sustain the west flank aquifer support which is about 20 times stronger than the east flank aquifer (Al-Mudhafer et al. , 2010, Kabir et al. , 2007). Throughout field development, 40 production wells were drilled in the regions that are under the investigation of this research. The development of the South Rumaila field included shutting of some of the reservoir layers as they were reason of high water cut values that reached about 98%. Until 2004, the total volume of the injected water reached approximately 1.1 billion barrels with various rates of injection. The maximum injection rate value was 426,000BPD for two months in 1988. Since water cut hit 80% in some wells, artificial lift (ESPs) has been used to sustain production. The main pay in South Rumaila has an original oil in place (OOIP) of 19.5 billion barrels and the estimated recovery factor is around 55%. The studied sector in this research has an OOIP of 6.13 billion barrels.

4. Compositional Simulation of GAGD Process

Comprehensive compositional reservoir simulation has been constructed to optimize the recovery of the bypassed oil by GAGD technique in the main pay reservoir. The geological description of main pay reservoir in South Rumaila depicts that it has three rock types: sand, shale and shaly sand which are distributed through the reservoir with different permeability ranges. To model lithofacies and petrophysical properties, a full detailed geostatistical model with 1,908,900 grids has been employed using the Multiple Point Geostaistics and Sequential Gaussian Simulation (Al-Mudhafar , 2016a).

The built geostatistical model has grids of 210, 202, 45 in I,J and K directions which was then upscaled to grids of 69, 66, 12 to simulate the GAGD process. This model was the base to build the compositional reservoir flow simulation by the use of CMG-GEM package (CMG , 2015). This model was then history matched to be used for the future filed development and planning by the trial and error technique depending on the production and injection rates along with the cumulative produced oil. The acquired matching is an excellent indicator of the model performance as it replicates water cuts and saturation distribution. The production and injection history that have been used in this research covered 56 years of production which is until the first quarter of 2010. Consequently, history matching was obtained between 1954 and 2010 as shown in Figures 2 and 3.

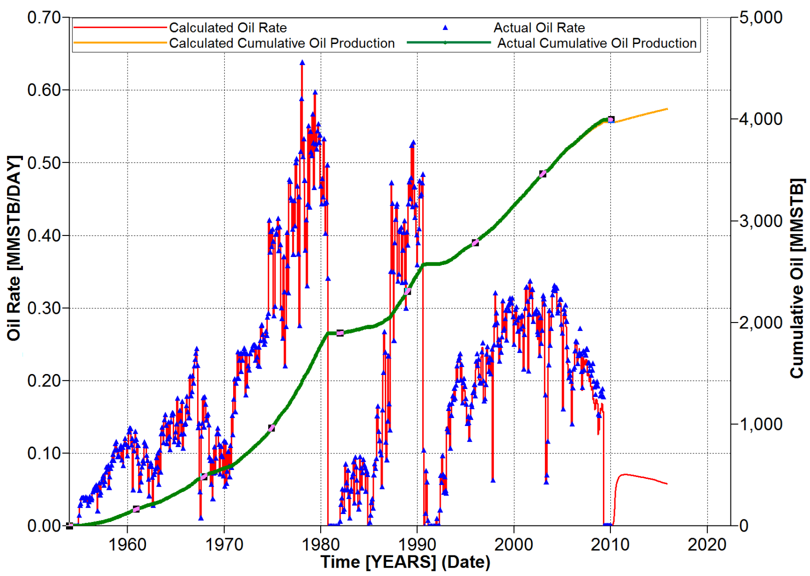

Figure 2: History Matching of Entire Field Production of South Rumaila Oil Field

A total of 33 wells have been used to implement the key concept of GAGD process. These wells included 22 vertical injection wells and 11 horizontal producers with 3000 m lateral length which are placed in the reservoir layers where the lithology is sand and shaly sand. At first, CO2 injection is commenced by the vertical injection wells at the shallower two layers. Simultaneously, the following three layers are utilized as a transition region to provide vertical space for gas gravity drainage. The next steps involve setting up the horizontal producers through layers 6-8 which contains the highest oil saturation in the reservoir. Eventually, the remaining four layers did not involve injection

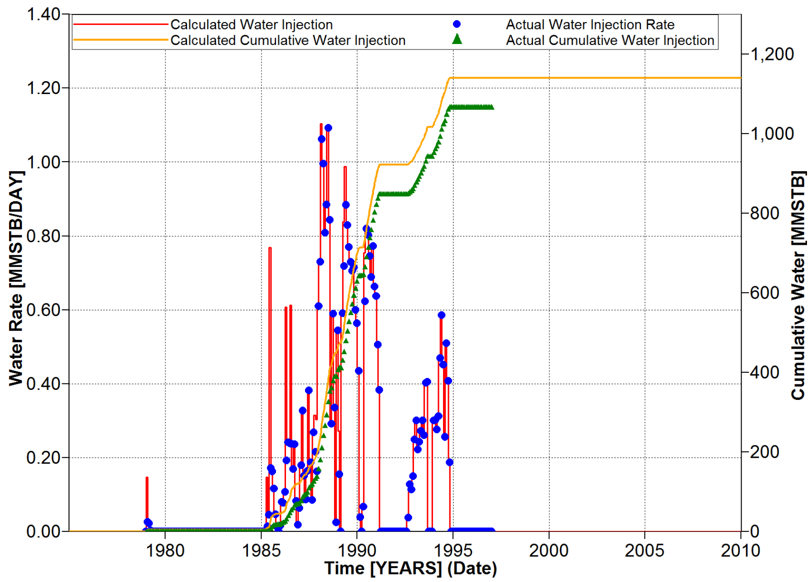

Figure 3: History Matching of Entire Field Injection of South Rumaila Oil Field

or production processes since the water saturation in these layers is 100% from the infinite water aquifer. The reservoir model was later simulated to assess the CO2-GAGD method with 10 years duration starting from 2016 and ending in 2026. Figure 4 illustrates the 3-D reservoir model with the positions of injection and production wells that have been used for the CO2 injection in the GAGD method. In Figure 4, the reservoir body is represented by the red color which symbolized the shale zones.

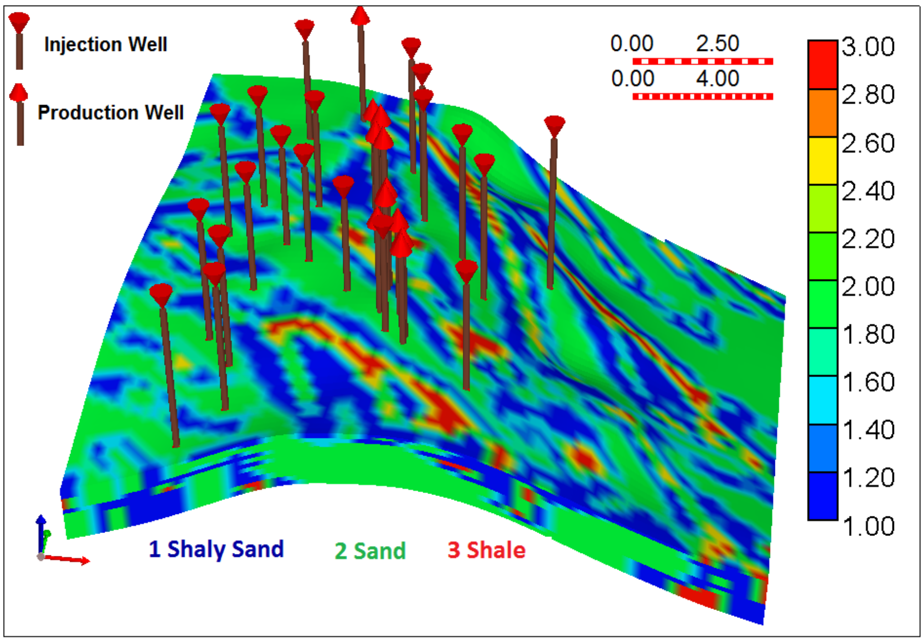

Figure 4: Production and Injection Well Locations in Sand and Shaly-Sand Zones

Sand zones and shaly-sand zones (indicted in 1 and 2 respectively in figure 4) were perforated in production and injection wells since they are considered to be high permeable zones.

