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PERFORMANCE ANALYSIS OF A WATER-DRIVE OIL RESERVOIR: AN OILFIELD CASE STUDY

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Abstract: One of the primary responsibilities of a reservoir engineer is to evaluate the performance of hydrocarbon reservoirs to estimate the original hydrocarbons in place, reserves, ultimate oil/gas recovery factor. This responsibility becomes complicated in the case of water-drive reservoirs due to the high uncertainty associated with aquifer properties, including rock properties and aquifer geometry. This paper presents a new method to find the optimum aquifer model based on the root mean square error (RMSE) values by using MBAL software. The study investigated the transmissibility between the X, Y, and Z reservoirs in the field. Additionally, the original oil-in-place (OOIP) was estimated by using material balance equation and Monte Carlo concepts.

Keywords: *aquifer, reservoir performance, MBAL, prediction production, Monte Carlo simulation.*

1. INTRODUCTION

Water influx into the reservoir comes from various sources, including aquifers, water injection wells, and surface water recharge from outcrops. It contributes to the driving mechanism used for hydrocarbon production. Other mechanisms affecting hydrocarbon production include gravity segregation, gas-cap drive, fluid expansion, connate water compressibility, and formation compressibility [1–4].

Accurately estimating water influx volumes in a reservoir during production is crucial for various applications, including material balance equation (MBE), reservoir simulation, production scheduling, and developing strategies for optimizing hydrocarbon recovery [5]. To achieve high accuracy in reservoir simulation and production prediction, it is crucial to select an appropriate aquifer model that can effectively capture the dynamic behavior of the aquifer system. Characterizing aquifers for modeling purposes can be challenging due to the high levels of uncertainty associated with their properties, including permeability, porosity, size, pore size geometry and distribution (PSD), capillary pressure (P_c) and water encroachment angle [6]. The purpose of this work is to conduct a case study in the SABA field in order to choose the most optimal aquifer model that exhibits the lowest Root Mean Square Error (RMSE). This will aid in enhancing our comprehension of reservoir performance, as well as predicting production conditions from the year 2021 to 2031.

Petroleum engineers have multiple methods to estimate hydrocarbon reserves, including analytical techniques such as volumetric or material balance estimates, as well as numerical methods such as 3D reservoir simulation models [7]. Material balance modeling and analysis is a commonly used analytical method, allowing for a comprehensive understanding of reservoir performance, drive mechanisms, and estimation of volumes in place. This is almost the main purpose of the MBE where dynamic reservoir data, including production history and changes in fluid properties, to estimate the original oil in place and gas initially in place. For instance, in water drive reservoirs, determining the initial oil in place or the amount of oil produced at a specific time interval requires knowledge of the amount of water influx into the reservoir. Similarly, incorporating the aquifer into a reservoir simulation model can help minimize model uncertainties when water influx into the reservoir is substantial.

Therefore, the main objective of this research is to study and evaluate a water-drive oil reservoir performance by material balance concept using MBAL software [8]. The study mainly investigates the following reservoir aspects:

1. Evaluate water influx models.
2. Estimate Oil initial in Place by using MBE concept.
3. Investigate transmissibility effect.
4. Prediction of oil production.
5. Determine the drive mechanisms.

2. LITERATURE REVIEW

The material balance equation hypothesis was first presented in 1935 by Schilthuis [8]. It states that the volume of the reservoir remains constant, and the volumetric balance between underground withdrawals (cumulative production) must be equal to the expansion of fluids in the reservoir due to pressure drop. Accurately estimating water influx into petroleum reservoirs is crucial for various applications, including material balance calculations, reservoir simulation studies, production forecasting, and developing strategies to optimize hydrocarbon recovery [5].

There are several aquifer models to calculate cumulative water influx into the reservoir. Each model has its assumptions based on the outer boundary conditions (finite or infinite), flow geometry (steady state, semi-steady state or unsteady state), flow regimes (linear edge water drive, bottom edge water drive or edge water drive) and on the degree of pressure maintenance (active water drive, partial water drive or limited water drive) [9–12]. A. F. Van Everdingen, [13] developed a method to combine MBE with the water influx equation to obtain reliable results of OOIP. The method was developed for an oil reservoir without a gas cap and for both linear and radial flow systems. M. Mcdowell [14] studied the effect of formation permeability and aquifer size on the behavior of a water drive reservoir. Also, he studied the way of the natural water influx changes with the pressure maintenance programs.

Dougherty [15] presented a method to predict the performance of a water-drive reservoir and to make optimal calculations of reservoir size, aquifer size, aquifer geometry and the fluid conductivity between the reservoir and the aquifer. Belhouchet [6] suggests a new empirical model for enhancing the reservoir characteristics using well log permeability prediction, and impact on production. Dejean and Blanc [16] presented several statistical methods dealing with the uncertainties in the reservoir parameters. The statistical methods are (a) Experimental Design, (b) Response Surface Methodology and (c) Monte-Carlo methods. Integrating these techniques enables to build a simplified model of a process and to estimate the uncertainties on the response predictions. Marques and Trevisan [17] investigated uncertainties in reservoir management and explored various models for quantifying water influx into reservoirs. Based on their findings, Marques and Trevisan concluded that the Carter & Tracy model provides accurate results in most cases studied, except for very small aquifers. Also, they concluded that Fetkovich model provided accurate estimates for Original Oil in Place (OOIP) in small aquifers. However, as the aquifer size increased, the model's accuracy began to decline, and the errors in its predictions became more pronounced. In addition, they found out that Leung modified model is the highest accuracy model in their study [17]. In 2019, Mahmoud and his colleagues [18] used some artificial intelligence (AI) techniques to estimate the oil recovery factor (RF) for water-drive sandy reservoirs. They presented an empirical correlation to estimate RF with 7.95% AAPE according to their study. Onuka and Okoro [8] used MBAL software to predict the performance of a water-drive oil reservoir. They used only two aquifer models (Schilthius steady state and the Hurst-Van Everdingen unsteady state models). They found that the difference in RF between both models was 0.4067 MM STB (stock tank barrel).

