



Static and dynamic modeling integrating the FZI approach with stochastic modeling for characterizing heterogeneous shale-sand reservoirs

Ahmed J. Ghadhab ^{a,*}, Nagham J. Al-Ameri ^a

^a Department of Petroleum Engineering, College of Engineering, University of Baghdad, Baghdad, Iraq

Abstract

Reservoir simulation is essential for optimal field development and recovery process planning. The present work aims at developing an integrated static to dynamic approach for modeling heterogeneous and shaly-sand Nahr Omr Formation in Subba oil field of Iraq. An updated dataset of production rates and PVT data from Dhi Qar Oil Company were used in constructing a high-resolution static model in Petrel involving 10 wells, sonic logs for assessing porosity, and 2D seismic data for structural modeling. In order to incorporate heterogeneities within the reservoir, the Flow Zone Indicator (FZI) technique was employed to classify intervals into 7 Hydraulic Flow Units (HFUs). According to petrophysical analysis, S21 and S22 are identified as the main reservoir units with a high proportion of clean sands, high effective porosity, and low water saturation levels. The static model was subsequently upscaled into a dynamic reservoir simulator (CMG IMEX), using lab measurements of fluid properties and multi-phase relative permeabilities. In addition, OOIP of 2.07 billion STB and an OWC at 2533m (SSTVD) were estimated based on volumetric calculations. As a result, an excellent history match, with $R^2 = 0.957$, was achieved for all fields while for Well A it was $R^2 = 0.981$.

Keywords: Static geological model; Dynamic geological model; Nahr Omar formation; Heterogeneous reservoir; FZI.

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1- Introduction

Numerical reservoir models are the essential cornerstone of industrial reservoir management and optimization of field development strategy. Such an approach implies the use of a coherent integration between 3D Static Geological Model, containing the structural setting of the deposit and its spatial petrophysical characteristics, and a Dynamic Reservoir Model [1-4]. The creation of a reliable static-to-dynamic workflow becomes particularly complicated for highly heterogeneous environments, such as shaly-sand reservoirs, due to their complex history and deposition conditions impacting fluid flow paths [5]. Building an adequate static model in the advanced modeling environment, such as Petrel, starts with creating accurate porosity characterization in terms of the volume of pores, V_p , effective porosity, water content (S_w) and volume of shale rock (V_{sh}) [6, 7].

Porosity models can be successfully implemented in the 3D grid by means of well logs analysis and geostatistical methods [8]. However, the most critical step and main source of uncertainty in such a process is predicting and distributing permeability parameters [9]. For this purpose, the Flow Zone Indicator (FZI) approach, using the Hydraulic Flow Unit (HFU) theory [10], offers a well-supported methodology for classifying individual rocks.

Including calculated FZI permeabilities within the 3D static grid assures an accurate representation of the true hydraulic characteristics of the geological environment [11]. On the other hand, a static model is nothing but a picture of the reservoir at one point in time. In order to verify its geological assumptions and make predictions about future performance, it is necessary to upscale the static model framework to CMG (Computer Modeling Group).

Transitioning from Petrel to CMG enables engineers to take advantage of dynamic parameters like PVTs, relative permeabilities, and capillary pressures. The final step of this process is to perform a proper History Matching [12], which would prove the validity of the FZI permeability distribution and static structure by matching simulated pressures and flow rates with the historical data of the field. Unlike the traditional modeling studies of a reservoir that use one permeability-porosity relationship, this study incorporates FZI-based characterization of hydraulic flow units with geostatistical modeling and dynamic reservoir simulation into one workflow. The application of this integrated approach ensures more accurate modeling of reservoir heterogeneities and provides improved distribution of permeability to better match the history of the reservoir.



*Corresponding Author: Email: ahmed.jabal2508m@coeng.uobaghdad.edu.iq

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The main goal of this research work is the design of an integrated static to dynamic reservoir modeling methodology for a shaly sand reservoir formation in Iraq. The study discusses the following tasks:

Petrophysical analysis using the FZI approach for identification of hydrodynamic flow units as well as accurate permeability modeling. Development of a 3D high-resolution Static Geological Model using Petrel to incorporate structural and petrophysical properties. Up-scaling and transfer of the model into CMG for dynamic reservoir simulation and production history matching. In addition, the process will facilitate increased repeatability of integrated static to dynamic reservoir modeling by providing a structured approach to hydraulic flow unit classification, stochastic property modeling, dynamic modeling and production history matching.

2- Static geological model and data set

2.1. Site location and structural setting

Subba oilfield is a doubly domal anticlinal structure found in the southern part of Iraq, in the governorate of Dhi Qar. It is about 70 km south-east of Nasiriya and 110 km north-west of Basra. Subba oilfield covers an area of about 210 km², covering a length of about 30 km and width of 7 km [13]. Structurally, Subba oilfield has a double-dome setting which consists of a larger southern dome and a smaller northern dome separated by a saddle-shaped structure. Seismic survey led to its discovery in 1973, where exploration drilling started from well SU-1 in 1975 and production operations in 1990 [14]. The stratigraphic unit studied in this work is Nahr Umr Formation, which serves as an important Middle Cretaceous (Albian Cycle) siliciclastic reservoir system within the southern Iraqi sector [15]. From a lithological standpoint, the formation ranges from 221 m to 270 m thick. The formation is stratigraphically separated into fourteen principal operational zones, which include seven sandstone zone and seven shale zones characterized by shaly-sand heterogeneities. This reservoir is used in this study as an example because of its high heterogeneity nature, which includes shale-sand [16], as well as the significant differences in terms of petrophysical parameters laterally and vertically, making this formation appropriate to test the suggested static-to-dynamic modeling approach.

2.2. Data availability and reservoir inputs

The integrated database included information obtained from well logs, core analysis, seismic interpretation, PVT report, and production data to match both static and dynamic models of reservoirs. To construct a realistic and predictive static-to-dynamic workflow, an appropriate subsurface data set was used from various operational wells within the Subba field as shown in Table 1. This data set was specifically optimized to fill the knowledge gap between measurements at core scale, logging scale, and the field scale dynamic response.

2.3. Estimating porosity from sonic logs

For developing a continuous porosity curve through the heterogeneous zones of Nahr Omar Formation, the data obtained from sonic logs were applied. The estimation of porosity Φ sonic is carried out by the Wyllie Time-Average Linear Equation, based on core derived porosity, so that the effect of lithology can be discounted by Eq. 1 [17]:

$$\Phi = \frac{\Delta t - \Delta t_{ma}}{\Delta t_f - \Delta t_{ma}} \quad (1)$$

Where, Δt is the calculated acoustic transit time, Δt_{ma} is the matrix transit time of the clean zone of sandstone, and Δt_f is the fluid transit time. Sonic logs were selected because of their accessibility at all wells analyzed and the ability of this type of logs to be calibrated according to core porosity values.

2.4. Flow Zone Indicator (FZI) and rock typing scheme

A stringent Hydrologic Flow Unit (HFU) categorization scheme was used based on Kozeny-Carman equation and FZI method to properly characterize reservoir heterogeneity and permeability prediction in uncored intervals [18]. RQI, and normalized porosity, Φ_z were obtained using the following Eq. 2, Eq. 3 and Eq. 4:

$$ROI = 0.0314 \sqrt{\frac{k}{\phi}} \quad (2)$$

$$\Phi_z = \frac{\Phi}{1 - \Phi} \quad (3)$$

$$FZI = \frac{ROI}{\Phi_z} \quad (4)$$

To objectively group the reservoir zones into discrete flow zones, free of any human intervention, Multi-Resolution Graph Clustering (MRGC) and Hierarchical Cluster Analysis (HCA) were performed using FZI values derived from the reservoirs by. Using K-means method to determine the ideal number of clusters, Silhouette analysis was conducted. From Fig. 1, the results show that the best clustering occurs when the dataset is divided into 7 groups using Silhouette width analysis, whereby the distance ratio between clusters is maximized and intra-cluster variance minimized. This clustering process involved the computation of FZI, performing the K-means clustering, testing different numbers of clusters using Silhouette analysis, and validating the classification using PCA. This process provided a scientific approach to HFU classification.