5. Optimization Approaches

Design of Experiments (DoE) is a methodical numerical technique which generates a suitable group of experiments to be the base of the simulation runs. DoE is mainly utilized for determining the highest critical parameters that impact the response during the sensitivity analysis practice. DOE tool provide a way to acquire the most likely case which accomplishes the optimum response from a certain procedure (Lazic , 2006). DOE technique was demonstrated as an efficient tool for carrying out several tasks such as system optimization, variable screening, risk evaluation, and robust design (Amudo et al. , 2009). It is essential to accomplish the most precise experimental design model that imitates the physical model or process for faster, cheaper and more flexible implementation. To accomplish this task, the necessary group of elements and interactions have to be investigated in order to enable the analysis and implementation of results to be accurate and trustworthy (White and Royer , 2003).

The key terms of Design of Experiments are response parameter which basically symbolizes the result from a specific experiment and factor. The factors are described as a variable which impacts the response parameter and can be classified as primary and secondary based on the different level of sensitivity. The overall count of designed experiments is defined by an exponential relationship. For illustration, the experiments count with k variables and 4 levels will be equal to 4^k. The Latin Hypercube Sampling was implemented in this research along with the proxy modeling to identify the optimal values of the operational production decision factors for the Gas Assisted Gravity Drainage (GAGD) method optimization.

Latin Hypercube Sampling (LHS) is described as a numerical sampling method which is employed to produce random samples out of given input factors to create several computer experiments and trials from a distribution with several levels (McKay et al. , 1979). To represent various stages of variation for every single factor with the lowest number of trials, the sampling procedures deliver restricted data points in the design field with a uniform distribution by the space filling strategy (Bhat , 2001). The Latin Hypercube sampling is considered as instance that represents these efficient designs which generates uniform and low discrepancy observations (McKay et al. , 1979). Figure Figure 5 illustrates the space-filling design by LHS for two variables. In this figure, the sampled data are allocated within the entire space randomly. All the points are uniformly distributed to capture the entire variation of the process being studied which is considered to be the power of Latin Hypercube Sampling technique.

Latin Hypercube sampling creates further effective experiments for K parameters compared with basic Monte Carlo sampling technique. More explicitly, LHS delivers a steady points design since it retains the highest space between each design point compared with the other points (Stocki , 2005). In LHS, K variables sampling is conducted by splitting every parameter into several equivalent parts. Moreover, LHS is an extension practice which randomly produces a new group of trials or experiments in case the given dataset does not characterize the problem. However, there is no explicit approach to define the required number of trials or experiments that can be generated. (Stein , 1987). The computer experiments, which were generated for optimization, were accomplished in R statistical

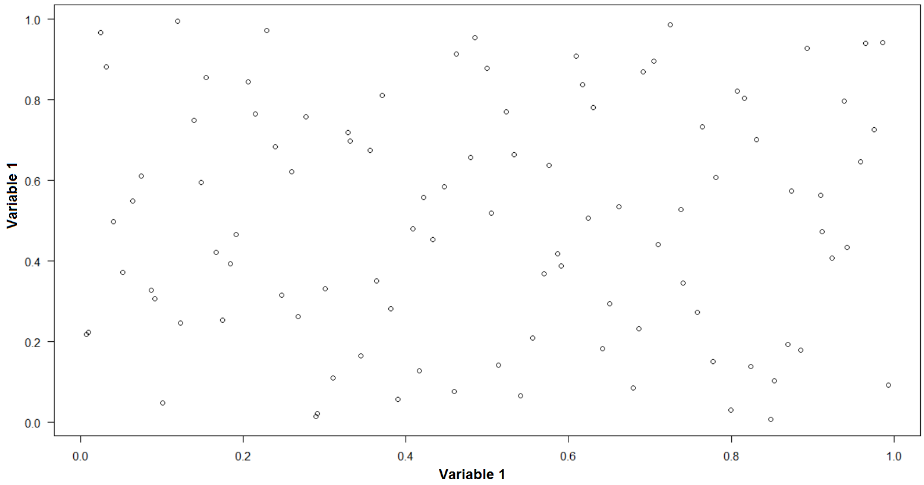

Figure 5: Latin Hypercube Sampling Design given Two Variables(R output)

language by [lhs] package (Carnell , 2015).

6. Proxy Modeling

The proxy approach deals with building a simplified model alternative to the complex model (metamodel). This proxy model empowers users to achieve results equivalent to the results acquired by the sophisticated models with significantly lower computational time which might be a few seconds for millions of simulation runs. Nonetheless, the complex model consumes several days to obtain the results of hundreds runs. The proxy model is performed by fitting the operational parameters training data to the response factor which is represented by the following relationship:

$$y = f(X_1, X_2, ..., X_k) + \epsilon_i \tag{1}$$

where $X_1, X_2, ..., X_k$ arepresent the input variables and y refers to the anticipated response factor.

Cross-validation is necessary to maximize the opportunity of achieving global optima and to enhance the forecast precision of the proxy model. The random sampling cross-validation is implemented on the entire experiments through sampling and dividing the given dataset into two groups: 30% testing set for forecast and prediction while 70% training set for building the model (Al-Mudhafar , 2016c). More explicitly, the training set has been used as the base for cumulative oil production modeling, obtained by the reservoir simulator, as a function of operational parameters. The prediction is then utilized for the purpose of the testing subset data by the simulator as well as the proxy model.

In this paper, the comparison between the proxy models was conducted for the missing match of the cumulative produced oil which was estimated through the reservoir simulation model and by the proxy model depending on the testing data set, not the same training dataset. That cross-validation approach confirms making exterior forecast from the same given data (the results can be trusted when implemented on external dataset). The mismatch was computed through estimating the Root Mean Square Prediction Error (RMSE) and the updated R2adj. RMSE quantifies the predictable squared variance of the reservoir simulator and proxy model response factors, for instance the cumulative produced oil. While, the updated R^2_{adj} is a modified version of R-squared, which shows how much variance can be described by a model. However, the updated R^2_{adj} is adjusted for several of predictors in the model and it grows only if the new term enhances the model.