3. METHODOLOGY

Figure 1 describes how the processes in MBAL will be done to achieve the objectives in this study. By using Petroleum Experts MBAL software, an iterative nonlinear regression is used to find automatically the best mathematical fit for aquifer model. Energy plot and prediction tools in MBAL were used to determine the drive mechanisms and the forecasting of oil production respectively.

The Root Mean Square Error (RMSE) is a commonly used metric to evaluate how well a model's predicted values match actual observations [19–21]. It calculates the square root of the average of the squared differences between predicted and observed values. The RMSE provides a measure of predictive power by aggregating individual differences, also known as residuals:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(X_{obs,i}-X_{model,i}\right)^2}{n}} \tag{1}$$

where represents $X_{obs,i}$ the i-th observed value and $X_{model,i}$ denotes the i-th modelled value.

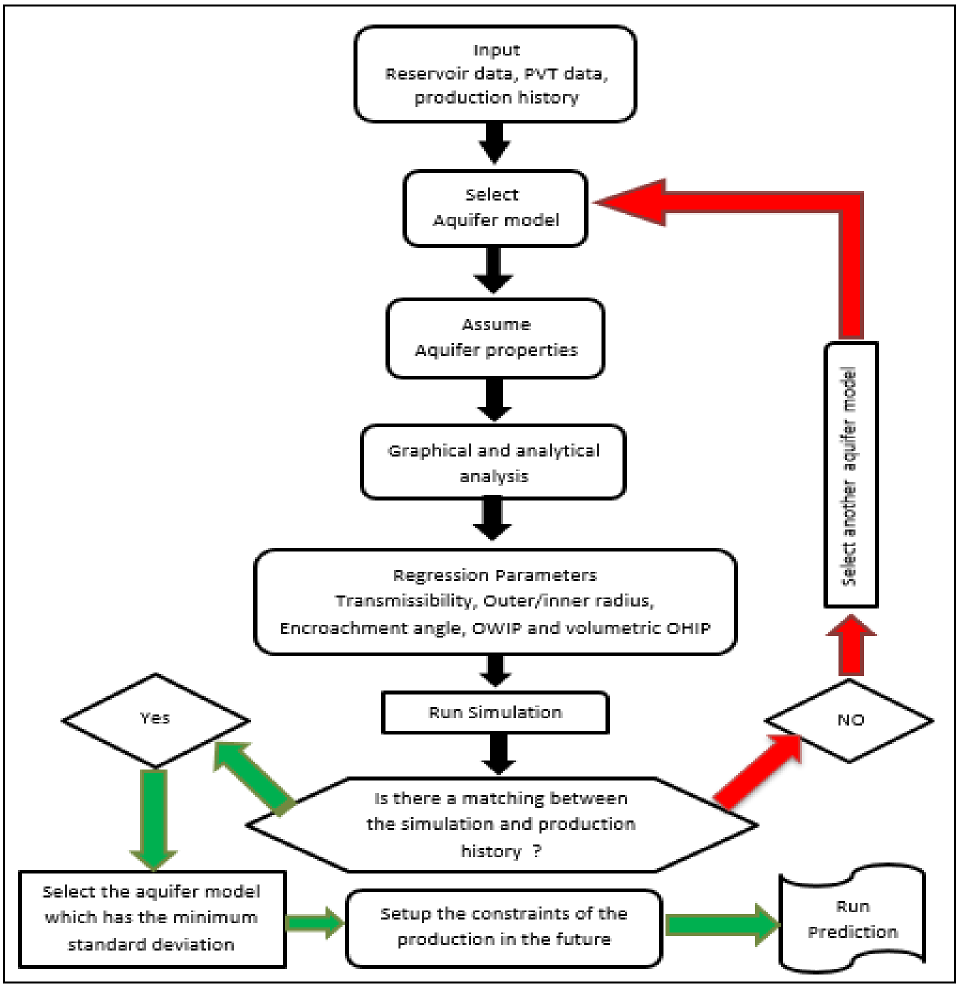

Figure 1
Flowchart of the applied evaluation algorithm

4. SABA FIELD CASE STUDY

SABA field is divided into three reservoirs (reservoir X, Y, and Z). The main source is supported by an aquifer and is separated by two important faults that play a significant role in its structural and saturation conditions. *Figure 2* shows the cross-section sketch of the studied field.

Exploration drilling began in 1971, and the production stage started in late 1985 with the X1 well. The initial reservoir pressure declined from 330.8 bar (approximately equal to 4,800.58 pounds per square inch [psi]) to 310 bar (4,501.18 psi) in the first four years of production. A secondary gas cap developed and occupied nearly 7.5% of the reservoir space, leading to gas breakthrough in some wells. To maintain the optimal reservoir pressure of 295 bar (4,278.91 psi), water injection in wells X3 and X6 started in September 1991, maintaining the average reservoir pressure at about 284 bars (4,125.59 psi). The cumulative oil production is 4.85 MM m^3 (171,034 MM ft^3) with a recovery factor of about 20.79%. *Table 1* and *Table 2* illustrate X, Y and Z reservoirs data and pressure-volume-temperature (PVT) of X reservoir respectively.