In order to statistically confirm the separation and independence of these 7 clustered sets, the PCA Crossplot was developed Fig. 2. By projecting the data set along the first two principal components, one could observe clear separation between the clusters with clearly visible non-overlapping centroids (indicated with grey diamond symbols) belonging to each individual HFU. Statistical spatial separation proves that the aforementioned 7 clusters represent unique petrophysical facies with

individual fluid flow. A unique permeability-porosity correlation was thus created for each individual HFU to better reflect the hydraulic nature of the reservoir.

Table 1. Available data of Nahr Omar formation

Reservoir modeling workflow component	Number of Wells	Data specifications & utilization
Petrophysical characterization	10	Vsh, ϕ_e , and Sw interpretations from continuous log suites (GR, Density, Neutron, Resistivity).
Core analysis & FZI calibration	5	Core plug porosity and permeability data for rock typing and HFU zoning.
Fluid behavior (PVT model)	4	Laboratory PVT reports for fluid property matching in the dynamic simulator.
Dynamic simulation & history matching	3	Historical oil/water production rates and reservoir pressure data constraints.

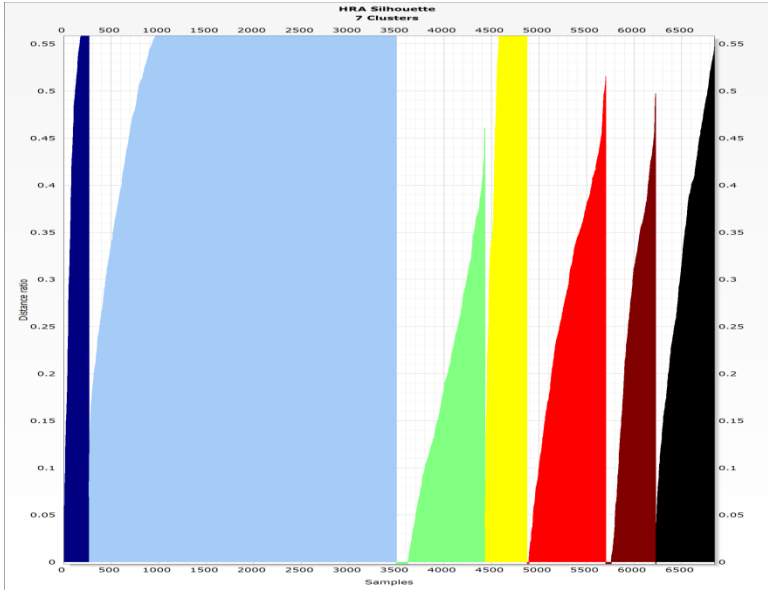


Fig. 1. HRA Silhouette analysis corroborating the selection of the most optimal number of 7 clusters used for classification of HFU

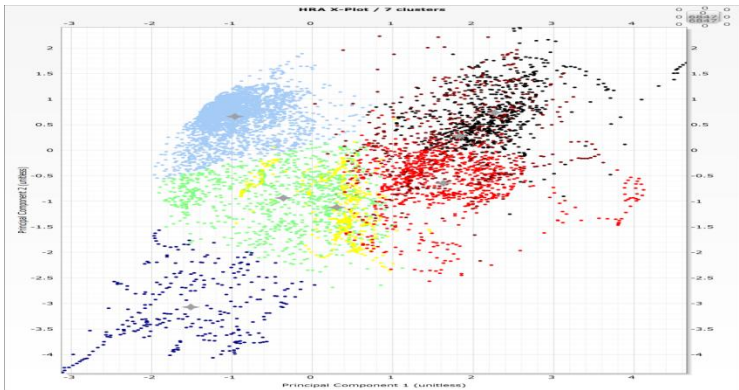


Fig. 2. HRA X-plot using principal component analysis (PCA)

Permeability Prediction Model & Core Regression Analysis Mathematical models specific to each one of the 7 HFUs were developed by correlating core permeability (K_{core}) against core porosity (Φ_{core}). As shown on the clustering Crossplot graph in Fig. 3, each of the 7 HFUs demonstrates a highly correlated response with R^2 coefficients going from 0.7623 (for Group 1) to 0.9952 (for Group 6). Empirical mathematical formulas developed using this segmented process are systematically reported. In contrast to a globally averaged

porosity-permeability regression formula, this particular set of equations enables the model to take into account the subtle variations in the micro-structure, pore throats shapes and tortuosity of the sandstone and shale rocks. Variations in the equation types (with HFUs 1, 5 and 6 being strictly exponential laws while HFUs 2, 3, 4 and 7 being purely power laws reflect the different types of micro-structures present in the reservoir formation as shown in Table 2. Unlike a general correlation that is globally applicable, the FZI approach takes into

consideration the variation in the pore architecture and flow dynamics in different types of rocks, resulting in

better permeability prediction.

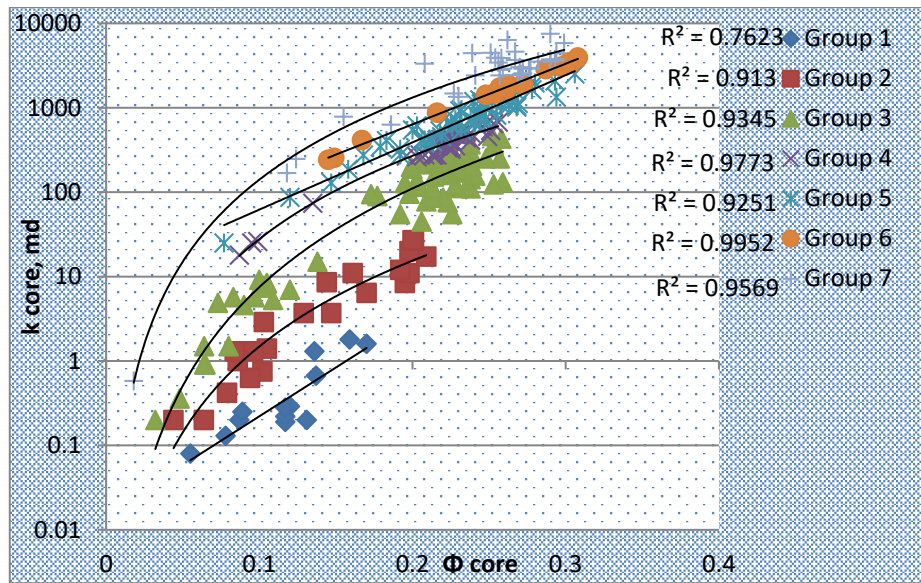


Fig. 3. FZI distribution based on comparing of K core and PHI core

Table 2. Porosity and permeability obtained relation based on FZI results

HFU number	Equation
HFU 1	$K = 0.0154e^{26.624\Phi}$
HFU 2	$K = 3557.3 \Phi^{3.3794}$
HFU 3	$K = 57790 \Phi^{3.8872}$
HFU 4	$K = 52754 \Phi^{3.2782}$
HFU 5	$K = 9.9339e^{18.34 \Phi}$
HFU 6	$K = 23.316e^{16.538 \Phi}$
HFU 7	$K = 239542\Phi^{3.231}$

In order to evaluate the accuracy of the final permeability log K_FZI produced from this FZI analysis workflow, a thorough statistical Crossplot analysis was conducted against the full hard-core database. The power-law regression curve generated for K core vs. FZI shows excellent agreement, resulting in a very accurate coefficient of determination $R^2 = 0.9026$. Such a clear Fig. 4 is a solid proof of predictive power and provides an effective solution for addressing the validity of the model during blind testing. Furthermore, the continuous K FZI curves were plotted vertically with respect to discrete values derived from the cores across two critical reservoir sections. As seen from the Figures below Fig. 5 a and b, the continuous blue line K FZI fits the discrete data points well, recognizing the thief and baffles zones with excellent resolution. Continuous vertical log comparison between calculated permeability based on FZI method, K FZI, and discrete core-derived permeability, K core, within the first reservoir section. Continuous vertical log illustrates exceptional tracking resolution of the proposed model against core points within the second reservoir section.