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(\hat{f}_j(x_i) - f_j(x_i))^2} \tag{2}$$

$$R^2_{adj} = 1 - \frac{(1 - R^2)(n - 1)}{n - k - 1} \tag{3}$$

Where n is the count of experiments and k is the count of predictors (operational decision factors).

Figure 6 illustrates, the comprehensive flowchart for Design of Experiments, Proxy model, and cross-validation.

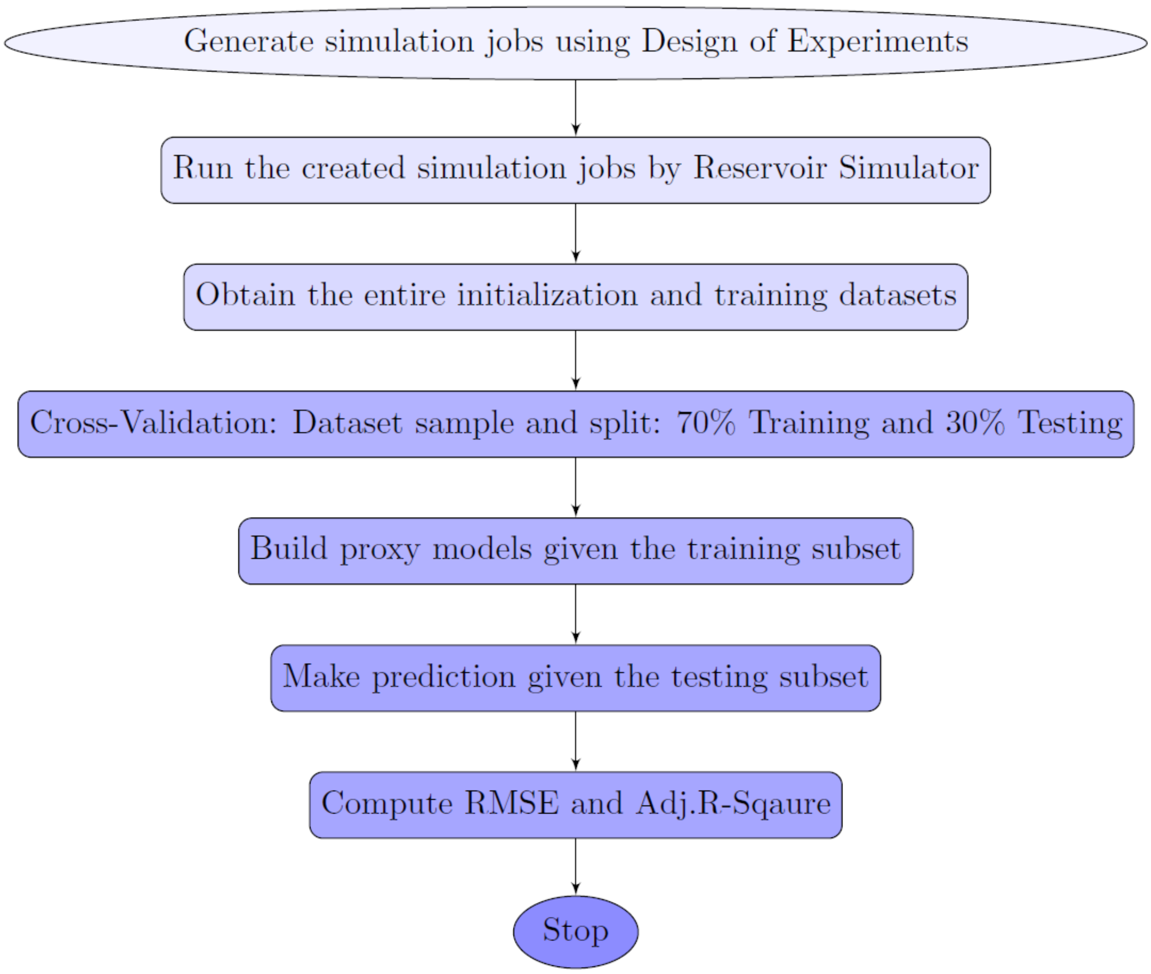

Figure 6: Flowchart of Design of Experiments-Proxy Optimization Algorithm

From the aforementioned Design of Experiments and proxy modeling, 643 simulation jobs (experiments of the operational parameters) were generated for the training and validation runs. These runs were then adopted for the comparison of four proxy models: Polynomial (Quadratic) Regression (QM), Multivariate Additive Regression Splines (MARS), Fuzzy Log-Genetic Algorithm, and Generalized Boosted Regression Model (GBM).

6.1. *Polynomial Regression*

The second degree polynomial regression has been employed to generate the response surface methodology (RSM) through constructing a nonlinear function that relates the input parameters with the response factor (Zubarev , 2009, Fedutenko et al. , 2013a). The common model for the polynomial RSM is the second-degree quadratic model. For models with parameters of more than two, it is characterized by the following formula:

$$y = \alpha_0 + \sum_{j=1}^{k} \alpha_j X_j + \sum_{j=1}^{k} \alpha_{jj} X_j^2 + \sum_{i<j} \sum_{j=2}^{k} \alpha_{ij} X_i X_j + \epsilon_i \tag{4}$$

where α_j is the linear coefficient while α_{jj} is the quadratic terms coefficient, and α_{ij} s the interaction coefficient of every two factors. The response surface methodology was entirely implemented via R-statistical programming language through *rsm* package (Lenth , 2009).

6.2. *Multivariate Additive Regression Splines*

MARS is described as an improved technique of linear regression which is a nonparametric regression approach that spontaneously formulate a function between variables considering the nonlinearity by utilizing piecewise linear slices which noun as splines (Friedman , 1991). The MARS technique employs a group of coefficients and functions that define a formula to relate the response parameters and the forecasted variables. MARS technique is proper for multidimensional predictors since the fundamental functions divide the given input data into sections where every section contains its own coefficients group to eliminate the potential outliers that might be available in the dataset (Kooperberg , 2006).

Modeling data by MARS is applied by two key stages: forward phase which explores possible knots to advance the performance of modeling, and backward procedure that removes the unimportant predictors (Adoko and Jiao , 2014). MARS model is characterized by the below function that apply the forward step (Samui , 2013):

$$y = c_0 + \sum_{i=1}^{N} c_i \prod_{j=1}^{K_i} b_{ji}(X_{v(j,i)}) \tag{5}$$

where:

y: the response or output variable.

c_0: constant.

c_i: vector of coefficients of the irregular fundamental functions.

$v(j,i)$: the index of independent parameters utilized in the i^{th} term of the j^{th} product.

$b_{ji}(X_{v(j,i)})$: the truncated power fundamental function with $v(j,i)$.

K_i: a parameter that limits the order of interactions.

b_{ji}: the spline function.