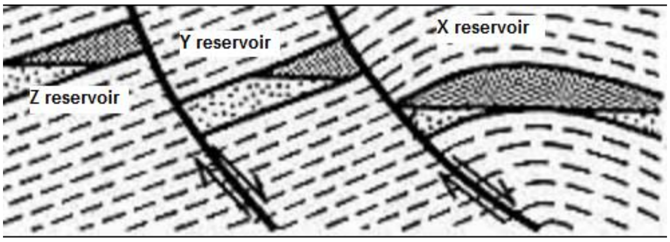

Figure 2

Geological cross-section sketch of SABA field

Table 1

Data of the reservoirs in Saba hydrocarbon field

Parameter	**Unit**	**Reservoir X**	**Reservoir Y**	**Reservoir Z**
Reservoir area	10^3 ft^2	35520.87	20451.41	11840.29
Elevation height	ft	590.5512	295.2756	213.2516
Average porosity	%	9.2	3.4	3.3
Connate water saturation	%	21.6	21.6	21.6
Initial reservoir pressure	Bar (psi)	330.8 (4801)	330.8 (4801)	330.8 (4801)
Reservoir temperature	C°	140	140	140
Original oil-in-place	MM m^3 (MM ft^3)	22.199 (783.9503)	2.362 (83.4132)	0.9585 (33.8491)
Average permeability	mD	113	160	28
Aquifer volume	10^3 m^3 (10^3 ft^3)	460 (16245)	300 (10,595)	250 (8829)
Water inflow constant	m^3/bar (ft^3/psi)	228.4 (556)	–	–

Table 2

PVT fluid and contents properties for reservoir X

Parameter	**Unit**	**Value**
Solution gas-oil ratio	ft^3/ft^3	259
Oil gravity	kg / m^3	817
Gas specific gravity	Sp. Gravity	0.89
Mole percent H_2S	%	0
Mole percent CO_2	%	5
Mole percent N_2	%	1.2
Water salinity	PPM	200000
Oil formation volume factor	m^3/Sm^3	1.93
Reservoir oil viscosity	mPa. sec	0.193

5. Results and Discussion

This study aimed to evaluate different aquifer models by comparing the measured and simulated reservoir pressures using the Root Mean Square Error from the start to the end of production history. A reservoir model called tank modeling was created using MBAL software, assuming no communication between reservoirs as sketched in *Figure 3*. The evaluation of aquifer models was conducted through history matching in MBAL and using regression and best-fit tools in analytical and graphical methods.

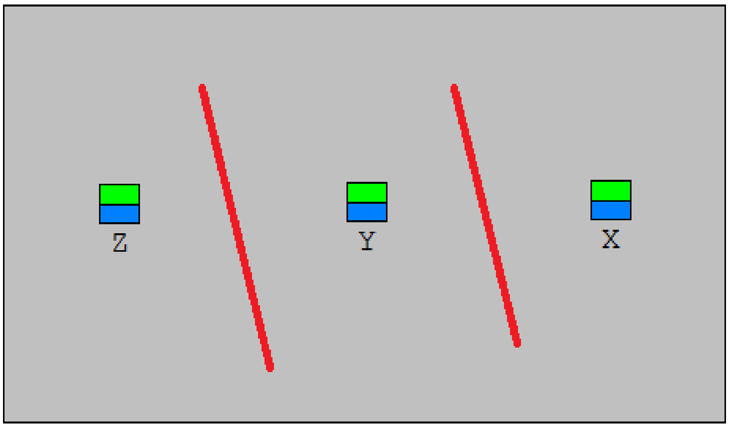

Figure 3

Single tank model assuming no communication between the reservoirs

Table 3 and *Figure 4* show that the small pot aquifer model has the lowest RMSE equals to 2.306568 with OOIP equal to 23.371 MM m^3 (825.3391 MM ft^3) while Hurst steady state aquifer model has the highest RMSE equal to 17.59313 with OOIP equal to 35.4277 MM m^3 (1251.1174 MM ft^3).

The evaluation of different aquifer models showed that the RMSE values of almost aquifer models were relatively similar due to the small size of the aquifer, which lacked sufficient energy to push the oil for an extended period. As a result, injection was started after seven years to maintain reservoir pressure.

Table 3

Evaluation results of aquifer models

Aquifer Model	**RMSE**	**OOIP (MM m^3)**	**OOIP (MM ft^3)**
Small Pot	2.306568	23.371	825.3391
Schilthuis steady state	12.56471	35.4277	1251.1174
Hurst steady state	17.59313	25.2682	892.3381
Hurst-Van Everdingen – Odeh radial aquifer	2.312731	22.718	802.2786
Hurst-Van Everdingen – Dake radial aquifer	2.498694	22.8464	806.8130
Hurst-Van Everdingen – Dake linear aquifer	2.402589	22.8831	808.1090

