Inferential Reservoir Modelling and History Matching Optimization using Different Data-Driven Techniques

A. B. Ehinmowo*, O. A. Ohiro, O. Olamigoke, O. Adeyanju
Department of Chemical and Petroleum Engineering, University of Lagos, Nigeria
*Email: *aehinmowo@unilag.edu.ng*

Abstract
One of the major problems associated with history matching is the non-uniqueness of the solutions. A major flaw in this traditional history matching is that it lacks robustness as it shows a bias to the production data being matched while neglecting the mechanics governing other production data and such solutions generated are erroneous and gives a poor representation of the reservoir being matched.
In this study, data driven and numerical modeling of a synthetic PUNQS3 reservoir were carried out. Single objective function, aggregated and multi-objective functions were adopted for the reservoir history matching. A proxy model was developed with data generated from a reservoir simulator using Artificial Neural Network (ANN) and the Response Surface Methodology (RSM). Firefly Optimization (FFO), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) algorithms were used for the history matching process.
The results showed that the history matching process was strongly influenced by porosity and permeability. The interaction between the two was also established. The ANN appeared to provide a better match of the simulated data compared with the RSM. Although aggregated method of optimization is less computational expensive, the multi-objective approach provided a superior history matching optimization. The observed misfit values were 0.074, 0.073, and 0.073 for GA, PSO and FFO algorithms respectively for cumulative oil production history matching. Better predictions were obtained using the FFO and PSO compared with GA for single and aggregated objective function optimization. This work can be extended to investigate the performance of FFO and other recent methods using multi-objective approach and the influence of objective function on history matching.

Keywords: Proxy Models; ANN; RSM; Genetic Algorithm; History matching; Optimization

1.0 INTRODUCTION

Reservoir modelling and indeed history matching can be complex, time consuming and yet laden with high level of uncertainty. A major problem encountered in reservoir modelling is the non-uniqueness of solutions to inverse problems in the reservoir parameters estimation. A reservoir model is said to be calibrated and useful in forecasting when it can accurately reproduce the historical data of the reservoir system. History matching is usually done to achieve this. History matching is a procedure in which certain reservoir parameters (porosity, permeability, saturation, relative permeability, e.t.c) are changed independently or on the whole to get a match between predicted values and the observed historical data. The parameters are tuned accordingly to fit historical rates such as oil, water and gas, percentage water cuts, pressure drops and their variations during the life of a field (Negash *et al.*, 2016). The heterogeneous distribution of the reservoir geology results makes history matching a complex undertaking. It can be a tedious exercise in any reservoir management process (Maschio and Schiozer, 2005).

The objective of a good history matching study is to get a reliable production forecast by improving reservoir models. Traditionally, this is done by tweaking model parameters randomly until the correct match is found. This is not only time consuming but also the calibrated model obtained from such process is less robust and may not be able to predict the reservoir behaviour outside the range of the tuned parameters. Automated history matching has been observed to help accelerate history matching process and also to obtain more robust validated reservoir models(Kabir, Chien and Landa, 2013; Shams, 2017).

The earliest efforts on automated history matching were not so successful as most of the published algorithms are of little applications due to high computational expense when applied to large reservoirs (Kabir, Chien and Landa, 2013). Example of such work was a simplified two dimensional, incompressible two phase reservoir model coupled with a Genetic Algorithm (GA) for history matching (Xavier *et al.*, 2013). Although such approach was useful in understanding the application of GA in history matching, a full-scale reservoir model coupled with the proposed algorithm would be impractical. The use of proxy models in estimating complex systems such as reservoirs and automated history matching process has been observed to yield excellent results. Some of the proxy model techniques available are: the Aenic Algorithm (Sun and Mohanty, 2005), Surrogate Models (Queipo *et al.*, 2000), Polynomial Models (Sarma and Xie, 2011) and so on. Although, proxy models can be helpful in estimating complex systems without solving the computationally involving mathematical equations which describe the physics of such system, they must be applied with caution as they function as a black-box model which is data driven and neglects the underlying principles of physics (Awasthi *et al.*, 2007). Many authors have recently concentrated efforts at developing approaches based on the use of proxy models and stochastic algorithms for automated history matching (Yeten *et al.*, 2005; Silva, Maschio and Schiozer, 2008; Negash *et al.*, 2016; Kim *et al.*, 2017; Shams, 2017; Wantawin, Yu and Sepehrnoori, 2017).

Yeten et al. (2005) focused on the development proxy models using multiple Design of Experiment (DOE) methods. Their results showed that the space filling design gave better results compared with traditional designs. However, their work was not extended to optimizing the history matching process.
Silva et al. (2008) developed a proxy model using Artificial Neural Network (ANN) and optimized the history process with an evolutionary algorithm. Although the developed model compared well with the field and synthetic data, other data driven approaches that might have given better predictions were not investigated.

Multi-objective algorithms were investigated for the optimization of a synthetic PUNQ-S3 reservoir model by Negash et al. (2016) using Multi-Objective Genetic Algorithm (MOGA) and Multi-Objective Goal Attainment Algorithm (MOGAA). The proxy model was obtained using Response Surface Method (RSM). The result from MOGAA was observed to possess superior accuracy compared with MOGA. Although this work provided a robust inroad to multi-objective history matching, the number of algorithms investigated was limited. In Kim et al. (2017), Fast marching method was used for proxy model and multi-objective evolutionary algorithm for the history matching of a shale gas reservoir. The evolutionary algorithm was tested for single objective, aggregated and multi-objective function. They reported a superior performance of the multi-objective approach compared to single and aggregated objective functions for this algorithm.

Wantawin, Yu and Sepehrnoori (2017) developed a workflow for the history matching of a tight oil reservoir using DOE, RSM, and Markov chain Monte Carlo (MCMC) algorithm. Their results showed a promising technique for automated history matching. However, the MCMC required some degree of tuning such as step sizes and variances.

The Firefly Optimization calculation (FFO) introduced by Yang (2009) was recently applied to history matching in Shams (2017). This algorithm was compared with Particle Swarm Optimization (PSO) and GA for a simple tank reservoir model using a single objective function approach. It was observed that FFO provided a better optimization of the history matching process. However, the application of FFO to aggregated and multi-objective functions was not investigated.

Other authors have worked on various methods for history matching optimization. The process has been optimized using PSO method (Mohamed *et al.*, 2010; Mohamed, Christie and Demyanov, 2011), GA (Romero *et al.*, 2000; Kumar and Rockett, 2002; Zhang *et al.*, 2012), Adaptive Neuro-Fuzzy Inference System (ANFIS) (Rammay and Abdulraheem, 2014) and FFO algorithm (Shams, 2017). Apart from Firefly algorithm, other methods have been applied to aggregated and multiple objective history matching in various degrees. It is therefore important to investigate this new algorithm (FFO) for multi-objective history matching optimization.

This study evaluated the efficiency of ANN and RSM in accurately predicting the reservoir behaviour. The performance of the proxy models was assessed using statistical indices such as the coefficient of determination (R^2) and Mean Square Error (MSE). The influence of reservoir parameters and their interactions were also investigated using Plackett-Burman and Central Composite Design. The well-investigated optimization algorithms (GA, PSO) were used for single objective, aggregated and multi-objective history matching while the Firefly Optimization (FFO) algorithm was extended to optimize aggregated multi-objective history matching optimization for the first time in this study and the results were compared.