Non-influential predictors are eliminated through the backward step depending on the global cross-validation (GCV) principle, which adaptively deals with the diverse trends of data (Friedman , 1991). The entire implementation of MARS approach was performed through *earth* package in the R-statistical programming language (Milborrow , 2016).

$$GCV = \frac{1}{N} \sum_{i=1}^{N} [y_i - f(x_i)]^2 / [\frac{N - (M + \delta(M-1)/2}{N}]^2 \tag{6}$$

6.3. Fuzzy Logic-Genetic Algorithm

Fuzzy logic is a method of knowledge illustration proper for notions that cannot be identified accurately, but it is governed by their contexts. Fuzzy Logic is a convenient way to build a fuzzy model of the input and output data. Fuzzy logic system comprises of three phases: fuzzifier, fuzzy inference system, and defuzzifier (Al-Mudhafer and Alabbas , 2012). In particular, the mechanism of fuzzy logic system can be described as follows: in the fuzzifier stage, the raw inputs to the system to form fuzzy inputs. Later, these fuzzy inputs are to be populated into the inference environment or system in which the real calculations are accomplished. The next step includes incorporating the rule base with fuzzy inputs along with the inference engine to generate fuzzy results for every single rule. The rule base is described as the confinement of the expert understanding. A fuzzy group is created by the fuzzy results and this group is converted into a crisp value through the defuzzifier stage (Hinterding et al. , 1997). However, Genetic Algorithm is a random search tool to generate potential answers that compete with each other to define the most suitable solution by applying operators of recombination, transformation and selection that mimics the genetic regeneration in a biological environment comparable to the Natural Section theory that was proposed by Darwin (Goldberg , 1989).

Fuzzy Logic-Genetic Algorithm (FUzzy-GEnetic) is an evolutionary algorithm of fuzzy systems population, which is randomly generated by Genetic Algorithm, to be used as a prediction model by fitting the given training data as labels. The full procedure of FUzzy-GEnetic proxy modeling was implemented through *fugeR* R-package (Bujard , 2015). In *fugeR*, the given data is used to verify the entire fuzzy system. The algorithm forecast is then compared with the labels and each system with have a quantified performance. The population of chromosomes is then utilized to create a 20% population for the subsequent creation based on the crossover and mutation. In the final creation, the fuzzy system which achieved the optimum performance is identified.

6.4. Generalized Boosted Regression Model

GBM is an influential technique that have various implementations in machine learning. GBM was developed by Friedman (2001, 2002) to imitate complicated dependencies of a non-linear relationship. In specific, GBM can be described as an application of augmentation to Freund and Schapire's AdaBoost algorithm and J. Friedman's gradient boosting machine (Freund and Schapire , 1997).In the literature GBM has been proven to have wide implementation within machine learning and data science subjects that achieves high accuracy of forecast and modeling of the response parameters. In GBM modeling, fitting new models repeatedly will lead to achieve a precise modeling as it helps to minimize the difference between the observed and the forecasted responses. A key concept of GBM is to train the data to attain the highest formulation with the negative gradient of the loss function (Natekinand Knoll , 2013).

The concept beyond GBM loss function is to eliminate high deviations from the objective results and to ignore the insignificant residuals (Natekinand Knoll , 2013). The GBM technique starts with allocating a differentiable loss function and begins with a base model F. Afterwards, iteration is executed to compute the next negative gradient and the process finishes when convergence is obtained.

$$-g(x_i) = -\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}. \tag{7}$$

Then, the regression tree h is matched to the negative gradients $-g(x_i)$. The full practice of GBM-based proxy modeling has been applied by *gbm* library in R language (Ridgeway , 2007).

7. GAGD Production Optimization

The five operational decision parameters investigated for the immiscible GAGD production optimization are: maximum oil production rates (MAX_STO), lowest bottomhole pressure (MIN_BHP), and water-cut (MAX_WCUT) in producers, along with the maximum gas rate (MAX_BHG) and minimum bottomhole injection pressure (MAX_BHP) in injectors. Table 1 illustrates the default parameters of the base simulation scenario of the GAGD technique in addition to the ranges of each parameter (minimum and maximum levels) within the optimization procedure.

Table 1: Parameters of the GAGD Production Optimization

Response	Min	Base Case	Max
CumOilProd, STB	4.2208E09	4.3887E09	4.6039E09
Factor	**Min**	**Base Case**	**Max**
MAX_STO, STB/DAY	350000	750000	625000
MIN_BHP, Psia	2000	2660	3500
MAX_WCUT	0.70	0.95	0.90
Skin Factor	5	0	15
MAX_BHG, ft^3/DAY	7.5E06	10E06	15E06
MAX_BHP, Psia	2000	3000	3500

The levels of each factors in Table 1 were combined by the Latin Hypercube Sampling to produce hundreds of simulation jobs (experiments). Then, the designed experiments were assessed by the compositional model to estimate the cumulative produced oil during 10 years of prediction period (January 1, 2026). The optimal solution referred to the simulation job that results to achieve the maximum cumulative oil production, as depicted in Figure 7. It also demonstrates that field cumulative produced oil through the base simulation scenario of the GAGD technique in addition to the general solutions that represent the non-optimal cases. The total number of the generated simulation jobs including the optimal solution was approximately 625 runs.

The optimal solution was identified and visualized relative to the field cumulative produced oil, as were outlined in Figure Figure 8. The optimum solution represents the maximum field cumulative produced oil during 10 years of prediction time. The general solutions in Figure 8, represented by the green curves, refer to the least flow response that combine low and/or poor combinations of the factors' levels. Hence, they led to low levels of field cumulative oil production.

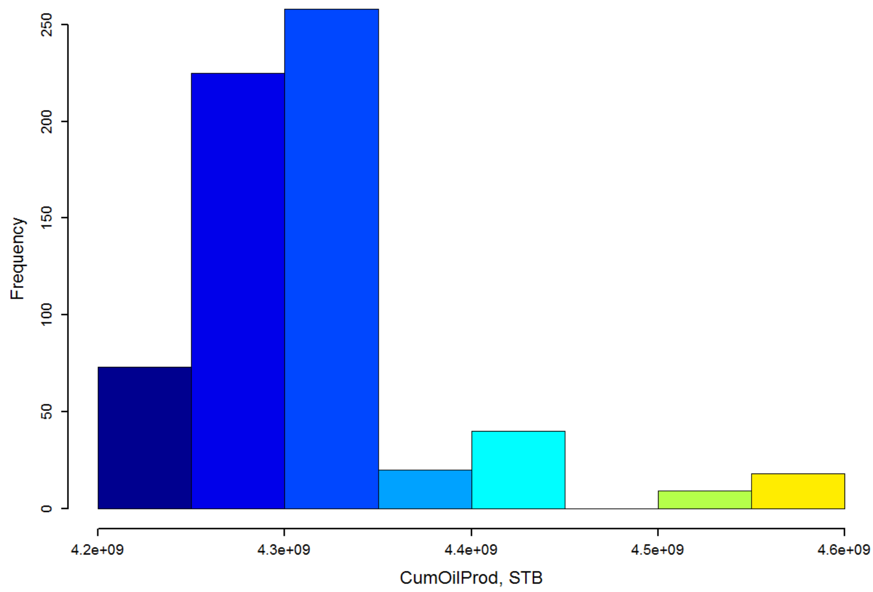

Figure 7: Histogram of the Base Case, General and Optimal Cumulative Oil Production through the Latin Hypercube Sampling-based GAGD Process Optimization