Aquifer Model	RMSE	OOIP (MM m^3)	OOIP (MM ft^3)
Hurst-Van Everdingen – Dake bottom aquifer	2.31206	22.718	802.2786
Fetkovich Semi Steady State radial aquifer	2.430987	23.0666	814.5893
Fetkovich Semi Steady State linear aquifer	2.719428	20.4745	723.0501
Fetkovich Semi Steady State bottom aquifer	2.314439	23.0391	813.6181
Fetkovich Steady State radial aquifer	2.539608	23.1492	817.5063
Fetkovich Steady State linear aquifer	2.641346	23.0574	814.2644
Fetkovich Steady State bottom aquifer	2.314371	22.8877	808.2715
Cater – Tracy	2.46166	23.2363	820.5822

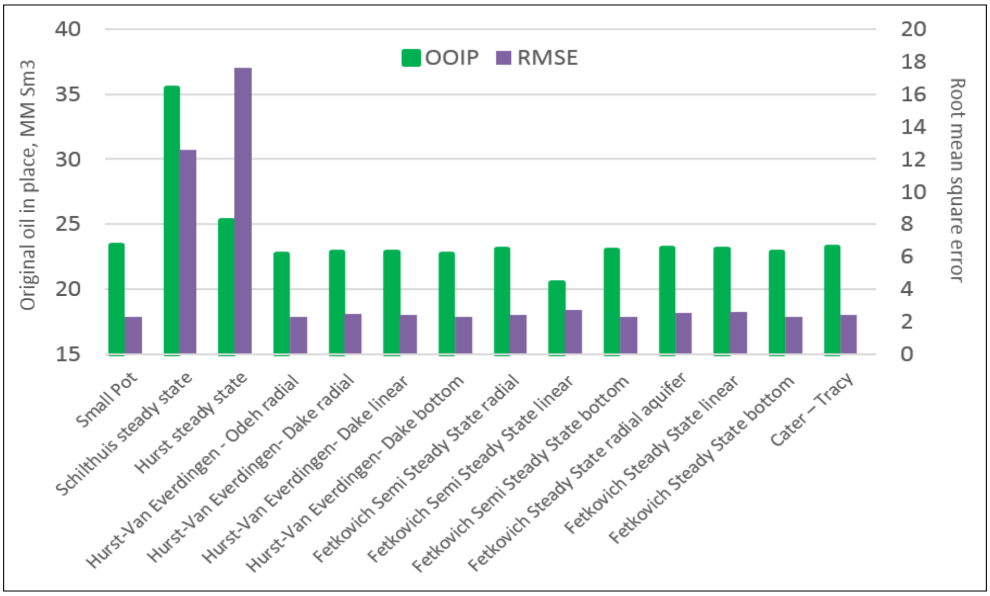

Figure 4
Predicted OOIP and RMSE values of the aquifer models

Figure 5 illustrates the pressure profile of the small-pot aquifer model, obtained through an analytical approach. The figure displays three distinct datasets, the starred data points represent the pressure profile derived from actual input data, the blue curve represents the simulation model of the pressure profile when an aquifer is present, and the red curve represents the simulation model of the pressure profile in the absence of an aquifer, characterizing a volumetric reservoir. Analysis of this figure unequivocally reveals that the reservoir cannot be categorized as a volumetric reservoir. This conclusion is supported by the absence of alignment between the red curve (representing the model without an aquifer) and the actual pressure profile. Conversely, good matching is achieved when utilizing the small-pot aquifer model, as evident from the performance of the blue curve.

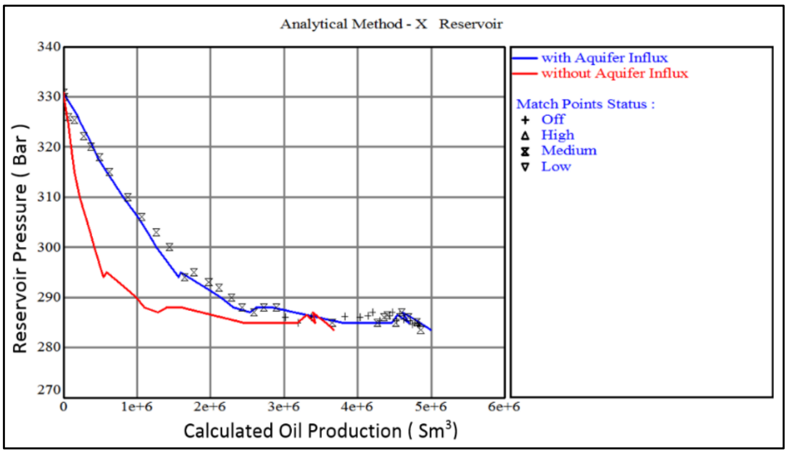

Figure 5
Analytical method used for calculating the reservoir pressure profile with/without aquifer influx

Figure 6 shows the F-We versus Et graphical method, where the symbol F stands for cumulative fluid withdrawal. This is the total volume of fluids that have been withdrawn from a reservoir, including oil, gas, and water. We symbol represents the cumulative water influx and Et represents the total formation volume factor. The best-fit tool was used in the graphical method to obtain a good match between the measured points (blue points) and the calculated points represented by a straight line. The OOIP obtained from both the graphical and analytical methods is equal to 23.371 MM m^3 (825.3391 MM ft^3).

