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Improved Estimation of Petrophysical Parameters Using Nuclear Magnetic Resonance and Conventional Well Logs in a Southwestern Oil Field of Iran

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Highlights

- Petrophysical evaluation of Sarvak reservoirs was conducted with conventional reservoir diagrams and NMR.
- Petrophysical parameters such as free fluid volume and total porosity were investigated.
- The MRGC clustering method was used to estimate the NMR output.
- NMR diagram output was interpreted using conventional reservoir diagrams (RHOB, NPHI).
- A cross diagram was drawn for two parameters: irreducible water saturation (SWir) log and reservoir porosity.

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Abstract

This study presents an advanced petrophysical evaluation of the Sarvak Formation in a major supergiant oil field in southwestern Iran, achieved by integrating Nuclear Magnetic Resonance (NMR) log data with conventional well logs. NMR measurements from Well-A were analyzed to extract critical reservoir properties—including total and effective porosity, as well as volumes of bound and free water—which significantly improved the accuracy of the petrophysical model. A multi-resolution graph-based clustering (MRGC) algorithm was developed to estimate NMR-derived parameters from conventional logs for the adjacent Well-B, where NMR data were unavailable. The MRGC model utilized gamma-ray, acoustic, density, neutron, and photoelectric logs to predict total and effective porosity, clay-bound water, irreducible water saturation, and other NMR-related parameters. The model was calibrated using data from Well-A and subsequently applied to Well-B, enabling NMR-informed petrophysical characterization in the absence of direct measurements. The optimized petrophysical model demonstrated consistent reservoir characteristics across both wells. Average total porosity was 10.7% in Well-A and 12.2% in Well-B, while effective porosity averaged 10.2% and 11.8%, respectively. Clay volume was approximately 3.2% in Well-A and 3.6% in Well-B, and water saturation was 85% and 84%, respectively. Based on cutoff thresholds of 5% porosity, 15% clay volume, and 50% water saturation, net pay intervals were delineated, yielding approximately 31 m of productive zone out of 411 m in Well-A and 30 m out of 380 m in Well-B. The NMR-augmented analysis provided a more precise differentiation of hydrocarbon-bearing zones and proved more cost-effective than traditional log-based methods. This refined petrophysical workflow significantly enhances reservoir characterization, improves the accuracy of hydrocarbon volume estimation, and supports more informed field development planning.

Keywords: MRGC, NMR log, Petrophysical evaluation, Sarvak formation, Well log

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1. Introduction

Characterizing subsurface reservoirs remains a fundamental challenge in the petroleum industry due to the inherent heterogeneity of geological formations and the variability of petrophysical properties (Yazynina et al., 2021; Nelson, 2001; Meng et al., 2023). These complexities often complicate drilling operations and reduce production efficiency (Bagheri et al., 2021). To address these issues, integrated data acquisition strategies—comprising tailored logging and coring programs—are implemented to generate high-resolution structural and facies maps (Doveton and Watney, 2015). Interpretation of well-log data plays a crucial role in identifying lithologies, determining hydrocarbon-bearing zones, and estimating reservoir parameters such as porosity, clay volume, permeability, and fluid saturation (Bagheri and Falahat, 2021; Mondal and Singh, 2022). Because petrophysical properties cannot be measured directly, well-log interpretation is essential. These techniques leverage relationships between physical measurements—such as resistivity, density, acoustic velocity, and hydrogen index—and rock and fluid properties to infer reservoir characteristics (Schlumberger, 1989; Tanha et al., 2023). Cutoff criteria based on porosity, water saturation, and shale content are then used to delineate net pay zones and compute hydrocarbon pore volume, which are critical for reserve estimation and development planning (Wang et al., 2018).

Accurate reservoir modeling is essential for predicting field performance and guiding economic decisions. Engineers rely on petrophysical models to estimate recoverable hydrocarbons, simulate fluid flow, and optimize well placement. Static reservoir models, built on log-derived rock properties and core data, feed into dynamic simulations to evaluate production performance and recovery strategies (Bagheri et al., 2024). A reliable reservoir model must reflect the interconnected pore structure that controls fluid storage and transport. Well logs provide continuous, high-resolution depth profiles of formation properties. When integrated across multiple wells, they enable field-wide characterization of lithology and fluid saturation (Bagheri and Mohebian, 2025). In wells lacking core data, calibrated petrophysical interpretation workflows become indispensable for estimating reservoir properties (Shedid, 2007; Fu et al., 2020). Core-calibrated log interpretations reduce uncertainty, support lateral correlations, and enhance the geological realism of reservoir models. Standard logs—such as gamma-ray, resistivity, density, neutron, and acoustic—form the foundation of most petrophysical analyses (Rios et al., 2016). In select wells, specialized logs such as NMR provide advanced information on pore structure and fluid types by measuring hydrogen-proton relaxation (Woessner, 2001; Kleinberg, 1996; Kenyon, 1997). NMR logs have become essential tools in reservoir evaluation, serving as downhole laboratories that provide continuous, detailed measurements of total and effective porosity, as well as volumes of movable and bound fluids (Asquith and Krygowski, 2004; Wang et al., 2018; Chen et al., 2019). In formations with complex mineralogy or significant shaliness, where conventional saturation models are often ambiguous, NMR data provide critical insights that enhance reservoir characterization (Masroor et al., 2022; Zargar et al., 2020).