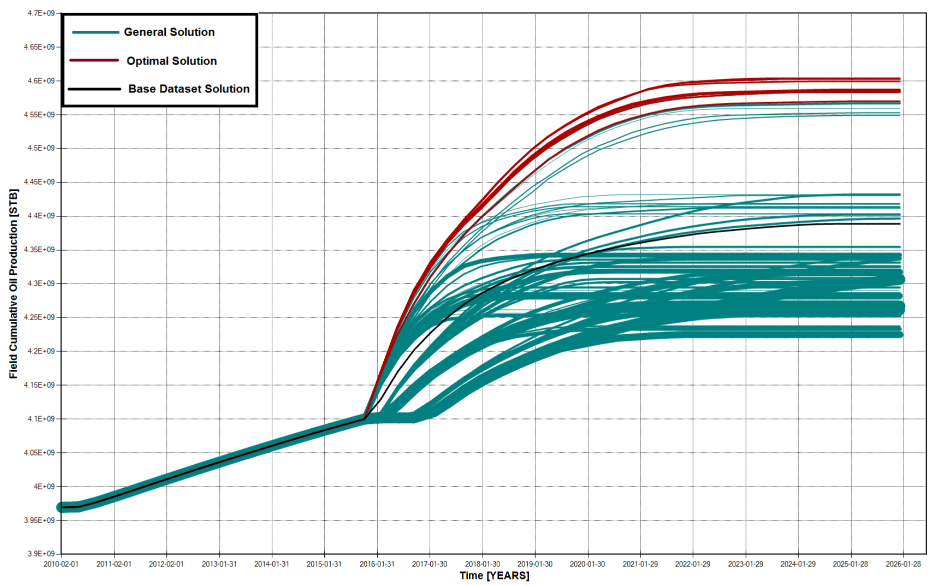

Figure 8: Base Case, General and Optimal Field Cumulative Oil Production through the LHS-based Proxy Optimization

The cumulative produced oil during the prediction time through base simulation scenario of GAGD technique was 4.39 bn STB. Nonetheless, the optimal solution, obtained from LHS-based proxy optimization (Optimal Case), managed to enhance the cumulative produced oil production to 4.6 bn STB. The incremental oil recovery is 215.2 million STB, as illustrated in Figure 9, which compares the base simulation case and optimal GAGD process performance along with the primary production case of no injection. The optimum cumulative oil production was acquired through achieving the optimal levels of the production control factors, which are illustrated in Table 2.

In Figure 9, substantial increment in oil recovery was acquired from the optimal solution in

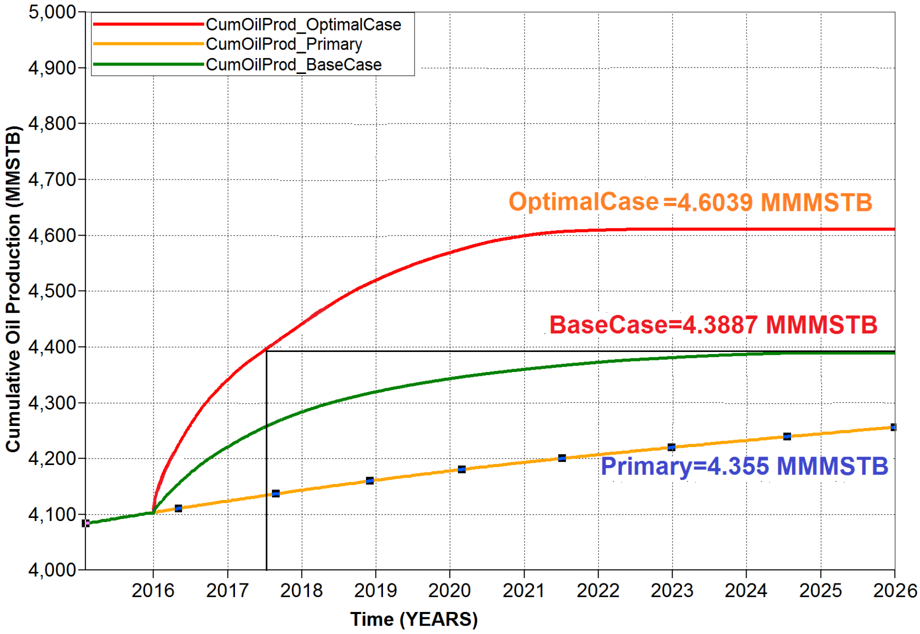

Figure 9: Comparison of Oil Production between Primary, Base, and Optimal Cases

comparison with the base simulation scenario of original conditions of the operational parameters. The field cumulative produced oil acquired through the base scenario in 10 years can be produced after only 18 months within the prediction period.

Table 2: Optimal Levels of the Operational Decision Factors in Comparison with the Base Case

Response	Base Case	Optimal
CumOilProd, STB	4.3887E09	4.6039E09
Factor	Base Case	Optimal
MAX_STO, STB/DAY	750000	500000
MIN_BHP, Psia	2660	2000
MAX_WCUT	0.95	0.9
Skin Factor	0	5
MAX_BHG, ft^3/DAY	10E06	15E06
MAX_BHP, Psia	3000	3500

7.1. Evaluation and Validation of the Proxy Models

The entire procedure of proxy based optimization was illustrated considering the iterative procedure of constructing a polynomial model. The 643 simulation jobs were used for a comparison of building new proxy models through four various approaches in a different procedure. The new four proxy metamodels are Polynomial Regression, Multivariate Additive Regression Splines (MARS), Fuzzy Logic-Genetic Algorithm, and Generalized Boosted Model (GBM). This method combines multiple techniques such as cross validation, Root Mean Square Error and adjusted R^2_{adj} aiming to identify the optimum proxy model that is possible to be assumed as an ideal metamodel of the nonlinear CO2 injection through GAGD technique.

After sampling and subdividing the dataset of 643 designed experiments into 75% training and 25% testing subsets, the modeling was implemented based on 450 simulation jobs (training subset) through the four aforementioned proxy approaches. The prediction from each of the four proxy models was then adopted based on 193 runs (testing subset). The RMSE along with the adjusted R^2_{adj} have been computed in order to differentiate the estimated cumulative produced oil from the simulation model and the forecasted through the proxy model. Figures 10, 12, 14, and 16 illuminate the matching of the estimated cumulative produced oil from the observed, which is from the simulation model, and the forecasted from the proxy models (Predicted) with respect to the test subset jobs for the QM, MARS, FUzzy-GEnetic, and GBM, respectively. Figures 11, 13, 15, and 17 depict the matching of the estimated cumulative produced oil from the simulation model (Observed) along with the forecasted based on the proxy models (Predicted) with respect to the full dataset jobs for the QM, MARS, FUzzy-GEnetic, and GBM, respectively. In the (Left) figures, the blue balls refer to the observed response values, cumulative oil production estimated from the compositional reservoir simulator. However, the red balls represent the predicted cumulative oil production from the four proxy models. In addition, the (Right) figures represent the scatter plots of matching of simulation and proxy models cumulative produced oil.