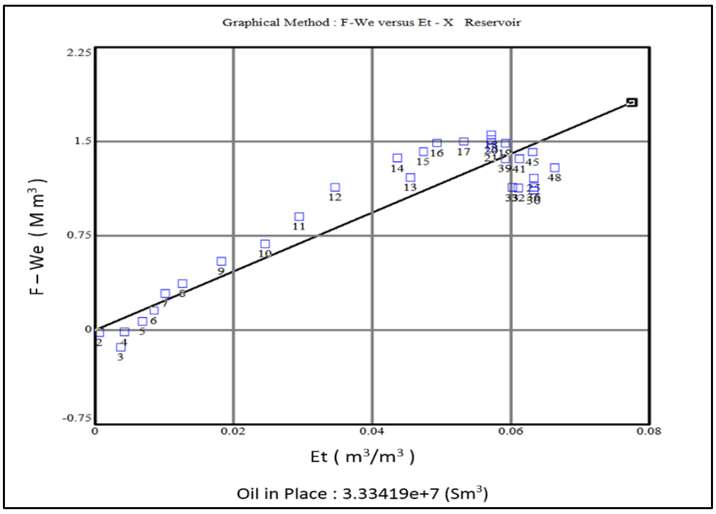

Figure 6
Graphical method using the F-We versus Et relation

In situations where both methods yield distinct OOIP values, the analytical method proves to be the more dependable option. This preference arises from the fact that the graphical method relies on graphical interpretation and assumptions that may not always hold true in complex reservoirs. It is more suitable for simplified cases and may be less accurate when dealing with reservoirs that have unconventional behaviors or complex geological features.

We assume that SABA field is divided into three reservoirs (X, Y and Z reservoirs); they are separated by two faults. The first fault is located between X and Y reservoirs. Another one separates Y and Z reservoirs. Thus, it is very important to find out whether there is a transmissibility between the reservoirs through the faults (opened/permeable faults) or not (closed/impermeable faults). *Figure 7* shows a multi-tank model created by MBAL software assuming that there is communication between the reservoirs. T1 and T2 in *Figure 7* represents the transmissibility between reservoirs X and Y and between Y and Z reservoirs, respectively.

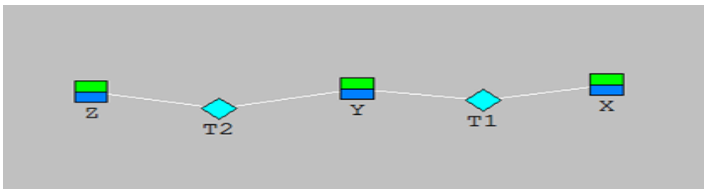

Figure 7

Multi tank model assuming full communication between the reservoirs

Table 4 presents the transmissibility values (T1 and T2). Before using the regression tool, the transmissibility values were assumed to be equal 1 m^3/day*mPa*s/bar because there is no available data. After using the regression tool in MBAL software, the values of transmissibility between X and Y reservoirs (T1) and Y and Z reservoirs (T2) are equal to $6.93416*10^{-9}$ and $1.38694*10^{-8}$ m^3/day*mPa*s/bar, respectively. It is observed that the transmissibility values after using the regression tool are very small (neglectable values), which indicates that both faults can be considered as closed/impermeable faults.

Table 4

Transmissibility values obtained by regression tools

Regression	**Transmissibility, m^3/day*mPa*s/bar**	
	Reservoirs X and Y (T1)	Reservoirs Y and Z (T2)
Before regression	1	1
After regression	$6.93416*10^{-9}$	$1.38694*10^{-8}$

The MBAL software provides Monte Carlo tool to calculate the OOIP. Statistical distributions signify the different factors in determining reserves, including PVT properties and pore volume. *Table 5* presents the input data utilized for the statistical distribution, which is used to determine the OOIP by using Monte Carlo tool. Due to the uncertainty in the area, thickness and porosity values, triangular distribution type was used to specify the lower limit the upper limits (minimum and maximum) and the mode (most frequent value). The other parameters are fixed values because they were measured in the lab with accurate equipment.

Table 5

Statistical parameters of the reservoir properties

Parameter	Distribution type	Unit	Minimum	Maximum	Mode
Area	Triangular	MM ft^2	32.3	36.6	35.5
Thickness	Triangular	ft	525	623	590
Porosity	Triangular	Percent	7	12	9.2
Oil saturation	Fixed value	Fraction	0.784	–	–
Solution GOR	Fixed value	ft^3 / ft^3	259	–	–
Oil gravity	Fixed value	Kg / m^3	817	–	–
Gas gravity	Fixed value	Sp.gr	0.89	–	–

Table 6 summarizes estimated OOIP values by Monte Carlo tool which contains three probabilities values, i.e., P10, P50 and P90. P10 is the value that is exceeded by 10% of the simulated outcomes. This is often referred to as the “low case” or “worst case” scenario.

P50 is the median value of the simulated outcomes. This is often referred to as the “most likely” or “base case” scenario. P90 is the value that is exceeded by 90% of the simulated outcomes. This is often referred to as the “high case” or “best case” scenario. Mean is the average of all the simulated outcomes. The P10, P50, P90, and Mean values are affected by a number of factors, including:

1. The probability distributions of the input variables.
2. The number of simulations performed.
3. The random number generator used.

Table 6

OOIP values estimated by Monte Carlo tool and MBE

Method		OOIP, MM m^3	OOIP, MM ft^3
Monte Carlo	P10	18.8344	665.1312
	P50	23.4051	826.5441
	P90	28.1044	992.4985
	Mean	23.2571	821.3175
MBE, Small pot aquifer		23.371	825.3391

Figure 8 shows the results of OOIP statistical distributions from Monte Carlo technique in MBAL software. The highest probability value (P90), the lowest probability value (P10) and the median probability value (P50) of OOIP are equal to 28.1044 MM m^3, 18.8344 MM m^3 and 23.4051 MM m^3 respectively.