2.0 MATERIALS AND METHOD

2.1 *Study Area*

The data used in this work was adapted from the production data of synthetic PUNQ-S3 reservoir which has been used as a benchmark standard previously (Maunde *et al.*, 2013; Hutahaean, Demyanov and Christie, 2016; Negash *et al.*, 2016). The reservoir model is characterised as a small-scale model made up of 19 x 28 x 5 blocks of which only 1756 are said to be active. It has five unique layers at a top structure of 2430 m at an angle of 1.5 degrees, the top structure map in Figure 1 shows that the reservoir is bounded by a fault, and is linked to a strong aquifer. More on this reservoir has been documented in literatures (Maunde *et al.*, 2013; Hutahaean, Demyanov and Christie, 2016; Negash *et al.*, 2016)

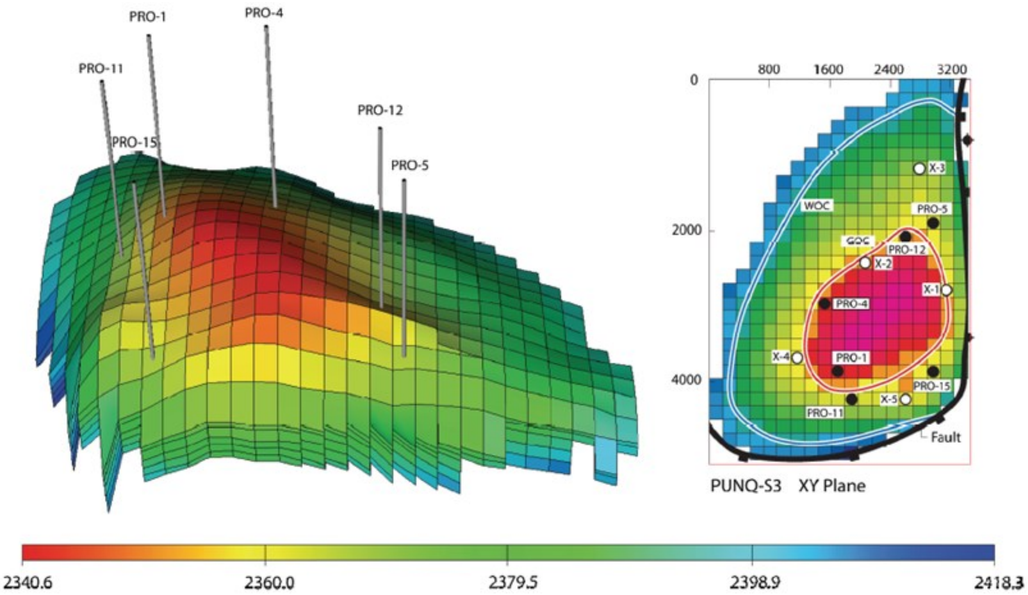

Figure 1 PUNQ S-3 Top Structure Map (Hajizadeh, Christie and Demyanov, 2011).

From these set of historical data, the field Cumulative Oil Production (Cum_Oil), Field Cumulative Gas Production (Cum_Gas) and Field Cumulative gas oil ratio (Cun_GOR) were set as the history matching objective parameters.

Table 1 Reservoir *Properties of the PUNQ S3*

Parameter	*Certain Value*	*Uncertain Range*
Pinchout thickness	0.0002	–
Aquifer 1 thickness (m)	19.6	–
Aquifer 1 porosity$\{fraction)$	0.2125	–
Aquifer 1 permeability (md)	137.5	–
Aquifer 1 radius (m)	3000	–
Aquifer 2 thickness (m)	6	–
Aquifer 2 porosity$\{fraction)$	0.2125	–
Aquifer 2 permeability (md)	137.5	–
Aquifer 2 radius (m)	3200	–
Reservoir size (x, y, z) (m)	$19 \times 28 \times 5$	–
Total compressibility $(1/kPa)$	0.0000045	–
Water formation volume factor	1.0042	–
Water compressibility $(1/kPa)$	0.000000543	–
Bubble point pressure $\{kPa)$	23446	–
Porosity ($fraction)$	–	$0.1 - 0.25$
Layer 1 permeability (md)	–	$30 - 800$
Layer 2 permeability (md)	–	$30 - 800$
Layer 3 permeability (md)	–	$30 - 800$
Layer 4 permeability (md)	–	$30 - 800$
Layer 5 permeability $md)$	–	$30 - 800$

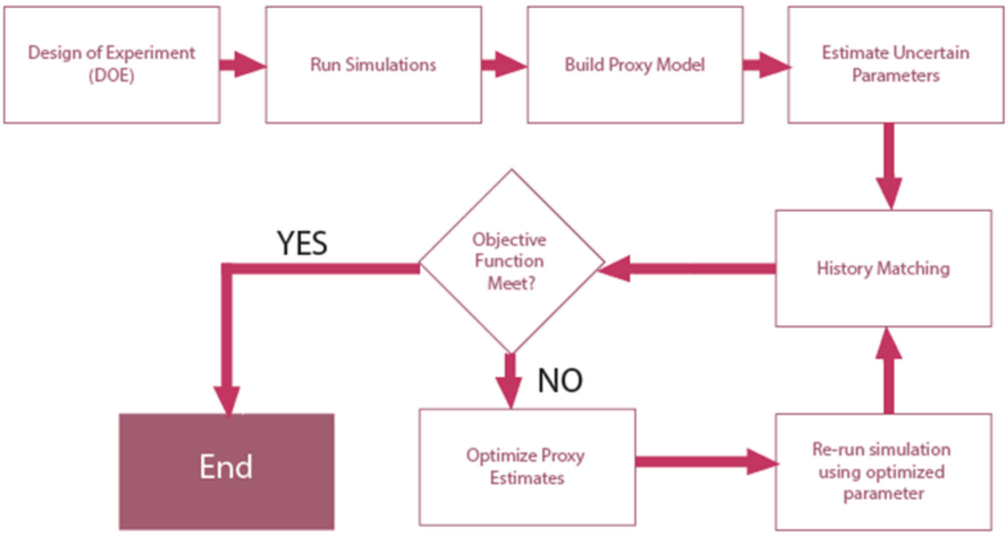

Figure 2 Work flow for the study

Figure 2 shows the work flow used for this study which was adopted from Negash et al. (2016)

2.2 Design of Experiment and Simulation

In order to evaluate the efficiency of ANN and RSM in accurately predicting the reservoir behaviour, proxy models were developed and their performance assessed. The first step in achieving this objective was to design experiments to investigate as many reservoir parameters upon which the reservoir behaviour depends and to minimise the number of simulation runs needed. Design expert software package was used for the design of experiment. For this work, vital reservoir parameters (the porosity and permeability in each of the five layers) were examined to see their influence and interaction using Plackett-Burman and Central Composite Designs (CCD). The Plackett-Burman design helped in characterising the parameters and thirteen interactions were observed while the Central Composite Designs (CCD) estimated forty experimental runs to adequately capture the response surface of the model. Table 2 shows a section of the experimental runs.