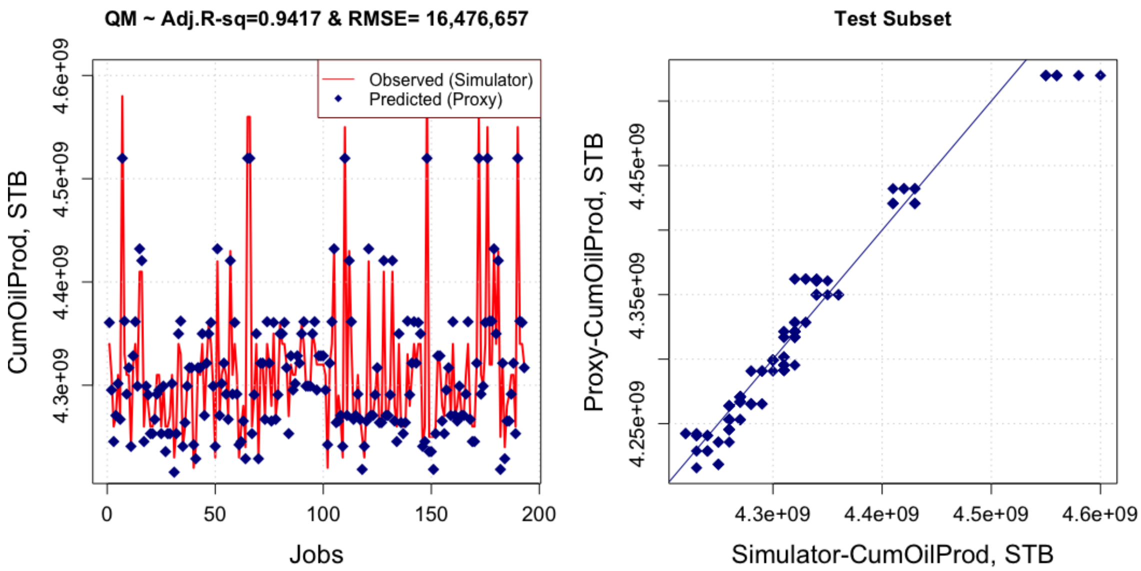

Figure 10: Comparison of Proxy-Predicted and Simulator Calculated-QM Given The Test Subset

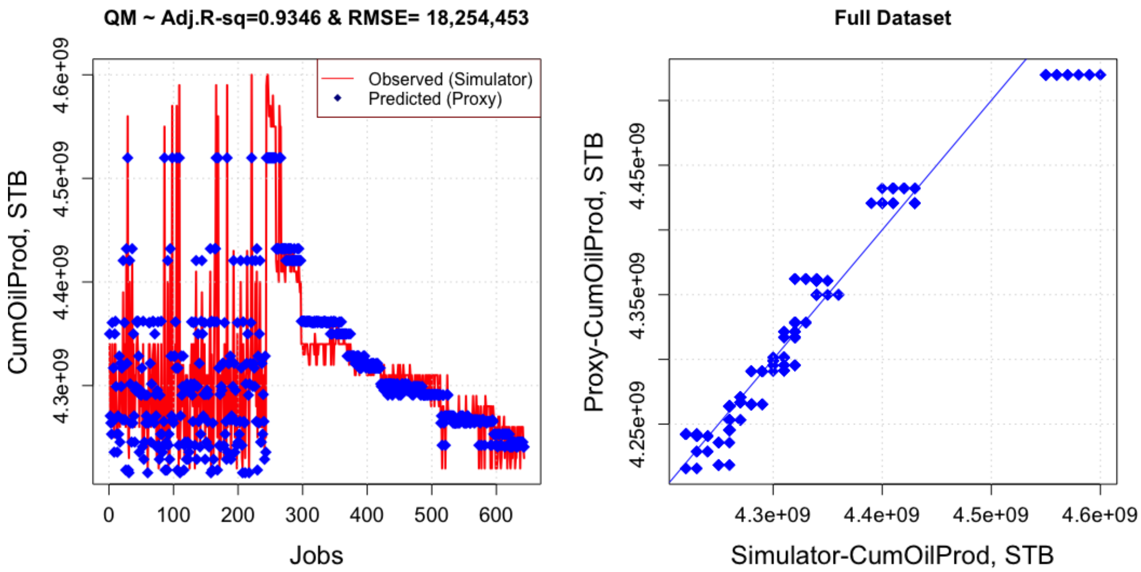

Figure 11: Comparison of Proxy-Predicted and Simulator Calculated-QM Given The Full Dataset

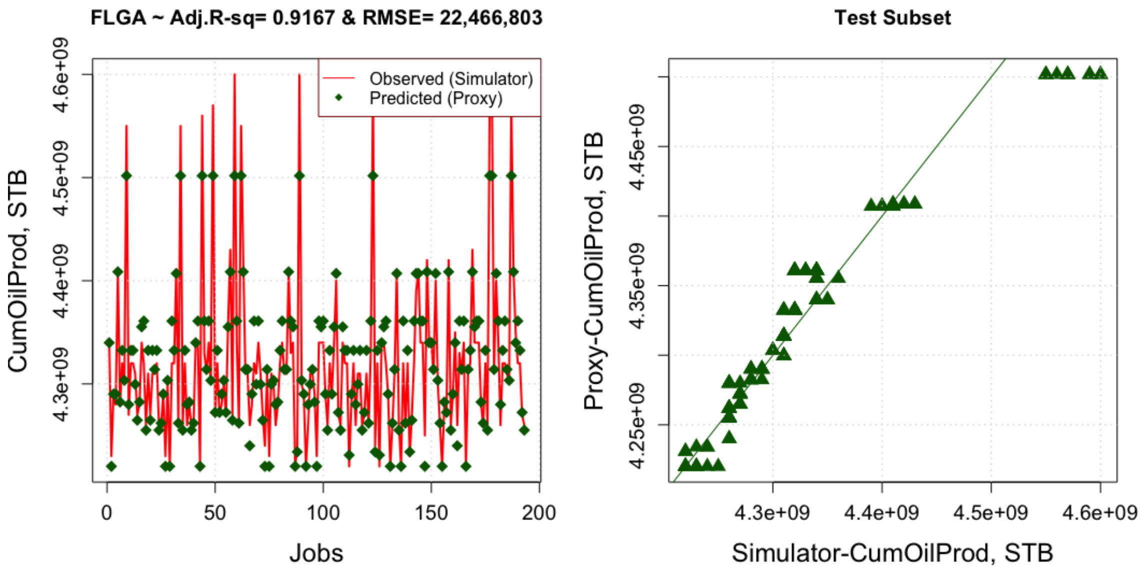

Figure 12: Comparison of Proxy-Predicted and Simulator Calculated-FUzzy-GEnetic Given The Test Subset