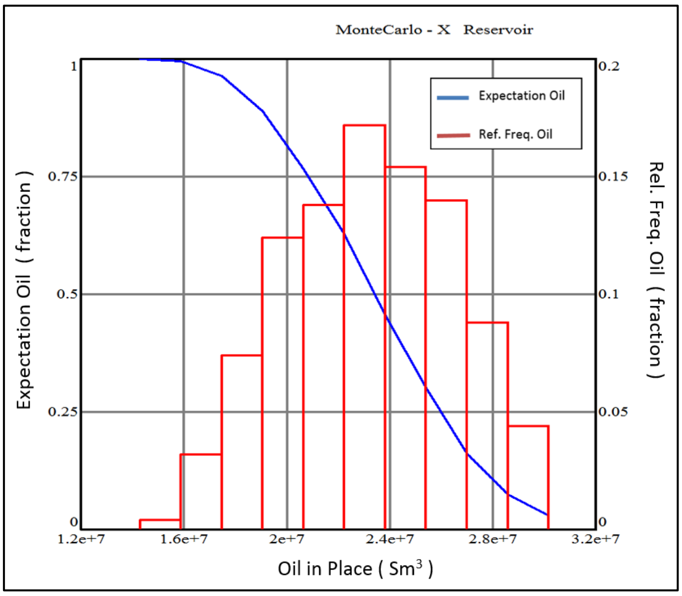

Figure 8
Volumetric reserve probability distribution obtained by Monte Carlo simulation

To understand and analyze the reservoir performance it is crucial to know the contribution of each drive mechanism and how it changes during production. *Figure 9* shows that the dominant drive mechanism from the beginning of production to around 1999 was water influx, with a drive index of around 0.5 in 1999. After that, due to continuous water injection, the water injection drive index gradually increased and became the dominant drive mechanism. By 2021, the water injection drive index was equal to 0.7. The fluid expansion and pore volume compressibility drive mechanisms are very weak in this reservoir.

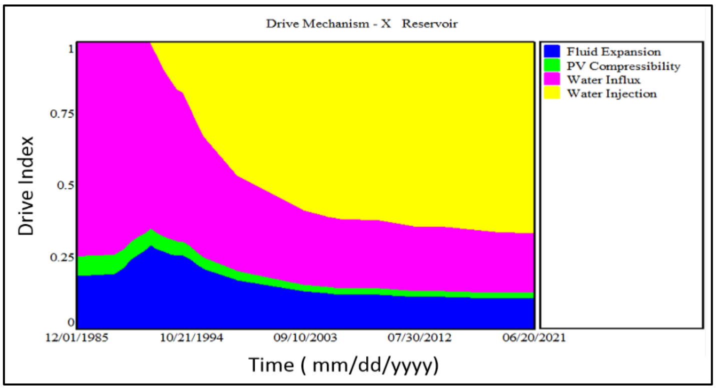

Figure 9
Energy plot of reservoir X

One of the objectives of this study is the production prediction of reservoir X for the next ten years. MBAL software provides this technique under name “production prediction” option. Before using production prediction tool one condition must be achieved. The condition states that there must be very good matching between the production history data and the simulation model. This condition was done as it was shown in *Figure 5*.

Figure 10 shows oil and water saturation versus date. Water saturation (red curve) increases, oil saturation (blue curve) decreases. From 2008, water saturation and oil saturation curves changed very slowly because some wells were shut in. *Figure 11* shows, the water cut and oil recovery factor versus date. Water cut (blue curve) increases rapidly. It is expected to be around 90% in 2031, which is so high value. To reduce the water cut, shutting down all wells for a certain period or changing the perforation interval position above the previous one can be considered as solutions. The oil recovery factor (red curve) is expected to be around 0.2 (20%) in 2031, which is low. This is due to the high water cut and heterogeneity of the reservoir. To maximize oil recovery and support reservoir pressure, using polymer water injection could be a good solution because it can improve the sweep efficiency of the waterflood by reducing channeling and fingering.

Figure 12 shows cumulative oil production and tank pressure versus date. Cumulative oil production (green curve) increased rapidly from the beginning of production until around 2008, then slowed due to well shut-ins and high-water cuts.