2.5. Integration into the static geological model

The calibrated high resolution continuous permeability profile (K FZI) and sonic porosity served as the key elements from which the 3D Static Geological Model was populated. Through utilizing the calibrated log data as the hard data trend at the wellbores, geostatistical methodologies (including the Sequential Gaussian Simulation – SGS method) were controlled in their population of the 3D grid. Such integration guarantees that the static model accurately captures the local-scale geological heterogeneity and flow barriers, hence avoiding any over-estimation of fracture heights and generating an appropriately geometrically realistic grid for subsequent MEM and dynamic production modeling. The incorporation of the permeability from the FZI into the geostatistical stochastic modelling created a clear relationship between the characterization of petrophysical properties and the three-dimensional geological structure before dynamic simulation [19, 20].

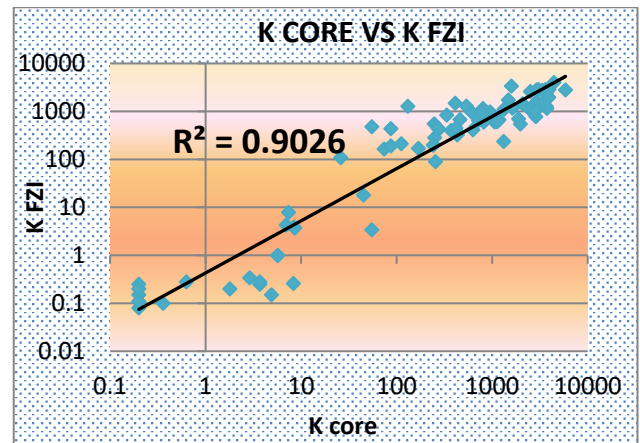


Fig. 4. Trend line of permeability calculated Vs FZI permeability

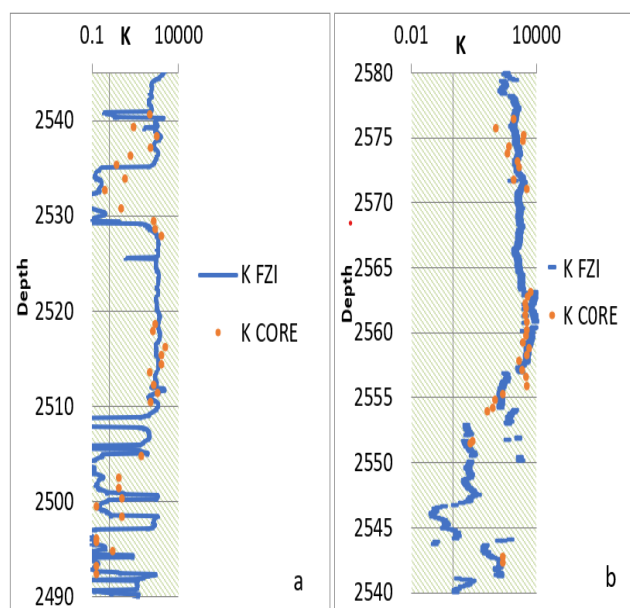


Fig. 5. Calculated FZI permeability Vs. core permeability for two wells A (a) and well B (b)

2.6. 3-D Static geologic modeling techniques

2.6.1. Data integration and quality of data base

Creation of 3D static geologic model was initiated with data integration of a comprehensive database created within the framework of Petrel 2018 software. The database contains complete petrophysical and geological data from 10 wells penetrating the Nahr Umr formation see Fig. 6. For creation of a trustworthy structure framework, structural contours map S23 was digitized based on the latest 2D seismic interpretation data. Well

logs were processed by conversion into LAS files, which were carefully correlated with core data to outline formation tops and main sandstone formations and shales acting as baffles.

2.6.2. Structural and fault framework modeling

Correlation had been carried out to establish the structure of the reservoir and provide uniformity in the classification of reservoir units within the field. The Nahr Omar Formation was divided into different units of sandstones and shales based on their lithology and response on the well logs as shown in Fig. 7, Fig. 8. Panels of correlation had been prepared to provide information on the continuity and thickness of the reservoir units [21, 22].

2.6.3. Pillar grid generation and formation layers

In order to be able to effectively capture spatial variability without compromising the computation efficiency, a 3D grid was created through pillar gridding [23]. The structural skeletons of the Nahr Omr formation are shown in Fig. 9. The volume of the reservoir was segmented into grid cells where there are 121 cells in the X-direction, 300 cells in the Y-direction, and 34 cells in the Z-direction Fig. 10. This leads to 1,234,200 cells this fine-grid was further upscaled before its exportation to the dynamic simulator. Using known geological horizon, the formation was divided into 14 major layers. Critical reservoir units were further subdivided into fine layers to capture vertical variability of facies and quality of the reservoir rock.