Table 2 ***Simulation runs to calibrate the proxy model***

		Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Response 1	Response 2	Response 3
Std	Run	A:Porosity	B:Perm 1	C:Perm 2	D:Perm 3	E:Perm 4	F:Perm 5	Cum_Oil	Cum_Gas	Cum_GOR
								m3	m3	m3/m3
39	1	0.175	415	415	415	415	415	1.20147E+06	1.43592E+08	119.513
34	2	0.175	415	415	415	415	1017.56			
11	3	0.25	30	30	800	800	30	1.20719E+06	8.98653E+07	74.4415
18	6	0.1	30	30	30	30	800	762382	6.79217E+07	89.0915
22	7	0.1	30	800	30	800	800	1.20719E+06	1.1128E+08	92.1807
20	11	0.1	800	800	800	800	800	1.20719E+06	1.24841E+08	103.414
1	12	0.1	30	800	800	30	800	1.04931E+06	1.09462E+08	104.318
16	13	0.25	30	30	30	800	800	1.20719E+06	8.68132E+07	71.9132

7	14	0.25	30	30	800	30	800	1.05499E+06	7.60552E+07	72.0913
37	16	0.175	415	415	415	415	415	1.20147E+06	1.43592E+08	119.513
40	17	0.175	415	415	415	415	415	1.20147E+06	1.43592E+08	119.513
9	18	0.25	30	800	30	30	30	595141	4.62586E+07	77.7271
12	19	0.25	800	30	800	800	800	1.20719E+06	1.10234E+08	91.3139
38	20	0.175	415	415	415	415	415	1.20147E+06	1.43592E+08	119.513

The experiments were performed using a reservoir simulator to simulate the reservoir production data on well basis.

2.3 Proxy Modelling and Unknown Parameter Estimation

The data generated from the forty simulation runs (experimental runs) were divided to train, evaluate and test the developed ANN model using MATLAB. The procedure in Ehinmowo, Bishop, and Jacob, (2017) was adopted. The Bayesian Regularization algorithm gave the best performance compared with the Levenberg-Marquardt and Scaled Conjugate Gradient algorithms.

The RSM was also used to generate a proxy model and its predictive capability compared with that of ANN model. The unknown parameters were estimated.

2.4 Objective Function and history matching optimization

A modified least square error was used in defining the misfit between the observed data and the response of the proxy model. Optimization was carried out on the single objective function for Cum_Oil eqn.(1), Cum_Gas eqn.(2), Cum_GOR eqn.(3), Aggregated objective function eqn.(4) and the Non-dominated multi-objective function. The bases for the oil, gas and gas oil ratio (GOR) are 110000 m^3, 110000000m^3 and 90 respectively in SI units. For each component objective function in aggregated objective function, weights value of 1 was assigned as shown in equation (4). Equations (1), (2) and (3) were optimized simultaneously using the multi-objective optimization algorithms to achieve the multi-objective history matching optimization while equation (4) was used for aggregated -objective approach.

$$M_1 = \sum_{i=1}^{T} \frac{(Cum\_Oil^{obs} - Cum\_Oil^{sim})_t}{(Cum\_Oil^{obs})_t} \qquad (1)$$

$$M_2 = \sum_{i=1}^{T} \frac{(Cum\_Gas^{obs} - Cum\_Gas^{sim})_t}{(Cum\_Gas^{obs})_t} \qquad (2)$$

$$M_3 = \sum_{i=1}^{T} \frac{(Cum\_GOR^{obs} - Cum\_GOR^{sim})_t}{(Cum\_GOR^{obs})_t} \qquad (3)$$

$$M_4 = w_1 M_1 + w_2 M_2 + w_3 M_3 \qquad (4)$$

The standard MATLAB algorithm for GA was used while the detailed algorithms for FFO and PSO, MOPSO are documented in Yarpiz (2018) and MOGA (Lin, 2018).

3.0 RESULTS AND DISCUSSION

3.1 Reservoir parameters' influence and their interactions

The results of the reservoir parameter influence and interactions are shown in Figures 3, 4 and 5. The pareto charts showed that the porosity and permeabilities have the greatest influence on the reservoir behaviour, a total of 13 interactions were observed from the Packett-Burman DOE for the three historical objectives and thy were ranked for their interactions. This suggests that, to reduce the history matching error, attention must be paid to these two parameters. These results are in consonance with the once obtained by Aulia, Jeong, Mohd Saaid, Shuker, & El-Khatib (2017) for a highly faulted reservoir where the fault transmissibilities and permeabilities dominantly influenced the reservoir.