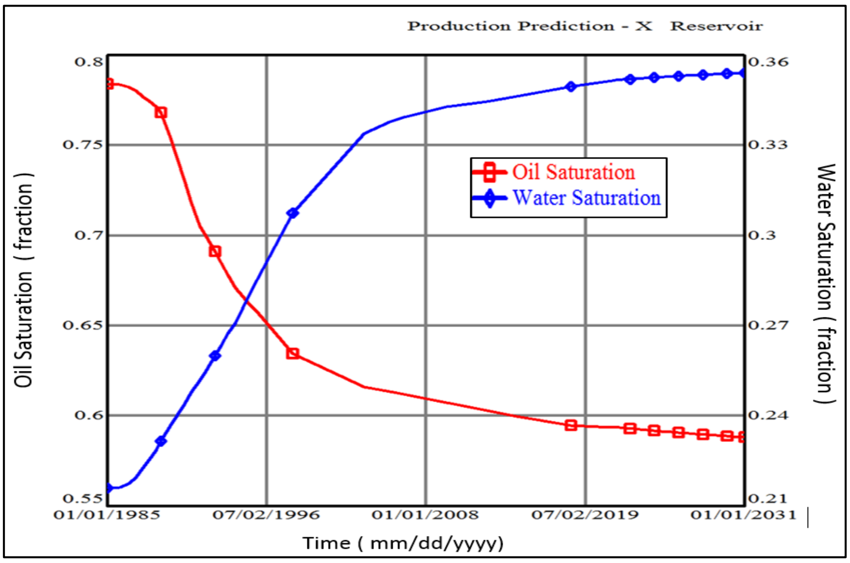

Figure 10
Oil saturation and water saturation versus time

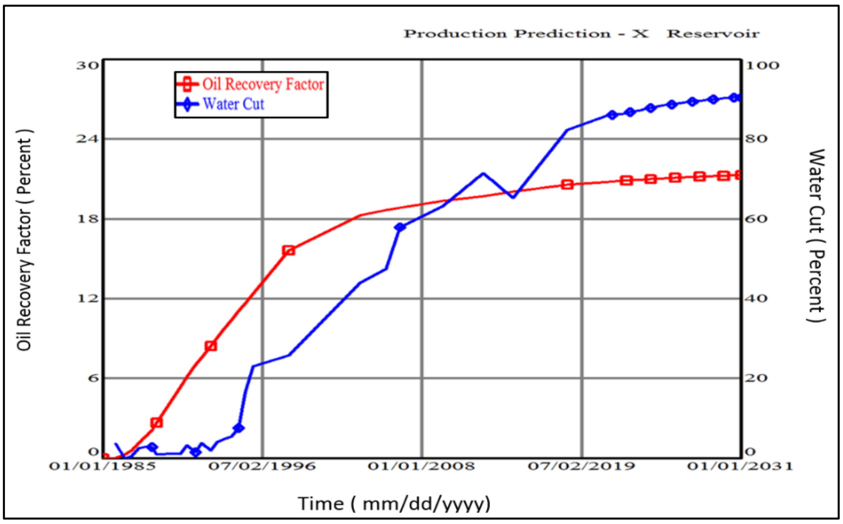

Figure 11
Water cut and oil recovery factor versus time

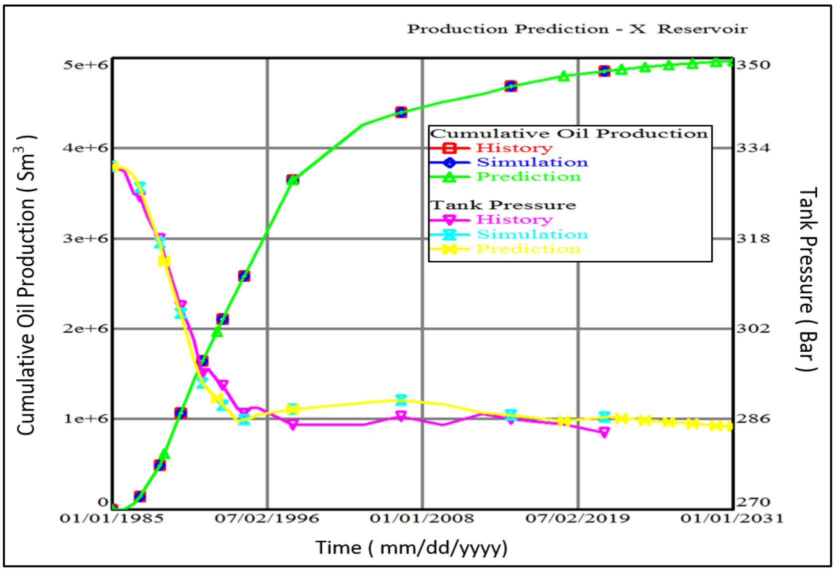

Figure 12
Cumulative oil production and tank pressure versus time

6. Conclusions

In summary, the OOIP values were calculated using MBE, Monte Carlo P50, and volumetric methods, resulting in slightly different estimates. The faults between reservoirs X and Y and Y and Z appear to be impermeable based on their negligible transmissibility values. After matching the simulation model and production history, the predicted oil recovery factor and cumulative oil production in 2031 are slightly higher than their 2021 counterparts. Due to the small aquifer size, the RMSE values of aquifer models are similar, leading to similar OOIP values. The best aquifer model was identified as the small pot model with the lowest RMSE value and a volume of 414.22 M m^3, compared to the input data's value of 460 M m^3.

To improve the understanding of the reservoir performance, it is suggested to utilize static and full 3D reservoir simulations. For more reliable results from MBAL, production history matching using the production history of all wells in the field is recommended instead of relying solely on cumulative tank production history. The production prediction results indicate a low incremental oil production over the next 10 years, which could be attributed to low sweep efficiency and high-water salinity. To enhance reservoir production, occasional acidizing to dissolve depositions and polymer flooding to decrease the mobility ratio could be considered. Other methods can be suggested using surfactants or microbial [22–23].

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REFERENCES

[1] L. Dean (2007). Reservoir engineering for geologists, Part 3 – Volumetric Estimation. *Reservoir*, Issue 11, December 2007, pp. 20-23.

[2] L. P. Dake. (1978). *Fundamentals of reservoir engineering*. Amsterdam, Elsevier Scientific Publishing Company, p. 443.