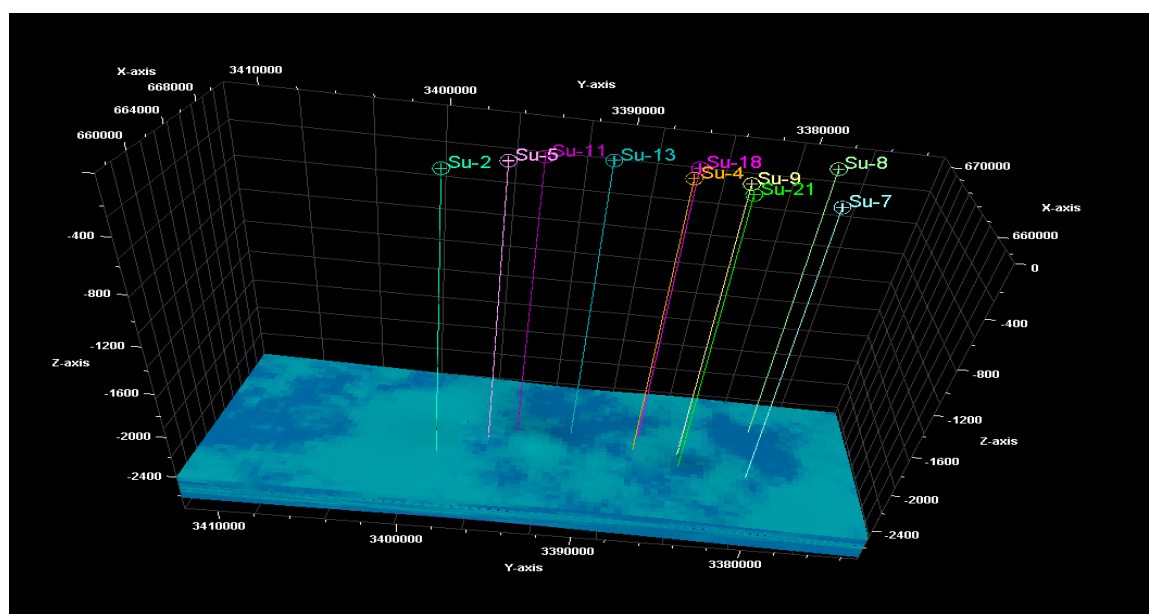


Fig. 6. Well section position in Nahr Omr formation

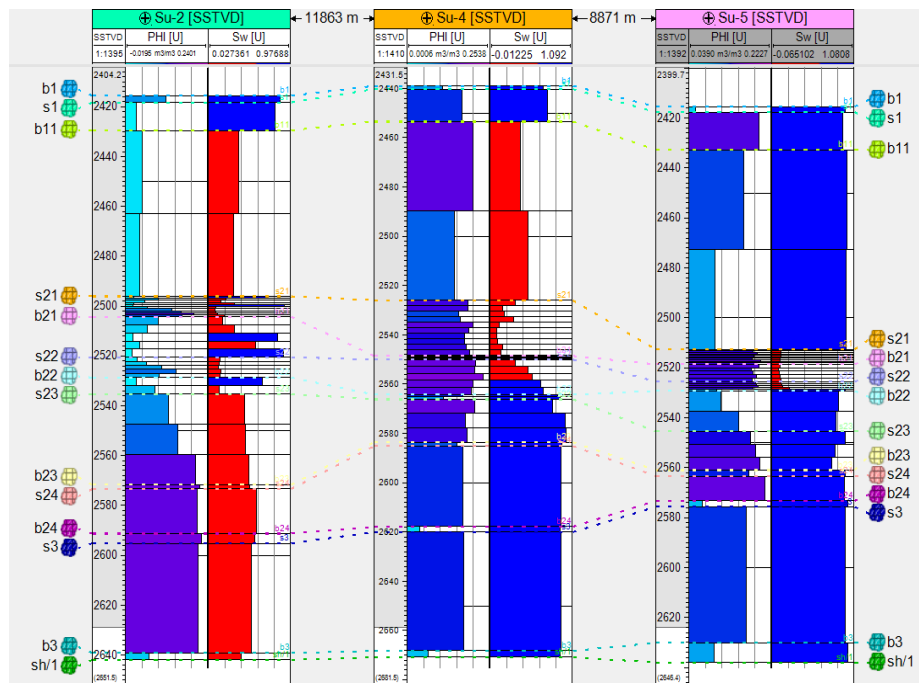


Fig. 7. Well section for wells Su-2, Su-4 and Su-5

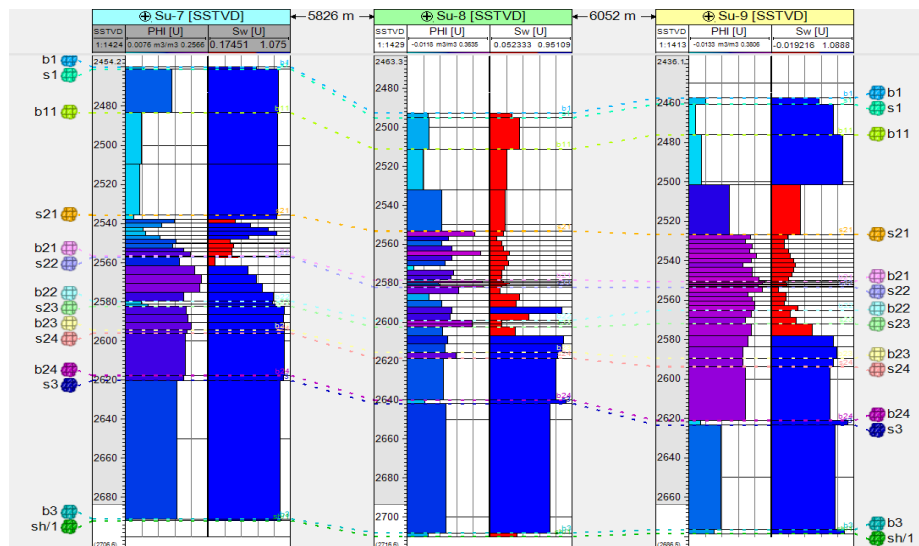


Fig. 8. Well section for wells Su-7, Su-8 and Su-9

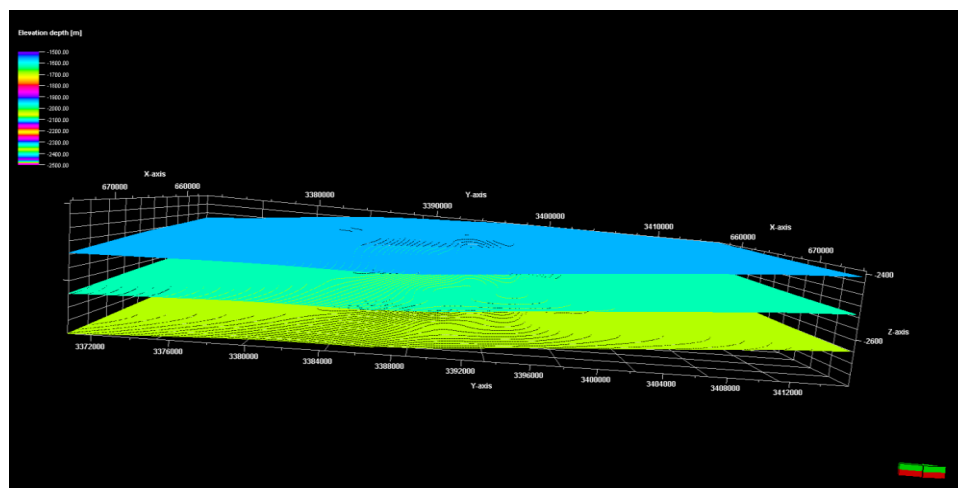


Fig. 9. The Skeletons for Subba oil field no formation

2.6.4. Well log property upscaling (scale-up of well logs)

Before assigning petrophysical properties on the 3D grid system, it was necessary to upscale the continuous well logs into cell values in the model Fig. 11. High-resolution petrophysical properties like porosity, water saturation, and permeability were averaged over all intersecting cells. Porosity and saturation properties were

arithmetically averaged, whereas permeability was averaged geometrically to correctly reflect fluid flow capability in the cells [24]. After up sampling, the simulation grid contained 122,026 active cells and provided a compromise between computational performance and the maintenance of reservoir heterogeneity.