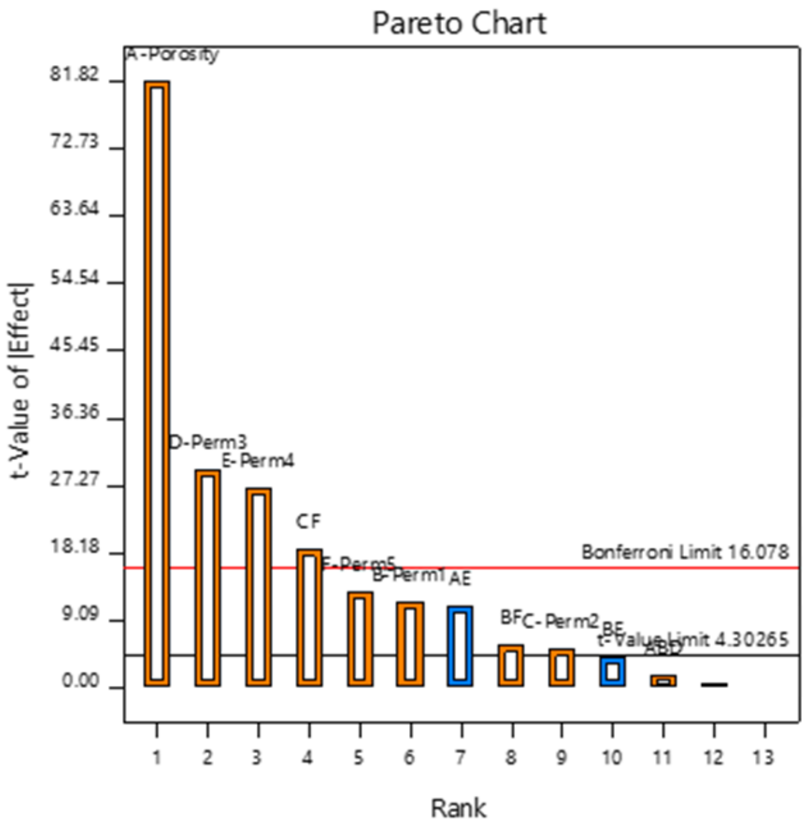

Figure 1 *Standardized chart for Field Cumulative Oil Production*

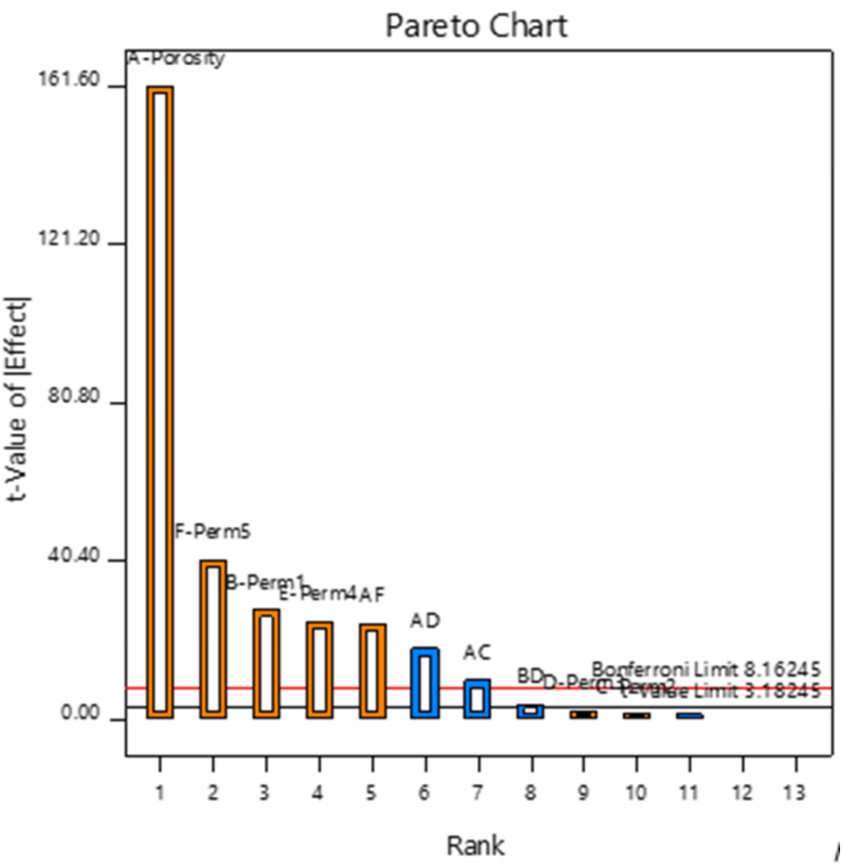

Figure 2 Standardized chart for Field Cumulative Gas Production

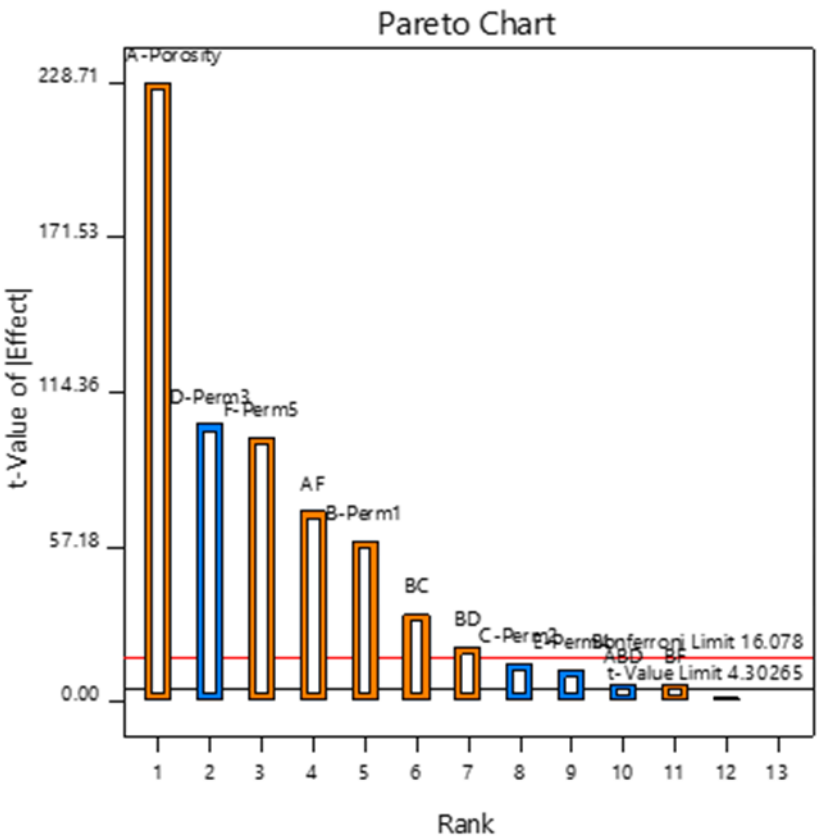

Figure 3 Standardized chart for Field Cumulative Gas Oil Ratio

3.2 Proxy Models and performance

Response Surface Model

Central composite design of experiment (CCD) which appears to give a better system calibration was used in developing the RSM. CCD produced forty experimental runs to be used in to adequately capture the response surface of the reservoir simulator.

The response surface plots as a function of porosity and permeability are shown in Figures 5, 6 and 7 for Cum_Oil, Cum_Gas and Cum_GOR respectively. And the proxy models generated for Cum_Oil is given by equation (5), while equation (6) is for Cum_Gas and equation (7) represents the Cum_GOR .

$$\begin{aligned} Cum_{Oil} = {} & 711540.11832215 + 46.867536113449 * Perm1 \\ & + 186.73516644019 * Perm3 + 1987.8563056083 * Perm4 \\ & + 229.91588559187 * Perm5 + 655011.1956053 * Porosity - 0.06512564 \\ & * Perm1 * Perm3 - 166.92933333333 * Perm1 * Porosity \\ & - 385.32473333333 * Perm3 * Porosity - 385.32473333333 * Perm3 \\ & * Porosity - 0.10835530166313 * Perm5^2 - 521671.93982466 \\ & * Porosity^2 \end{aligned} \tag{5}$$

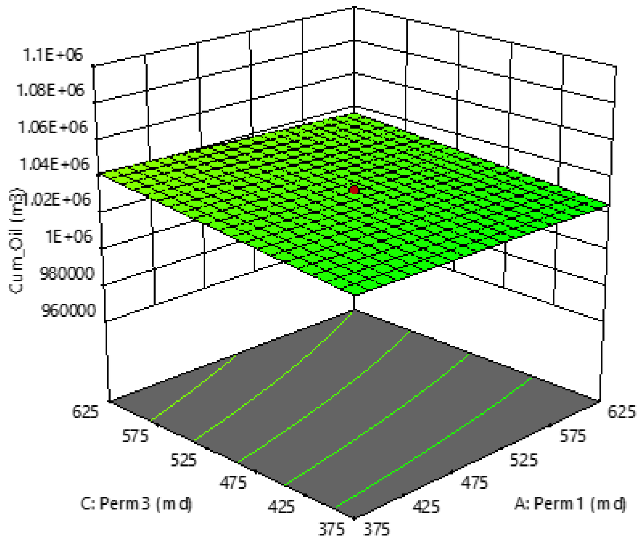

Figure 4 RSM plot for Cum_Oil varying only Porosity and Perm1

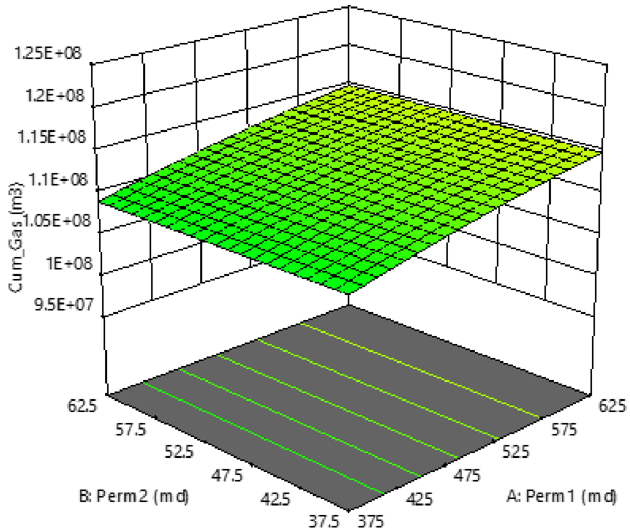

Figure 5 RSM plot for Cum_Gas varying only Porosity and Perm1

$$Cum_{Gas} = 78076560.62658 + 30973.929327668 * Perm1 + 3018.4341420088 * Perm2 - 53865.45142146 * Perm3 + 182042.23648699 * Perm4 + 52675.516341683 * Perm5 + 94627681.193923 * Porosity + 100.66232 * Perm1 * Perm4 + 34.717936 * Perm3 * Perm5 + 34.717936 * Perm3 * Perm5 - 41944.16 * Perm3 * Porosity - 137.24536 * Perm4 * Perm5 + 187658.26666667 * Perm4 * Porosity - 29.056652938854 * Perm1^2 + 22.818967432441 * Perm3^2 - 40.338545456028 * Perm5^2 - 281423551.03026 * Porosity^2 \quad (6)$$