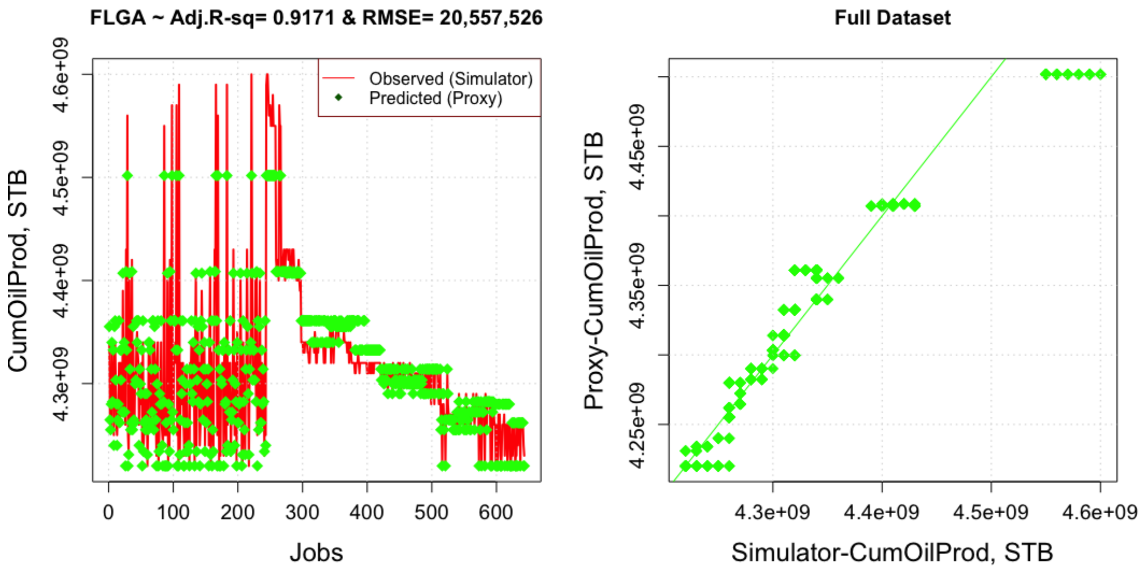

Figure 13: Comparison of Proxy-Predicted and Simulator Calculated-FUzzy-GEnetic Given The Full Dataset

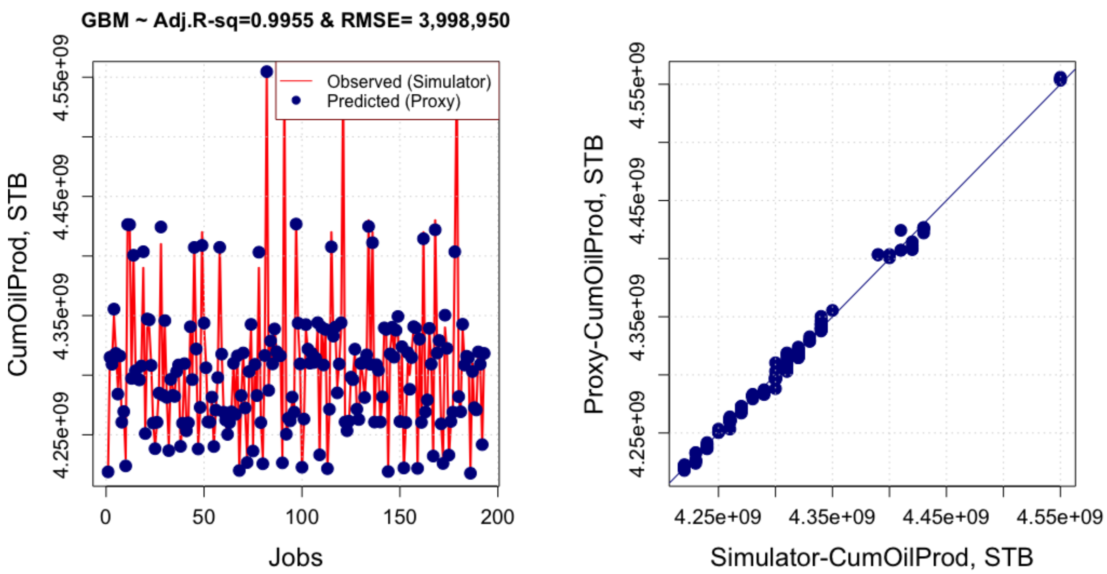

Figure 14: Comparison of Proxy-Predicted and Simulator Calculated-GBM Given The Test Subset

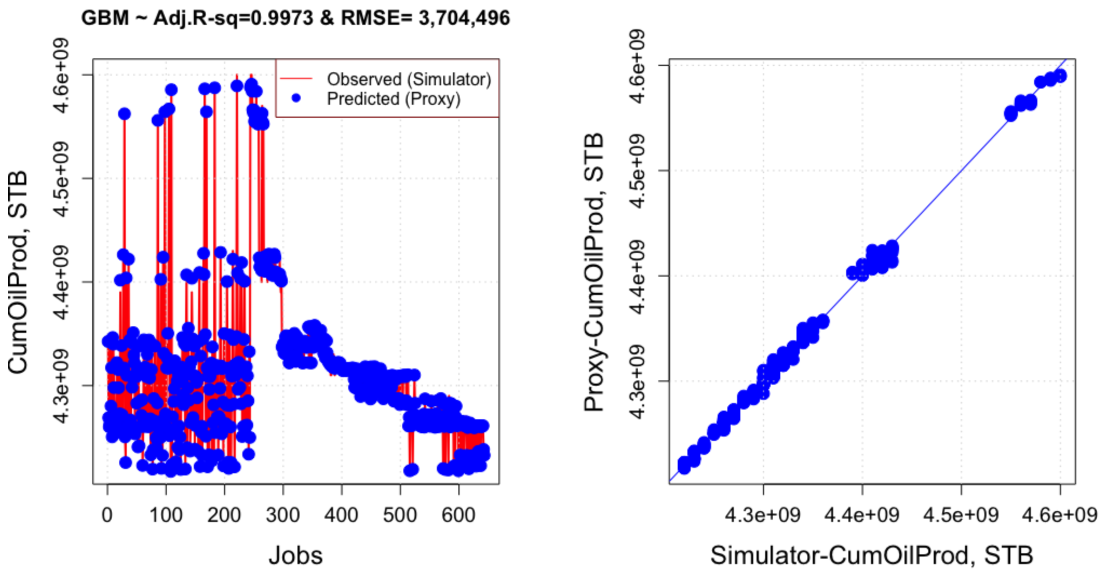

Figure 15: Comparison of Proxy-Predicted and Simulator Calculated-GBM Given The Full Dataset

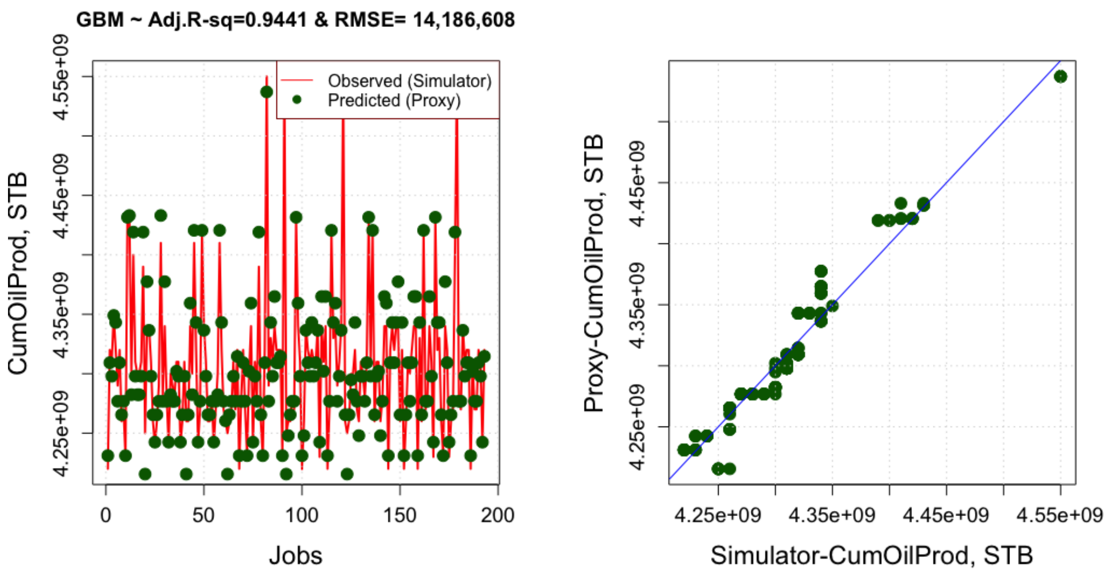

Figure 16: Comparison of Proxy-Predicted and Simulator Calculated-MARS Given The Test Subset