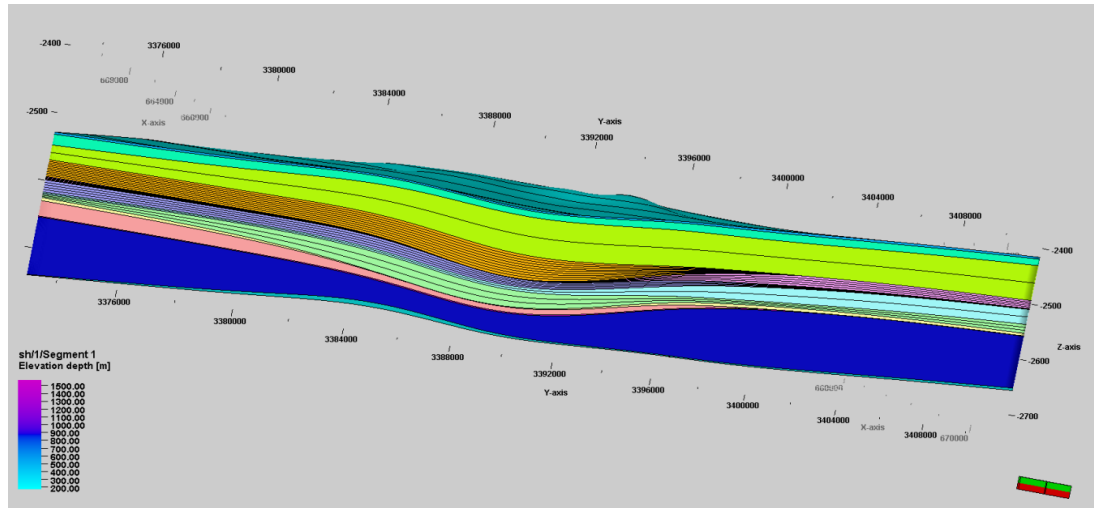


Fig. 10. Layering and horizon for no formation

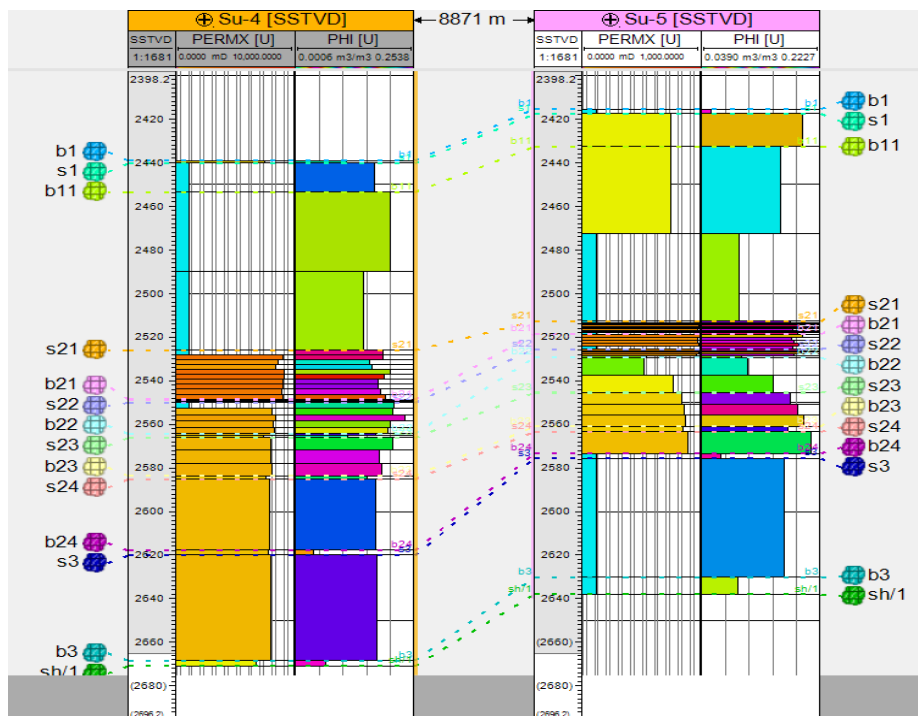


Fig. 11. Scale-up porosity and permeability for well Su-4 and Su-5

2.7. Petrophysical property modeling (stochastic modeling)

Distribution of petrophysical properties was performed through geostatistical techniques that respect not only the well data but also spatial trends in petrophysical property variation:

2.7.1. Effective porosity modeling

The effective porosity of the 3D model was generated by applying Sequential Gaussian Simulation (SGS) technique [25]. This is a probabilistic method used to capture the variability of the upscaled well log data along

with the distribution statistics obtained from the analysis of Techlog data and core samples shown in Fig. 12.

2.7.2. Modeling water saturation (Sw)

Based on the SGS technique along with Archie's parameters, the distribution of water saturation was modeled. The placement of Sw was entirely dependent upon structural elevation and porosity of the rock to ensure physical continuity as shown in Fig. 13.

2.7.3. Permeability modeling

In this process, FZI (Flow Zone Indicator) technique was employed together with SGS technique to create the distribution of permeability. This is a regional approach which ensures proper representation of different hydraulic flow units along with high contrasts in permeability values throughout the reservoir shown in Fig. 14. The result of permeability distribution obtained from the FZI-SGS process represents a real description of flow behavior since it retains heterogeneities both laterally and vertically.

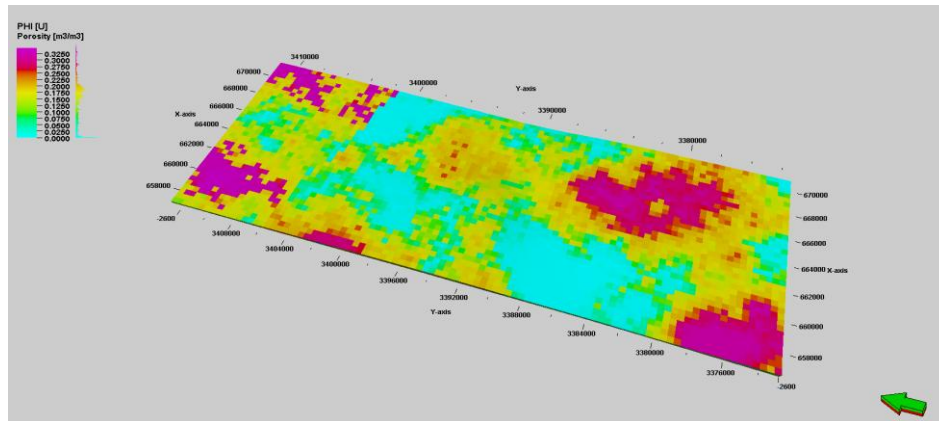


Fig. 12. 3D porosity distribution modeling of unit S21

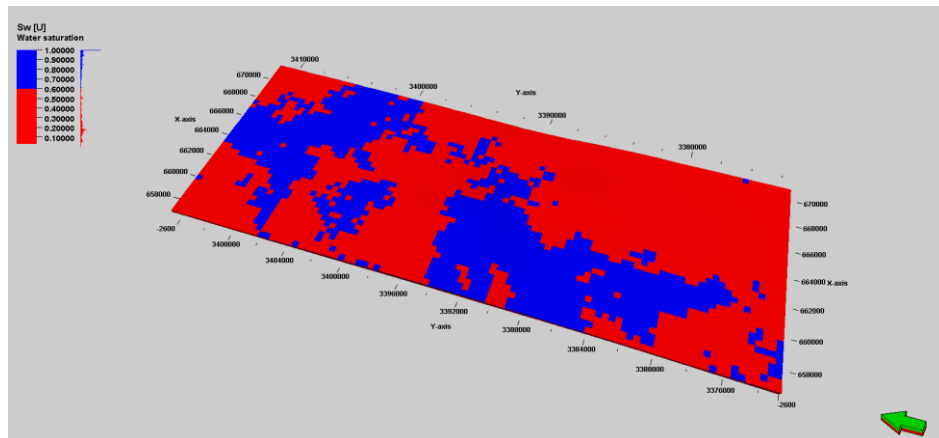


Fig. 13. Water saturation distribution for unit S21

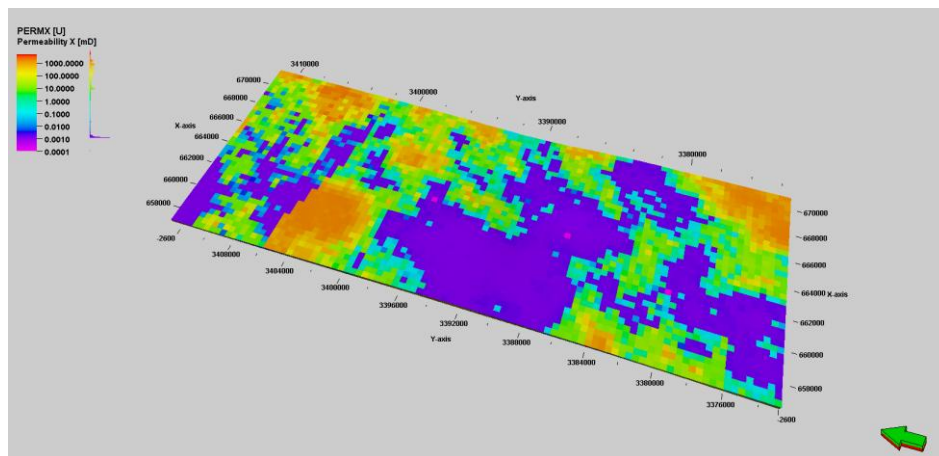


Fig. 14. Permeability distribution for unit S21

2.7.4. Net to gross ratio (NTG) modeling

Deterministic thresholding was done based on effective porosity > 0.065 and $S_w < 0.7$. This helped distinguish between good reservoir and shale formations or tight formations within the grid shown in Fig. 15. Units S21 and S22 have the best reservoir quality as compared to other units in the Petrel model since they have higher porosity, higher permeability, higher net-to-gross ratio, and lower water saturation levels; thus, they are the reservoir units that produce oil.

2.8. Calculation of initial oil in place (IOOP)

The determination of the Original Oil in Place (OOIP) constitutes the last step in the building of the 3D static geological model. As for the OOIP for the Nahr Omr Formation in the Subba field, this parameter has been calculated by applying the volumetric method that is known to be one of the most reliable ways to determine reserves of hydrocarbons. The computation has been done

using Eq. 5 that considers the reservoir volume, the effective porosity, initial water saturation, and the formation volume factor:

$$OOIP = \frac{7758 A h \Phi (1 - S_{wi})}{B_{oi}} \quad (5)$$

Where, OOIP = initial oil in place STB, A=area of reservoir acre, h=net thickness ft, S_{wi} = initial water saturation %, B_{oi} = initial oil formation factor. The formation volume factor (B_{oi}) is calculated from the available PVT analysis and then applied to estimate reserves.