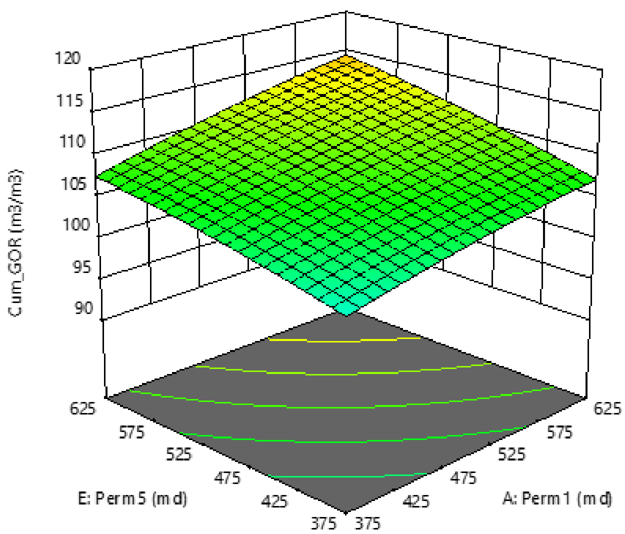

Figure 6 RSM plot for Cum_GOR varying only Porosity and Perm1

$$Cum_{GOR} = 102.56703942129 + 0.036769927384073 * Perm1 - 0.065842589272766 * Perm3 + 0.037356279355006 * Perm4 + 0.034838397967846 * Perm5 + 8.2754799761304 * Porosity + 0.000027812074 * Perm1 * Perm5 + 0.025621076666667 * Perm1 * Porosity - 0.00013789482 * Perm4 * Perm5 - 0.00013789482 * Perm4 * Perm5 + 0.28032736666667 * Perm4 * Porosity - 0.000031131817102455 * Perm1^2 + 0.000023933757430934 * Perm3^2 - 0.000032124546305411 * Perm5^2 - 202.07766302704 * PorosityA \qquad (7)$$

Artificial Neural Network

The dataset obtained from the central composite design of experiment was used as input to the MATLAB construct of the neural network. Twenty hidden neurons were selected to fit the network. Three different training algorithms, the Levenberg – Marquardt, Scaled Conjugate Gradient and Bayesian Regularization were all used in training the network. The training of the neural network models was done using 70 % of the data while validation and testing used 15 % each of the data. The network architecture used for this work is shown in Figure 9. From the training exercise, Bayesian Regularization was selected to train the neural network as it effectively handled the noise in the dataset and gave the least mean square error when compared to the Levenberg – Marquar and Scaled Conjugate Gradient training algorithms. This is similar to the results obtained in Ehinmowo, Bishop, and Jacob, (2017) for the prediction of riser-base pressure in multiphase flow pipeline-riser systems. The Bayelsian Regularization plots for the cumulative oil, cumulative gas and gas oil ratio are shown in Figures 10, 11 and 12 respectively with R^2-values of about 99.9 % for cumulative oil, 99.6% for cumulative gas and 99.5% for gas oil ratio.