[3] B. Wang and R. R. Hwan. (1997). Influence of reservoir drive mechanism on uncertainties of material balance calculations, in SPE Annual Technical Conference and Exhibition, San Antonio, Texas, October 1997. https://doi.org/10.2118/38918-MS

[4] T. H. Ahmed. (2010). Reservoir engineering handbook, Gulf Professional Pub., https://doi.org/10.1016/B978-1-85617-803-7.50001-8.

[5] J. A. Al-Ghanim, I. S. Nashawi, A. Malallah. (2012). Prediction of Water Influx of Edge Water Drive Reservoirs Using Nonparametric Optimal Transformations. *North Africa Technical Conference and Exhibition*, Cairo, Egypt, February 2012, https://doi.org/10.2118/150662-MS.

[6] H. E. Belhouchet, M. S. Benzagouta, A. Dobbi, A. Alquraishi, and J. Duplay. (2021). A new empirical model for enhancing well log permeability prediction, using nonlinear regression method: Case study from Hassi-Berkine oil field reservoir–Algeria, *Journal of King Saud University-Engineering Sciences*, vol. 33, no. 2, pp. 136–145. https://doi.org/10.1016/j.jksues.2020.04.008

[7] G. Vega Riveros et al. (2011) Reserves Estimation Uncertainty in a Mature Naturally-fractured Carbonate Field Located in Latin America, *OTC Brasil*, Rio de Janeiro, Brazil, October 2011, https://doi.org/10.4043/22517-MS.

[8] A. U. Onuka, F. Okoro. (2019). Prediction of Oil Reservoir Performance And Original-Oil-in-Place Applying Schilthuis And Hurst-Van Everdingen Modified Water Influx Models. *SPE Nigeria Annual International Conference and Exhibition*, Lagos, Nigeria, August 2019. https://doi.org/10.2118/198714-MS

[9] W. Hurst. (1943). Water influx into a reservoir and its application to the equation of volumetric balance. *Transactions of the AIME*, vol. 151, no. 01, pp. 57–72.

[10] M. J. Fetkovich, P. Petroleum Co. (1971). A Simplified Approach to Water Influx Calculations-Finite Aquifer Systems. *Journal of Petroleum Technology*, pp. 814–828, https://doi.org/10.2118/2603-PA.

[11] R. D. Carter, J. Member, A. G. W. Tracy. (1960). An Improved Method for Calculating Water Influx, Trans. 219, pp. 415–417. https://doi.org/10.2118/1626-G

[12] A. F. Van Everdingen and W. Hurst. (1949). The application of the Laplace transformation to flow problems in reservoirs. *Journal of Petroleum Technology*, vol. 1, no. 12, pp. 305–324.

[13] A. F. Van Everdingen, E. H. Timmerman, J. J. McMahon. (1953). Application of the Material Balance Equation to a Partial Water-Drive Reservoir. *Journal of Petroleum Technology*, vol. 5, no. 02, pp. 51–60. https://doi.org/10.2118/229-g

[14] J. M. McDowell. (1955). Performance of Water Drive Reservoirs, Including Pressure Maintenance, as Determined by the Reservoir Analyzer. *Trans.*, 204, pp. 73–78, https://doi.org/10.2118/412-G.

[15] E. L. Dougherty, B. M. Zagalai, D. Khairkhah. (1978). Generalized Method for Making Optimal Estimates of Reservoir-Aquifer Parameters. *Soc. Pet. Eng. AIME J.*, vol. 18, no. 2, pp. 123–132, https://doi.org/10.2118/5361-pa.

[16] J. P. Dejean, G. Blanc. (1999). Managing uncertainties on production predictions using integrated statistical methods. *Proceedings – SPE Annual Technical Conference and Exhibition*, vol. 2, https://doi.org/10.2118/56696-ms.

[17] J. B. Marques, O. V. Trevisan, S. B. Suslick. (2007). Classic models of calculation of influx: a comparative study. *Latin American & Caribbean Petroleum Engineering Conference*, Buenos Aires, Argentina, April 2007. https://doi.org/10.2118/107265-MS

[18] A. A. Mahmoud, S. Elkatatny, W. Chen, A. Abdulraheem. (2019). Estimation of oil recovery factor for water drive sandy reservoirs through applications of artificial intelligence. *Energies* (Basel), vol. 12, no. 19, pp. 1–13. https://doi.org/10.3390/en12193671

[19] R. L. Ott, M. T. Longnecker, (2015). *An introduction to statistical methods and data analysis*. UK, Cengage Learning, p. 1296.

[20] R. S. Tsay. (2010). *Analysis of financial time series*. Hoboken, New Jersey, USA, John Wiley & Sons, p. 720.

[21] W. C. Navidi. (2010). *Statistics for engineers and scientists*. Vol. 3. McGraw-Hill New York, p. 928.

[22] Mabkhot S. BinDahbag, Hassan Hassanzadeh, Abdulrahman A. AlQuraishi, Mohammed S.Benzagouta (2019). Suitability of ionic solutions as a chemical substance for chemical enhanced oil recovery – A simulation study. *Fuel*, Vol. 242, pp. 368–373, https://doi.org/10.1016/j.fuel.2018.12.125.

[23] Mohammed M S Benzagouta, Inas Muen AlNashef, Wimpy Karnanda, Khalid Al-Khidir. (2013). Ionic liquids as novel surfactants for potential use in enhanced oil recovery. *Korean Journal of Chemical Engineering*, Vol. 30, Issue 11, pp 2108–2117, https://doi.org/10.1007/s11814-013-0137-1.