The water contact is one of the key boundaries for this volumetric analysis, especially the Oil-Water Contact (OWC). The OWC True Vertical Depth Subsea was calculated using RFT data obtained from the Su-4 well, and the value was determined to be 2533 m SSTVD, as shown in Fig. 16. In addition, the initial Oil formation volume factor B_{oi} was determined using PVT reports, and it was used to calculate the reserves.

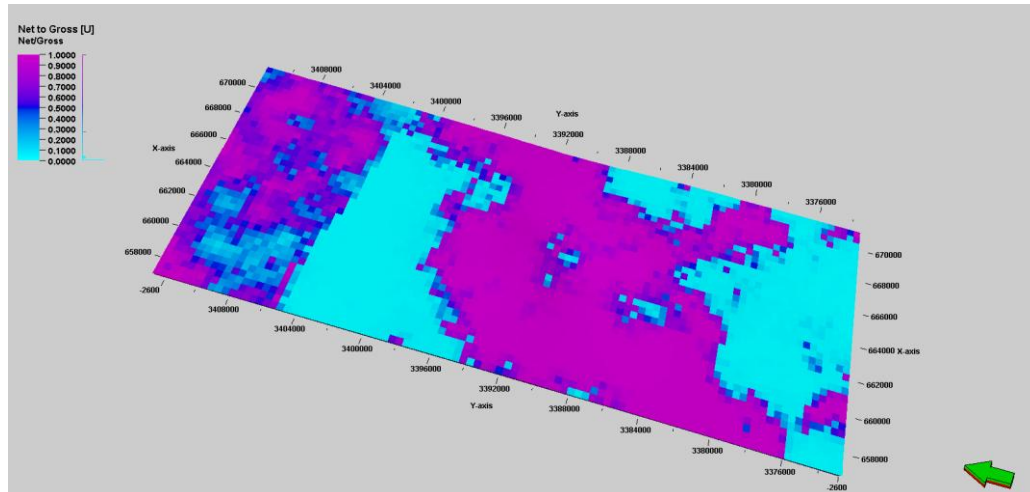


Fig. 15. NTG distribution for unit S21

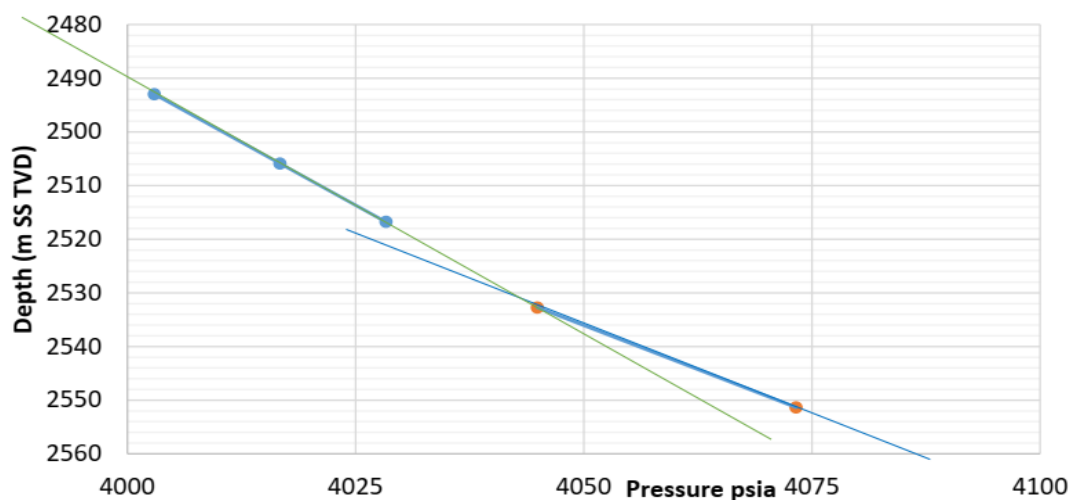


Fig. 16. RFT points test for Su-4 and OWC (Mahdi M. Jawad, 2024)

Then, 15 g of activated carbon is precisely weighed and added to the solution under ultrasonic homogenization for 2 hr.

- Comparative analysis with previous studies

Many researchers estimated the OOIP in the Nahr Omr formation of Subba field. Their estimates were compiled as shown in Table 3.

Table 3. OOIP findings derived from earlier research with current study

Studies	OOIP
INOC (1978)	1.283 (MMM STB)
INOC (1979)	2.459 (MMM STB)
INOC (1987)	1.289 (MMM STB)
MoO/RFDD (1993)	1.603 (MMM STB)
Anadarko Petroleum (2009)	1.984 (MMM STB)
Israa J. (2015)	1.522 (MMM STB)
Ahmed R. (2016)	1.05 (MMM STB)
MoO/RFDD (2020)	1.8995 (MMM STB)
Mahdi M. Jawad (2024)	2.03 (MMMSTB)
Current Study	2.07 (MMMSTB)

The result of 2.07 billion stock tank barrels (STB) for OOIP is in line with recent studies, even though there may be slight differences because of variations in geological modeling and petrophysical interpretation.

3- Dynamic reservoir modeling workflow (CMG)

After constructing the static 3D geological model of the Nahr Omr (NO) reservoir, the process moved onto the numerical reservoir simulation utilizing Computer Modeling Group (CMG) software; more particularly, the IMEX simulator. This stage intends to develop a dynamic sound model that can help forecast the reservoir's performance in the future. Moreover, model accuracy will be validated through history matching. Below is a description of the detailed step-by-step sequential workflow carried out in CMG:

3.1. Grid upscaling and geometric export

In order to improve computational efficiency and reduce simulation time without losing geological heterogeneities, a procedure called grid Upscaling was conducted on the geological structures and rock properties. As a result, the number of grid cells created in the reservoir is 37 grids in the X-direction, 97 grids in the Y-direction, and 34 grids in the Z-direction, producing a total reservoir volume of 122,026 active grid cells. The geometric grid and rock properties were successfully exported using RESCUE file format and were successfully initialized in CMG builder platform as shown in Fig. 17. The scaling ratios were selected in such a way that the key geological heterogeneity would be preserved, while the simulation time would be greatly reduced.

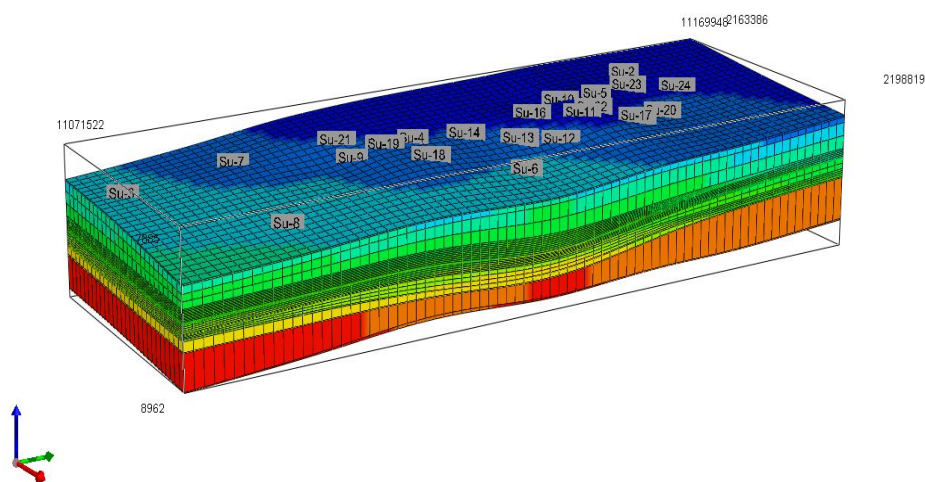


Fig. 17. Exported model for NO formation in CMG

3.2. Incorporation of rock-fluid properties and relative permeabilities

Once the grid was established, the rock-fluid properties from laboratory experiments were incorporated to model the multi-phase flow. Rock Compressibility: The basic parameters describing rock compressibility and its

relation to varying pore volumes under different pressures of the fluids in the reservoir were set. Relative Permeabilities (K_{rw}, K_{ro}, K_{rg}): The curves obtained for the relative permeability values and the capillary pressures (P_c) were considered. The modeling of this step was performed by considering the flow dynamics of oil,

water, and gas phases inside the sandstone structure see Fig. 18.