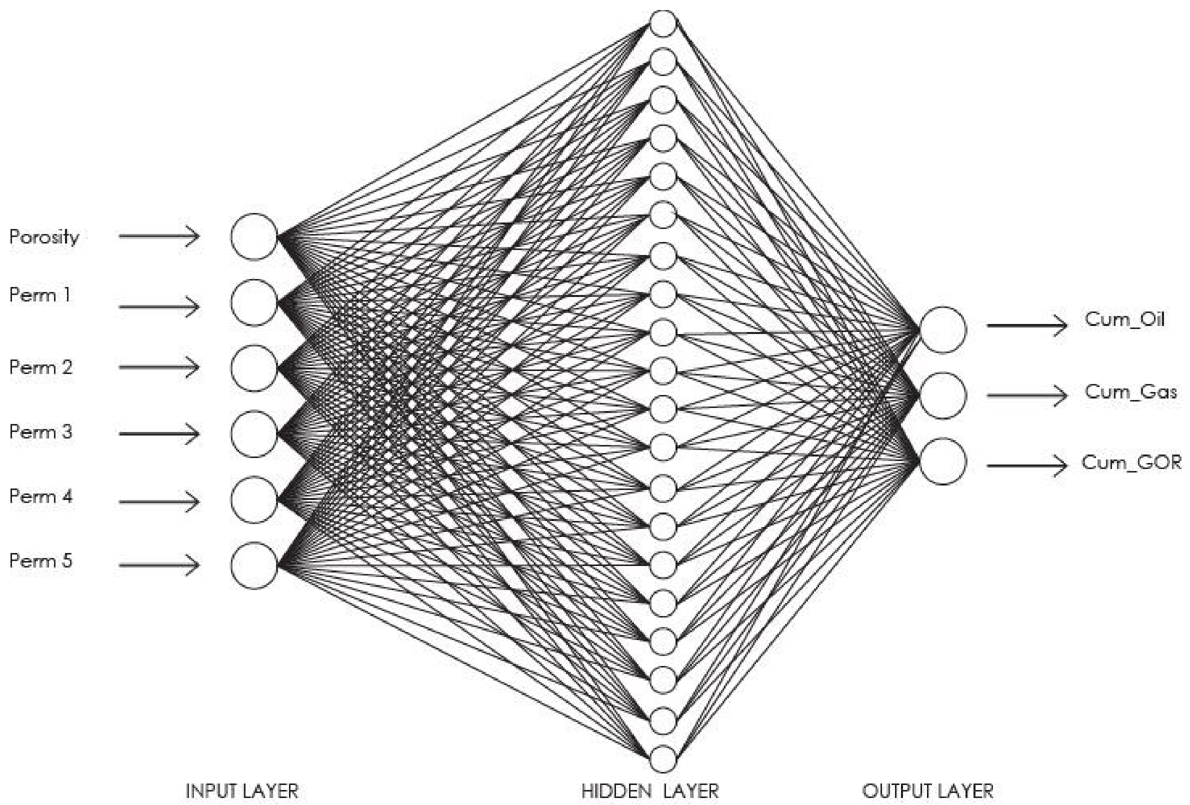

Figure 7 Network Architecture for the Neural Network

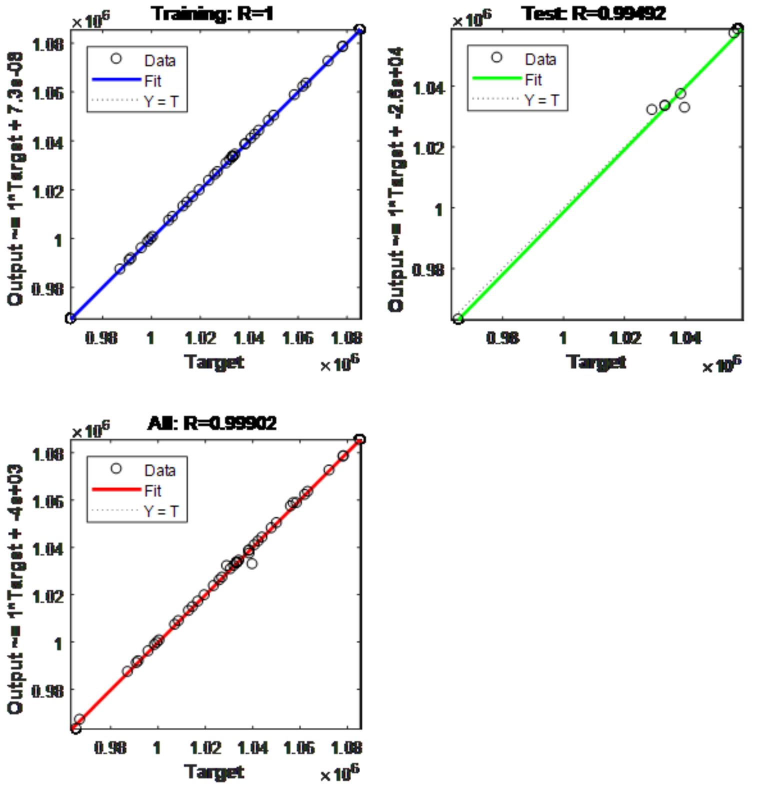

Figure 10 Bayesian Regularization Training for the Cum_Oil response

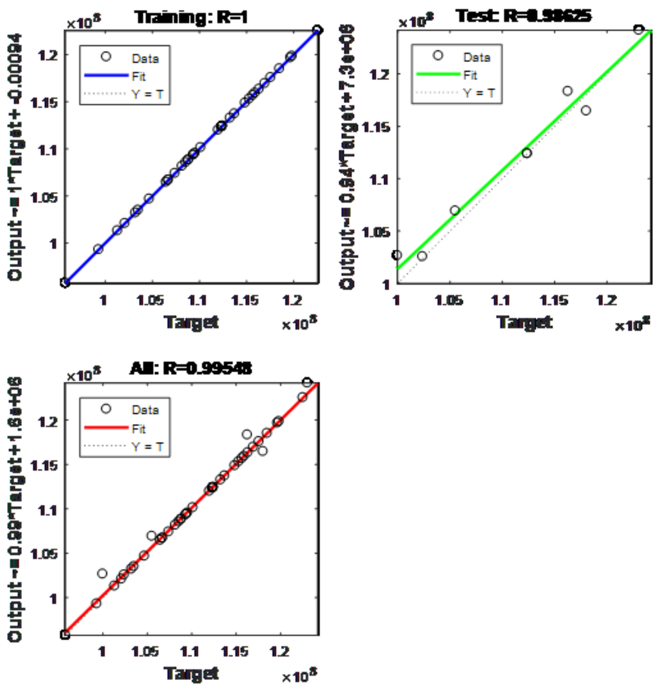

Figure 8 Bayesian Regularization Training for the Cum_Gas response

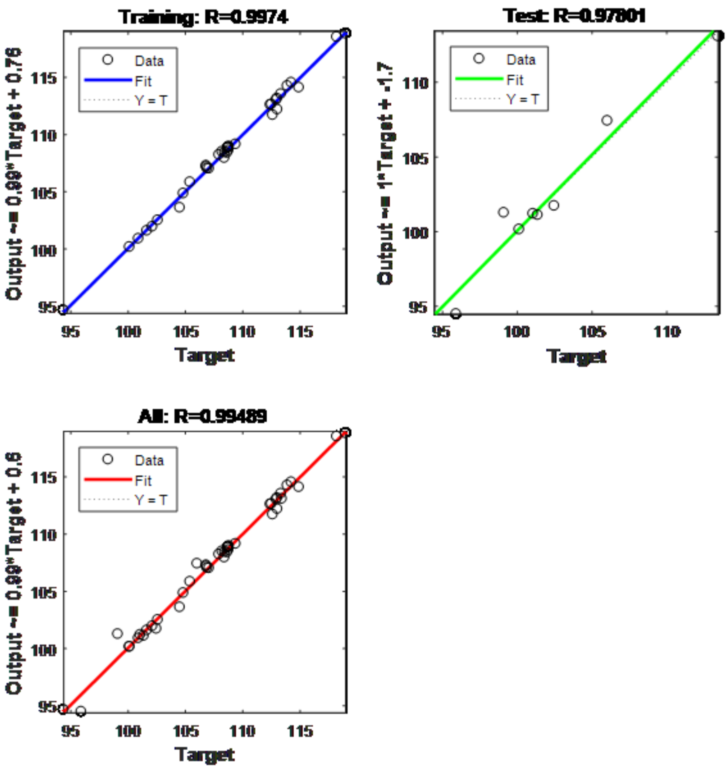

Figure 9 Bayesian Regularization Training for the Cum_GOR response

Performance evaluation of ANN and RSM models.

Table 3 shows the performance indices for the ANN and RSM proxy models. For the three models, the ANN proxy model predicted the reservoir properties at a higher degree of accuracy compared to the RSM and the ANN model was used for further optimization studies. The coefficient of determination and the mean square error values tabulated in Table 3 shows a superior performance of ANN model over RSM except for slightly higher R^2 value for RSM prediction of Cum GOR. However, the MSE value of 6.02 was far greater than that of ANN 1.0 * 10^{-19}. This results confirmed the previous work of Ogaga *et al.*, (2017) on the superior performance of an ANN-based data driven method over RSM.

Table 3 Statistical indices for evaluating ANN and RSM models

Objectives	*ANN*		*RSM*	
	R^2	MSE	R^2	MSE
Cum_Oil	*0.99902*	$3.42 * 10^{-17}$	*0.9908*	$5.53 * 10^{9}$
Cum_Gas	0.99607	$2.31. * 10^{-16}$	0.9954	$9.92 * 10^{12}$
Cum_GOR	0.99697	$1.00 * 10^{-19}$	*0.9972*	*6.02*

3.2 Stochastic history matching optimization

The relevant reservoir parameters (porosity, permeabilities of all the five layers were optimized for best history matching of the cumulative oil, cumulative gas and cumulative gas oil ratio. The results are compared for all the optimization algorithms (GA, PSO and FFO) investigated and the methods (Single objective, aggregated and multi-objective).

Table 4 History matching Optimization for Cum_Oil single Objective function

Optimizer	**Best Values**						**Cum_Oil Misfit**
	Perm1 (md)	**Perm2 (md)**	**Perm3 (md)**	**Perm4 (md)**	**Perm5 (md)**	**Porosity**	
GA	30.031	232.388	799.989	82.471	694.769	0.247	0.074
PSO	30.000	230.393	800.000	81.517	710.793	0.250	0.073
Firefly	30.000	228.323	799.999	82.469	681.234	0.250	0.073

Table 4 shows the predicted optimal conditions for GA, PSO and FFO algorithms. The optimal values predicted by PSO and FFO were better than that of GA. This confirms the recent report of Fu & Wen (2018) that PSO possesses better performance compared with GA. Although Shams (2017) has also reported a superior performance of FFO over GA and PSO, in this study, it was observed that, FFO and PSO perform at the same level but FFO showed an added advantage in terms of speed . The difference in this performance can be as a result of the type of the objective function used (Bertolini and Schiozer, 2011).

Table 5 History matching Optimization for Cum_Gas single Objective function

Optimizer	**Best Values**						**Cum_Gas Misfit**
	Perm1 (md)	**Perm2 (md)**	**Perm3 (md)**	**Perm4 (md)**	**Perm5 (md)**	**Porosity**	
GA	800.000	58.050	31.607	117.656	800.000	0.166	-0.115
PSO	30.000	155.861	800.000	800.000	800.000	0.250	-0.029
Firefly	30.000	155.866	800.000	800.000	800.000	0.250	-0.029

Table 5 shows the predicted optimal conditions for GA, PSO and FFO algorithms for cumulative gas single optimization. Results similar to the cumulative oil history matching optimization shown in Table 4 were observed. However, for Cum_GOR shown in Table 6, FFO, GA and PSO all predicted the optimum conditions at the same level.