In parallel, artificial intelligence (AI)—particularly machine learning (ML)—has emerged as a powerful tool for subsurface characterization. ML techniques are increasingly used to estimate petrophysical parameters, identify fractures, and predict missing log data (Mohebian et al., 2021; Sarker et al., 2021). Their ability to uncover patterns in large, high-dimensional datasets makes them invaluable for modern reservoir analysis. Among these, unsupervised learning techniques such as clustering algorithms have proven particularly effective for classifying unlabeled data and characterizing complex lithological variations (Suyal and Sharma, 2024; Rabiller, 2005). However, the performance of ML models is highly sensitive to the quality, representativeness, and volume of training data. Recent advances have demonstrated the utility of ML methods—including artificial neural networks, fuzzy logic, and regression models—in predicting porosity, water saturation, and other reservoir attributes from conventional well logs (Mohebian et al., 2021). Graph-based clustering techniques, particularly multi-resolution graph-based clustering (MRGC), have also shown promise in estimating missing logs and defining electrofacies without requiring prior knowledge of the number of clusters (Ye and Rabiller, 2000; Rabiller, 2005; Azizzadeh et al., 2024). Additionally, hybrid models, such as neural networks combined with fuzzy logic, have been applied to generate synthetic NMR responses and identify fluid types (Fu et al., 2024; Rezaeeparto and Bagheri, 2023). Despite these advances, most existing models remain deterministic and often neglect the inherent uncertainty in petrophysical interpretation, limiting their applicability in risk-sensitive decision-making environments.

In this study, we propose an integrated methodology that advances reservoir characterization by combining MRGC-based NMR parameter prediction with a probabilistic petrophysical evaluation framework. The MRGC model is first trained on a key well with actual NMR measurements to estimate critical NMR-derived properties—including total and effective porosity, bound-fluid volume, and free-fluid volume—in neighboring wells lacking NMR data. These synthetic outputs, together with conventional logs, are then incorporated into a probabilistic interpretation scheme to quantify reservoir properties and fluid saturations while explicitly accounting for uncertainty. This dual approach not only expands the availability of high-quality petrophysical data but also ensures that uncertainty is propagated throughout the interpretation workflow. The novelty of this research lies in its fusion of graph-based machine learning and probabilistic modeling to create a robust, scalable framework for synthetic NMR generation and uncertainty-aware petrophysical analysis. Unlike previous studies that treat NMR prediction and reservoir evaluation as isolated tasks, our methodology enables a seamless and cost-effective extension of high-resolution petrophysical insights to wells without advanced logging. This approach substantially improves the reliability of reservoir models, enhances the delineation of productive zones, and ultimately supports more informed field development decisions in data-limited settings.

2. Workflow

This study employs a multi-stage, integrated workflow to enhance petrophysical evaluation of carbonate reservoirs by combining conventional well logs, NMR data, and machine learning methods. Standard wireline logs—including gamma ray, density, neutron, sonic, and photoelectric factor—were collected from two wells, with NMR data available for one of them. All logs underwent comprehensive preprocessing, incorporating environmental corrections based on continuous formation temperature, pressure, and drilling fluid properties extracted from header data, thereby ensuring reliable log responses. Initial petrophysical interpretation was performed using a probabilistic framework that enables simultaneous inversion of multiple logs to estimate critical reservoir properties, such as total and effective porosity, shale volume, and fluid saturation, while explicitly accounting for uncertainties. The NMR data from the reference well were processed using an inversion algorithm to obtain T_2 relaxation time distributions. From these distributions, volumetric parameters—including total porosity, effective porosity, bound-fluid volume, and free-fluid volume—were derived and integrated into the petrophysical model, refining reservoir characterization. To extend these enhanced insights to the neighboring well lacking NMR data, a multi-resolution graph-based clustering model was developed. This model was trained using conventional log inputs and the NMR-derived properties from the reference well as targets. Following validation, the MRGC model predicted synthetic NMR attributes in the adjacent well. These synthetic NMR parameters were incorporated into a re-optimized probabilistic petrophysical interpretation, enabling improved lithological and fluid characterization in the well without direct NMR measurements. The workflow concludes with the delineation of productive hydrocarbon-bearing intervals by applying established cutoff criteria to the refined petrophysical results.