3.3. Fluid properties modeling (PVT data input)

To be able to model phase properties and volume changes at varying reservoir pressures, the datasets were

obtained using laboratory experiments for the reservoir fluids. Models describing the phase properties of both oil and water were created in CMG's PVT tool. The basic parameters that were set include the oil formation volume factors (B_o), gas-oil ratios (R_s), fluid viscosities (μ_o, μ_w), and bubble point pressures (P_b) Fig. 19.

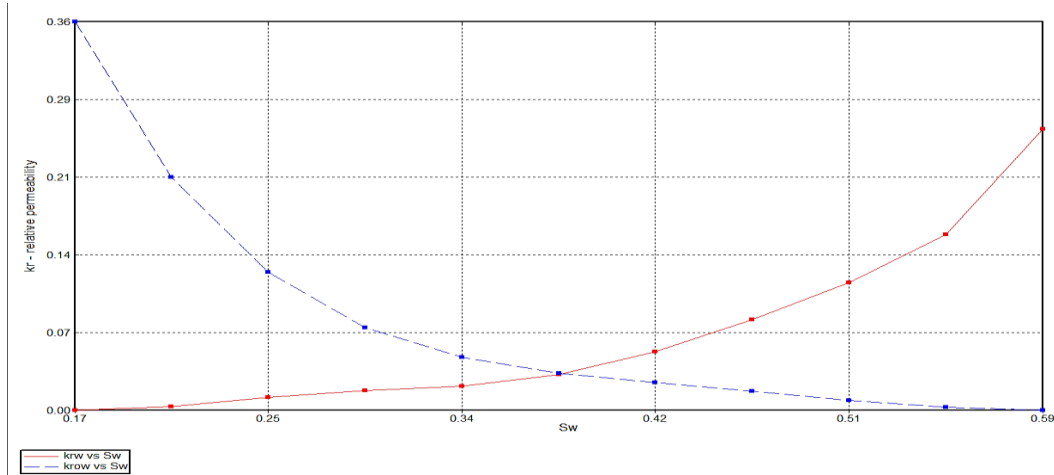


Fig. 18. Relative permeabilities of oil and water (K_{row}) and K_{rw} to water saturation (S_w) for Nahr Omr formation

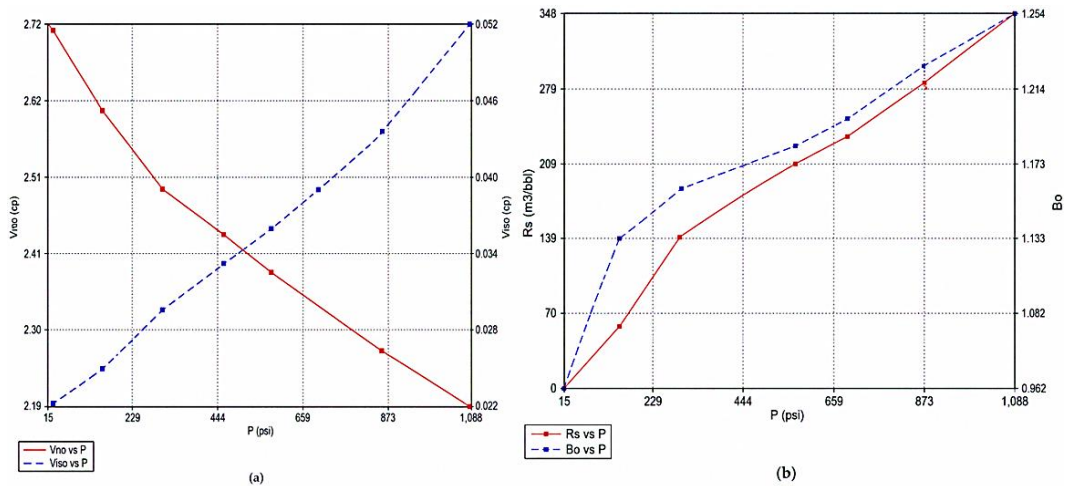


Fig. 19. (a) Variation of oil and gas viscosities (μ_o and μ_g) as a function of reservoir pressure, (b) Solution gas-oil ratio (R_s) and oil formation volume factor (B_o) to reservoir pressure (P) based on PVT laboratory test

3.4. Well trajectory and production data initialization constraints and production data were provided to the dynamic model

Well Placement: The exact positions of each well along its trajectory, including its perforation and coordinates in the field, were determined inside the upscaled grid blocks. **Production History:** Historical constraints of production, i.e., daily oil production, water cuts, and pressure of reservoirs, were allocated to three production wells to use as the initial constraints for the dynamic model.

3.5. Reservoir initialization and history matching (history matching) this step is part of the final stage of the dynamic simulation workflow

Initialization: The initial distributions of fluid saturations (S_{oi} , S_{wi}) and equilibrium pressure

distribution were calculated using the Oil-Water Contact (OWC) predefined above. **History Matching:** The model was continuously calibrating based on comparison with real historical data. Properties of rock and relative permeability were adjusted in order to minimize the deviation between simulated results and actual results as shown Fig. 20, Fig. 21. The history matching procedure was performed through an iterative technique, in which permeability multipliers, relative permeability functions, and rock compressibility were tuned within reasonable geological limits.

4- Result

Spatial Petrophysical Properties Distribution: Stochastic 3D modeling using Sequential Gaussian Simulation (SGS) successfully provided mapping of the petrophysical properties throughout 1,234,200 grid cells. It was evident

that the core sands have outstanding developments, which showed very high effective porosity (Φ_e) and NTG values. Volume Estimation:

Through analysis of RFT log and laboratory PVT, a new OWC at a depth of 2533 m SSTVD was determined, while the updated OOIP estimation stood at 2.07 billion STB.

It is obvious from the modeling of the petrophysical distribution that S21 and S22 are the most productive reservoir layers owing to the better reservoir properties and flow performance.

Dynamic Framework Setup: Grid-Up-scaling was applied to establish the structural sizes within 122,026 simulation cells using CMG IMEX. With incorporation of lab-derived multiphase relative permeabilities (K_{rw} , K_{ro} , K_{rg}) as well as pressure-sensitive fluid parameters (B_o , R_s , u_o), dynamic initialization was set up successfully.

History Matching: Field-wide production history matching resulted in a high coefficient of determination (R^2) of 0.957 for the production rate. For Well A, the history match reached an outstanding R^2 of 0.981 with 28 data points.