Table 6 History matching Optimization for Cum_GOR single Objective function

Optimizer	**Best Values**						**Cum_GOR Misfit**
	Perm1 (md)	**Perm2 (md)**	**Perm3 (md)**	**Perm4 (md)**	**Perm5 (md)**	**Porosity**	
GA	800.000	30.001	30.001	30.003	800.000	0.100	-0.178
PSO	800.000	30.000	30.000	30.000	800.000	0.100	-0.178

Firefly	800.000	30.000	30.000	30.000	800.000	0.100	-0.178

Table 7 History Matching Optimization for Aggregated Objective function

Optimizer	Best Values						Aggregated Misfit
	Perm1 (md)	Perm2 (md)	Perm3 (md)	Perm4 (md)	Perm5 (md)	Porosity	
GA	800.000	32.849	183.079	102.289	799.996	0.152	-0.131
PSO	800.000	32.925	183.972	102.182	800.000	0.153	-0.131
Firefly	800.000	32.916	184.090	102.183	800.000	0.153	-0.131

Three stochastic algorithms were used in optimizing aggregated objective function and the results shown in Table 7. The table shows that all the three algorithms performed at the same degree of optimization. Although Shams (2017) reported a superior performance of FFO over GA and PSO for a single objective function, similar was expected in this work. However, the results showed that they all performed at the same level and this can be due to the nature of the objective function adopted in this work. Bertolini & Schiozer (2011) observed that the type of objective function used has a great influence on the optimization process.

Multi-objective history matching optimization

The Multi-Objective genetic algorithm (MOGA) and Multi-objective particle swarm (MOPSO) algorithm were used for the multi-objective history matching optimization and their results compared.

Figure 13 shows the pareto front plot for the MOGA while Figure 14 shows that of the MOPSO.

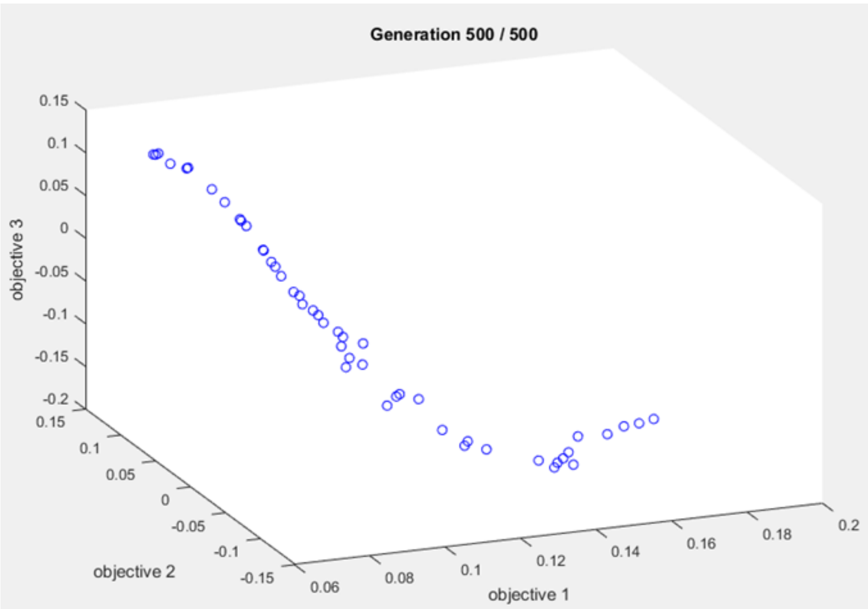

Figure 13 Non-dominated solutions of Multi-Objective Optimization using MOGA

Table 8 shows the optimum non-dominated solution of the pareto front plots shown in Figures 13 and 14 for MOGA and MOPSO respectively. MOPSO yielded more highly ranked individuals than MOGA with 200 to 50 solutions at the end of the run and obtained a wide diversity on its Pareto front. This observation confirms the recent work of Fu and Wen (2018).

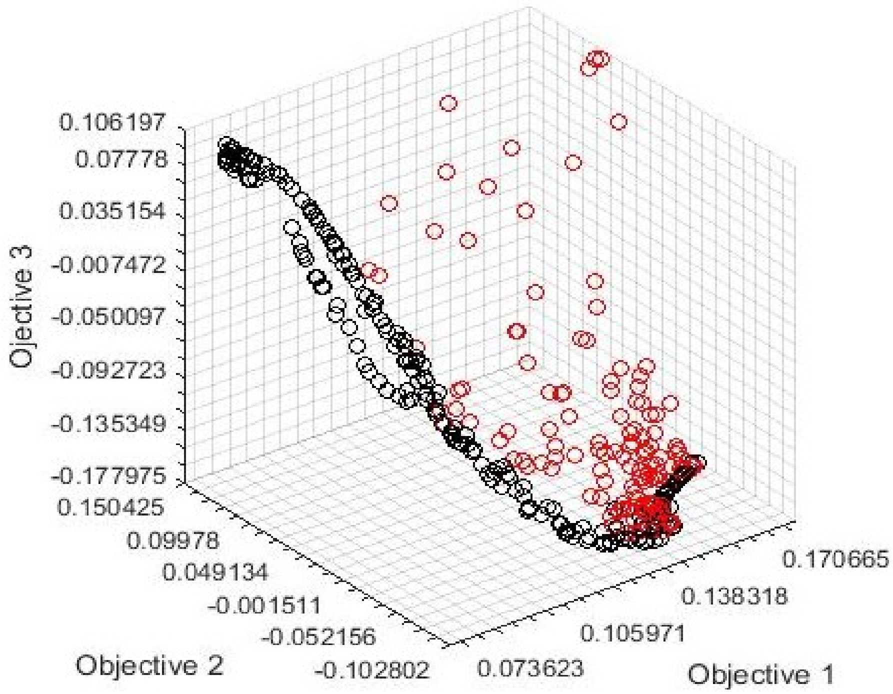

Figure 14 Non-dominated solutions of Multi-Objective Optimization using MOPSO

Table 8 Multi-objective History matching Optimization

	Unknown Parameters						Misfit Value		
	Perm1 (md)	Perm2 (md)	Perm3 (md)	Perm4 (md)	Perm5 (md)	Porosity	Cum_Oil	Cum_Gas	Cum_GOR
MOGA	585.815	224.722	771.887	73.371	800.00	0.243	0.092	0.028	-0.006
MOPSO	582.470	198.772	793.339	74.227	793.154	0.235	0.074	0.117	0.105

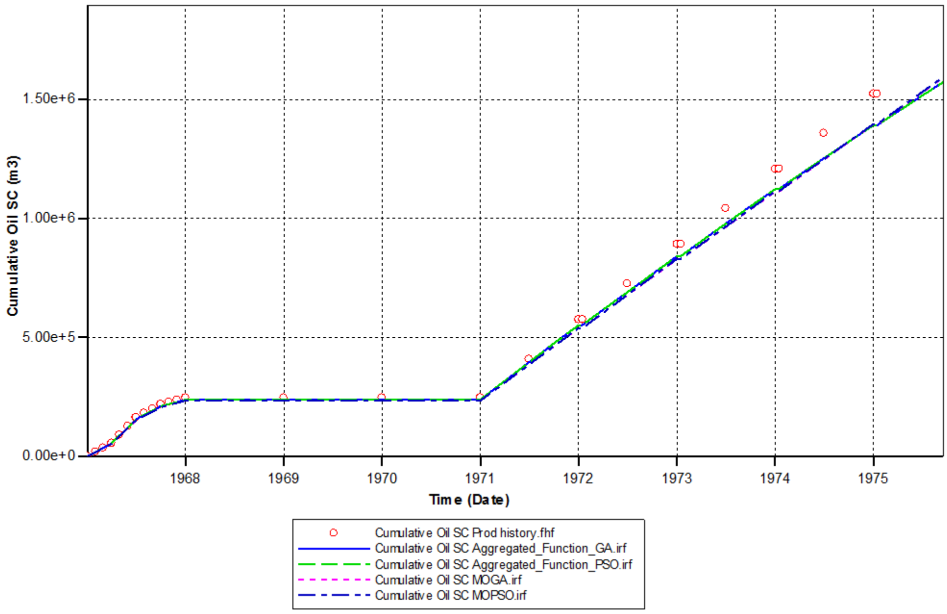

Figure 10 Comparison of predicted data and various Dataset from Aggregated Functions and Multi-Objective Optimization for Cumulative Oil Production