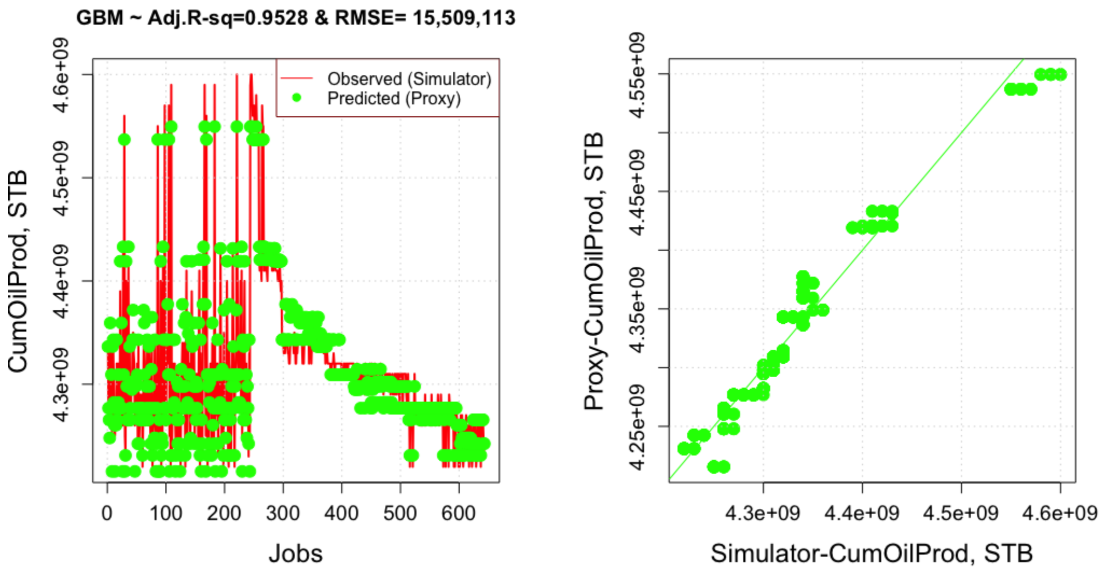

Figure 17: Comparison of Proxy-Predicted and Simulator Calculated-MARS Given The Full Dataset

The comparison between the four proxy metmodels: QM, FUzzy-GEnetic, GBM, and MARS was justified based on the RMSE and R^2_{adj} with respect to the test subset and full datasets, as illustrated in Table 3: The GBM proxy model was much better than the QM, FUzzy-GEnetic and

Table 3: Accuracy Comparison between the Four Proxy Models

	Test Subset		Full Dataset	
Algorithm	R^2_{adj}	RMSE	R^2_{adj}	RMSE
QM	0.9417	16.476E+6	0.9346	18.254E+6
FUzzy-GEnetic	0.9167	22.466E+6	0.9171	20.557E+6
GBM	0.9955	3.999E+6	0.9973	3.704E+6
MARS	0.9441	14.186E+6	0.9528	15.509E+6

MARS models as it had the least RMSE and highest R^2_{adj}. Moreover, the scatter matching of the simulation along with proxy models cumulative produced oil from the Gradient Boosting Regression model was more matched than QM, FUzzy-GEnetic and MARS models as most the points in GBM fit the 45^0 degree line.

8. Summary and Conclusions

The compositional reservoir simulator was conducted for the GAGD technique within nonhomogeneous main pay reservoir in South Rumaila field. After achieving the history matching, 10 years of future production was set as a prediction period to acquire the optimum recovery ratio through changing the operational decision parameters which govern the injection and production processes. The Latin Hypercube Sampling was implemented based on a low-discrepancy Experimental Design technique in order to generate several hundreds of trails and experiments to be assessed by the simulation model in order to identify the optimum recovery ratio and to construct the proxy model.

That DoE and proxy modeling approach includes determining an ideal group of operational decision parameters through immiscible GAGD technique. The parameters are CO2 injection rate and highest BHP in the injectors, along with the highest oil production rate, lowest BHP, and maximum water cut in the horizontal producers. This optimal case led to obtain 4.6039 million STB with increment of 212.5 million STB of oil over the base GAGD case (360 million STB over the primary production case).

The first proxy modeling workflow includes generating simulation jobs as training runs to build the proxy model, which was iteratively validated through four sets of validation tests (verification runs). In order to create an accurate proxy model that truly models the compositional reservoir simulator (metamodel), the polynomial regression in addition to three more approaches were adopted to build proxy models. The four constructed models are Polynomial Regression, Fuzzy Logic-Genetic Algorithm (Fuzzy GEnetic), Generalized Boosted Model (GBM), and Multivariate Additive Regression Splines (MARS). The accuracy comparison between the four proxy models was conducted with respect to the R^2_{adj} and RMSE for the prediction of test subsets and full datasets.

It was observed that the GBM model was the most accurate metamodel for the GAGD process as it attains the minimum RMSE and the maximum adjusted R^2_{adj} that both reflect the lowest mismatch of the cumulative produced oil estimated through the simulation model and forecasted by the GBM-proxy models. In addition, MARS proxy model was the second best matching model, followed by the polynomial and FUzzy-GEnetic proxy models. Additionally, the cumulative produced oil of both the simulation and proxy models from the GBM has better scatter points matching than the MARS, QM and FUzzy-GEnetic. Consequently, the GBM can be implemented as a simplified substitute metamodel instead of the high resolution compositional reservoir model by the GAGD technique assessment and forecast.

Abbreviations

- CGI: Continuous Gas Injection
- DoE: Design of Experiments
- EOR: Enhanced oil recovery
- FUzzy-GEnetic: Fuzzy Log-Genetic Algorithm
- GAGD: Gas-Assisted Gravity Drainage
- GBM: Generalized Boosted Regression Model
- GCV: Generalized cross-validation
- LHS: Latin Hypercube Sampling
- MARS: Multivariate Additive Regression Splines
- MAX_BHG: Maximum gas injection rate
- MAX_BHP: Minimum bottom hole pressure

- MAX_STO: Maximum oil production rates
- MAX_WCUT: Maximum water-cut
- MIN_BHP: Minimum bottom hole injection pressure
- QM: Polynomial (Quadratic) Regression
- R^2: Coefficient of Correlation
- R^2_{adj}: Adjusted Coefficient of Correlation
- RMSE: Root Mean Square Prediction Error
- WAG: Water-Alternating-Gas

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