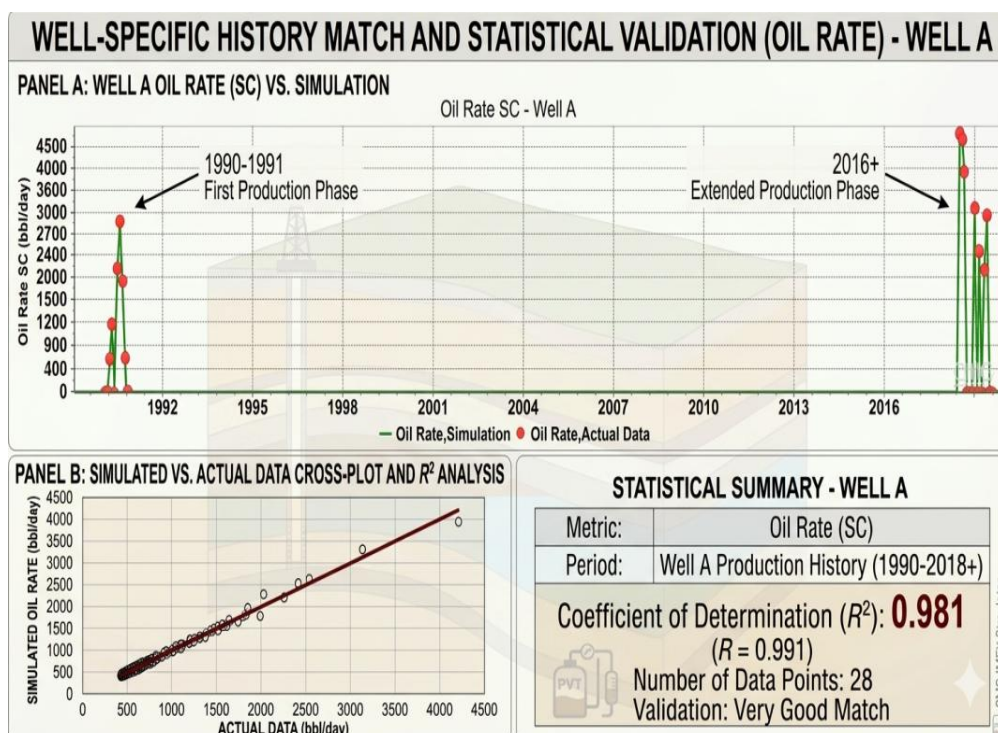


Fig. 20. Cumulative oil flow rate matching well A

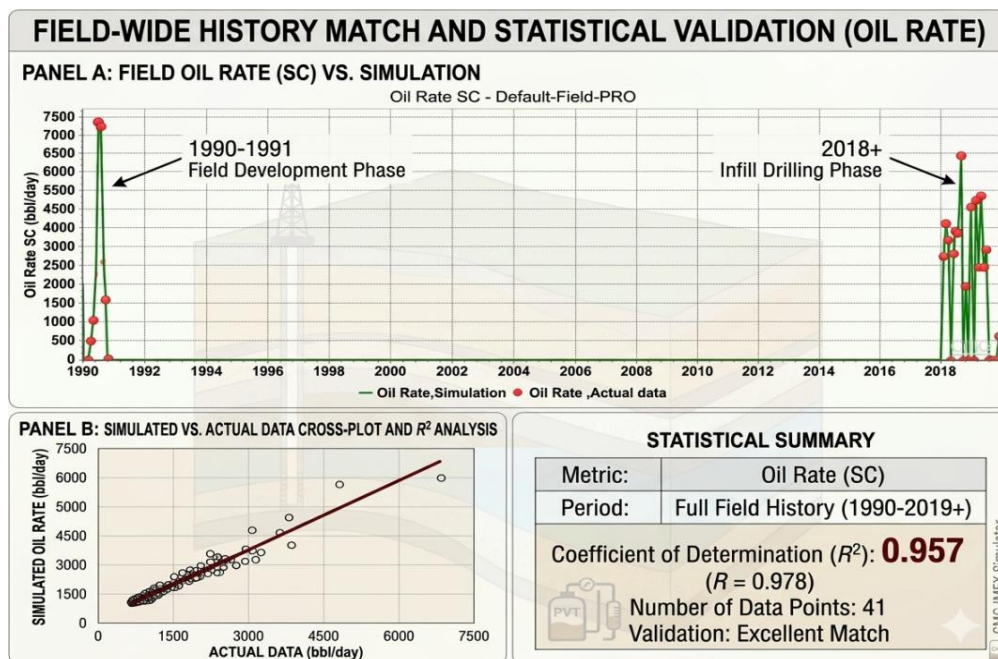


Fig. 21. Cumulative oil flow rate matching the Field

5- Discussion

Due to the complex nature of the Nahr Umr Formation, a zone-wise petrophysical analysis was necessary as opposed to using global average parameters of reservoirs. Based on petrophysical analysis, the S21 and S22 zones were found to be the main reservoir rocks with high porosity, low water saturation, and good reservoir properties. They have always shown the highest effective porosity, permeability, and net/gross ratio in the static Petrel model, which made them major components in reservoir storage and fluid movement. Classifying the reservoir zones as seven flow zones was sufficient in representing changes in pore system properties and heterogeneity of the reservoir rocks.

Validity of the hydraulic flow unit (HFU) classification was established based on different behaviors exhibited during PCA Crossplot and high correlations between permeabilities from FZI analysis and laboratory testing ($R^2 = 0.9026$). Moreover, an estimate of 2.07 billion STB of OOIP obtained for this reservoir was comparable with other studies validating the adopted modeling methodology. History matching of the reservoir resulted in good correlation with observed production data with coefficients of determination (R^2) of 0.957 at the field level and 0.981 for Well A.

6- Conclusion

The inclusion of Petrel static modeling with the CMG simulation allows the formation of a reliable predictor of the Nahr Umr shale-sand reservoir.

Unit S21 and S22 are established to be the main routes of fluid movement with high effective porosity, low water saturation, and high-quality sand facies.

The segmentation approach based on the 7-HFU classification system effectively accounts for vertical and lateral heterogeneities without exaggerating the fluid movement routes.

The history matched dynamic model and the determined OOIP of 2.07 billion STB represent an accurate database that meets corporate data protection standards and also acts as a base for future developments.

This workflow can be applied to other clastic heterogeneous reservoirs, if the petrophysical and dynamic data are correctly calibrated.

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النمذجة الثابتة والديناميكية التي تدمج نهج FZI مع النمذجة العشوائية لتوصيف خزانات الطين الرملي غير المتجانسة

احمد جبل^١، نغم جاسم^١

^١ قسم هندسة النفط، كلية الهندسة، جامعة بغداد، بغداد، العراق

الخلاصة

تُعد محاكاة المكامن ضروريةً لتطوير الحقول على النحو الأمثل وتخطيط عمليات الاستخراج. يهدف هذا العمل إلى تطوير منهجية متكاملة تجمع بين التحليل الثابت والديناميكي لنمذجة تكوين نهر عمر غير المتجانس والرملي الطيني في حقل صبة النفط بالعراق. استُخدمت مجموعة بيانات مُحدّثة لمعدلات الإنتاج وبيانات الخصائص الفيزيائية والكيميائية والحرارية (PVT) من شركة ذي قار للنفط في بناء نموذج ثابت عالي الدقة باستخدام برنامج بترول، يشمل ١٠ آبار، وسجلات صوتية لتقييم المسامية، وبيانات زلزالية ثنائية الأبعاد للنمذجة الهيكلية. ولإدراج عدم التجانس داخل المكن، استُخدمت تقنية مؤشر منطقة التدفق (FZI) لتصنيف الفترات إلى ٧ وحدات تدفق هيدروليكي (HFUs). ووفقاً للتحليل البتروفيزيائي، تم تحديد الوحدتين S21 و S22 كوحدتي المكن الرئيسيتين، حيث تتميزان بنسبة عالية من الرمال النظيفة، ومسامية فعّالة عالية، ومستويات تشبع منخفضة بالماء. تم لاحقاً توسيع نطاق النموذج الثابت ليصبح محاكاة ديناميكية للمكن (CMG IMEX)، باستخدام قياسات مخبرية لخصائص السوائل والنفاذية النسبية متعددة الأطوار. بالإضافة إلى ذلك، تم تقدير احتياطي النفط الأصلي في المكان (OOIP) بـ ٢,٠٧ مليار برميل قياسي، ومستوى التماس بين النفط والماء (OWC) عند عمق ٢٥٣٣ متراً (SSTVD) بناءً على حسابات حجمية. ونتيجة لذلك، تم تحقيق تطابق تاريخي ممتاز، حيث بلغت قيمة معامل التحديد ($R^2 = 0.957$) لجميع الحقول، بينما بلغت ٠,٩٨١ للبئر A.

الكلمات الدالة: نموذج جيولوجي ثابت، نموذج جيولوجي ديناميكي، تكوين نهر عمر، خزان غير متجانس، FZI.