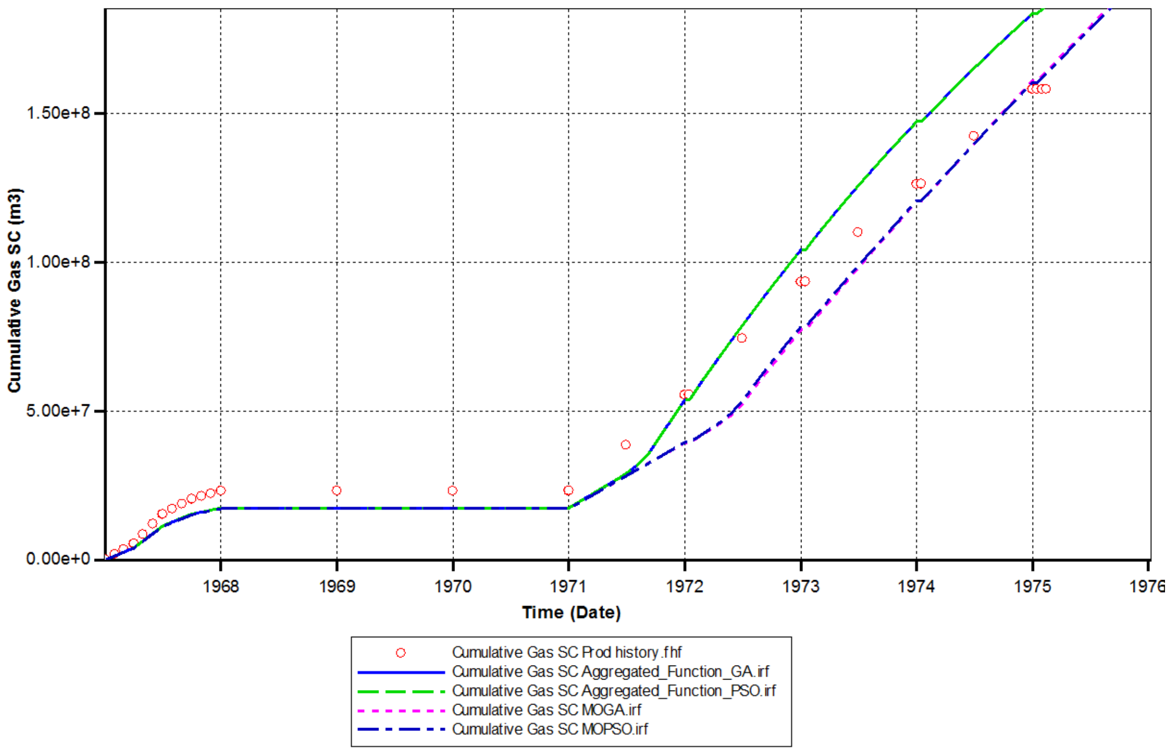

Figure 11 Comparison of predicted data and various Dataset from Aggregated Functions and Multi-Objective Optimization for Cumulative Gas Production

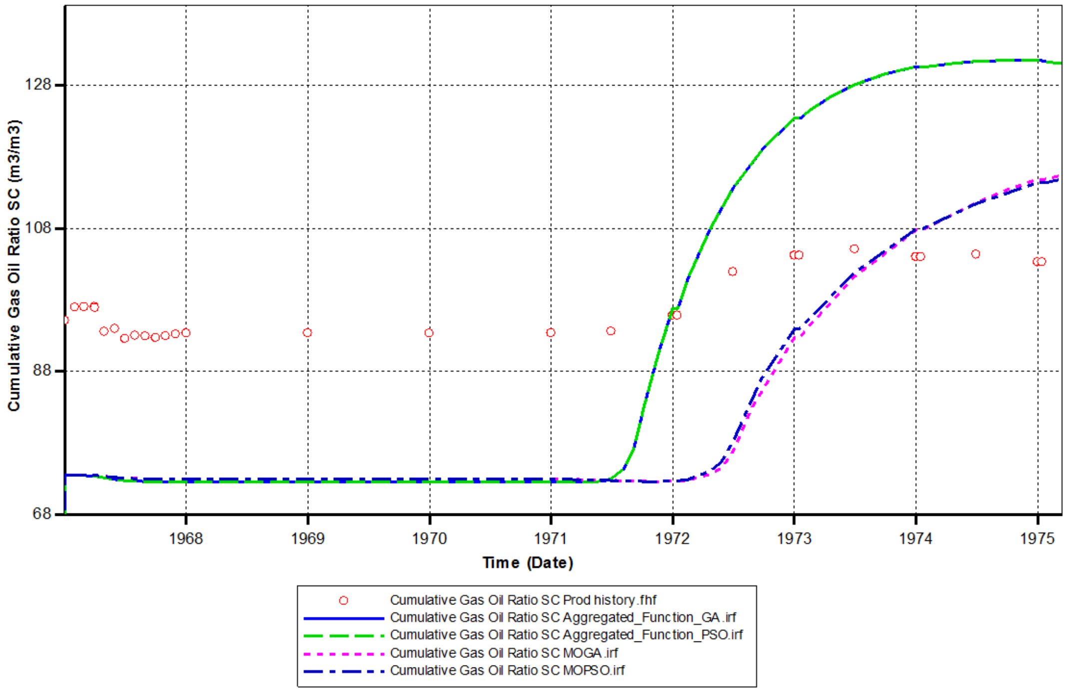

Figure 12 Comparison of predicted data and various Dataset from Aggregated Functions and Multi-Objective Optimization for Cumulative GOR

Figure 15 shows the comparison of the aggregated and Multi-objective history matching performances of PSO, GA, MOPSO and MOGA. Interestingly, all these algorithms were able to provide a robust match for cumulative oil production. However, Figures 16 and 17 provided a different degree of performance for the aggregated function compared with the multi-objective history matching optimization. The results shows that, effective history matching of cumulative gas production and Cum_GOR can be better achieved through a multi-objective history matching approach. This is in tandem with the work of Mohamed et al.(2011) that a complex system can be best optimized using a multi-objectives approach.
MOGA gave better a faster misfit convergence than the MOPSO and utilized less individuals in obtaining the result. This is supported by the work of Hutahaean et al.(2016).

4. CONCLUSION

This study focused on the comparison of multi-objective optimization approaches and different algorithms in solving history matching problem. The following conclusions can be drawn.

- Porosity and permeabilities of the reservoir layers greatly influenced the history matching process. Thus, these parameters must be closely watched if the history matching error is to be minimised.
- The ANN generated proxy model performed better than that of RSM.
- The single objective function and aggregated approaches to optimizing history matching are limited to simple incompressible systems while the multi-objective approach performed better for more complex compressible systems
- The new FFO algorithm extended in this work for aggregated optimization approach performed at the same level with PSO and GA.
- The nature of objective function may greatly influence the optimization of history matching process and this is a subject of further studies

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