3. The study area and formation

The study area, located in southwestern Iran approximately 80 km west of Ahvaz, hosts the country's largest oil field, which is characterized by multiple stacked carbonate reservoirs, including the Fahliyan, Ilam, Gadwan, and Sarvak formations (Movahed et al., 2015). Among these, the Sarvak Formation (Upper Cretaceous, Albian–Turonian) represents the primary reservoir interval, with particular emphasis on its Upper Cenomanian subunit (Hajikazemi et al., 2010). This formation comprises a thick marine carbonate succession deposited along the southern margin of the Neo-Tethys Ocean (Figure 1).

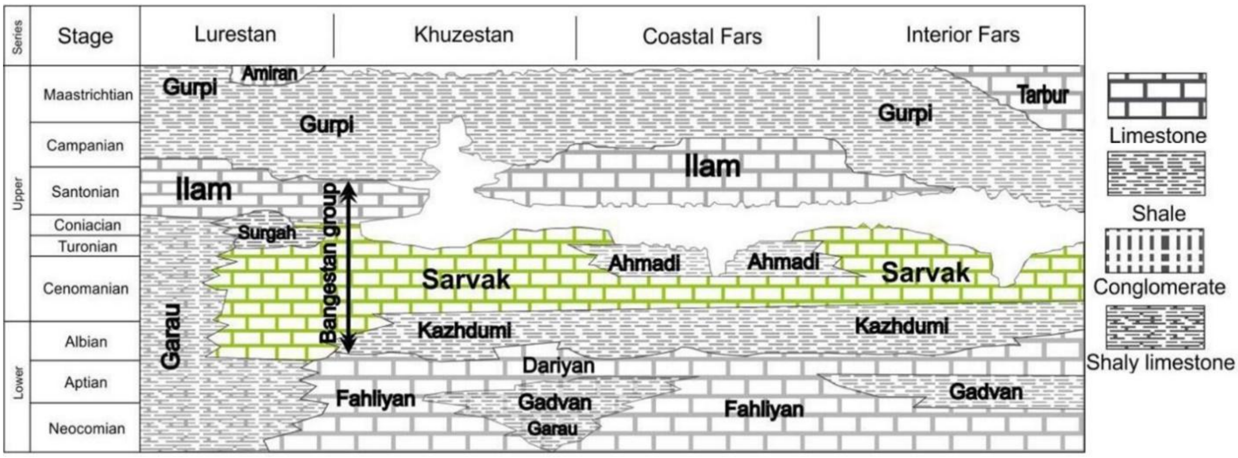


Figure 1

Cretaceous stratigraphic chart of the Zagros region showing the position of the Sarvak formation (Nazari and Hajizadeh, 2023)

Its type section at Tang Sarvak, located on the Bangestan anticline northwest of Behbahan, is well documented (Kalanat et al., 2021). The Sarvak Formation serves as a major hydrocarbon-bearing horizon across southwestern and western Iran (Assadi et al., 2016). Internally, it is subdivided into three main lithologic units: (1) a lower ~255 m interval dominated by gray to dark, fine-grained limestone interspersed with clay-rich nodular layers and thin dark marls; (2) a middle ~524 m section comprising coarse brown to black limestone rich in rudist fragments, with the upper 110 m containing distinctive brown–red silica nodules; and (3) an upper ~43 m unit of thick limestone exhibiting irregular weathering patterns and iron-oxide staining. These lithofacies indicate deposition on a shallow carbonate platform. However, post-depositional diagenetic processes—including cementation, stylolitization, and minor dolomitization—have variably modified primary porosity, either enhancing or occluding pore space. Reservoir productivity is strongly influenced by fine-scale facies heterogeneity and diagenetic texture variations. Structurally, the Sarvak reservoir is hosted within anticlines and associated traps of the Zagros fold belt, such as the Bangestan anticline, where faulting and folding, combined with internal facies architecture, control hydrocarbon accumulation and distribution.

4. Data preparation

In this stage, well header data were utilized to perform the pre-calculation (Precalc) process, which involved computing key parameters related to temperature, pressure, and drilling mud physical properties within the evaluated reservoir interval. The primary parameters included the depths marking the top and bottom of the studied formation, formation temperatures at these depths, drilling fluid density, and the resistivity and temperature values of the drilling mud, its filtrate, and the mud-cake. These parameters were calculated individually for each well. The resulting values were then compiled into continuous logs depicting the variations of temperature, pressure, and drilling fluid properties throughout the Sarvak Formation in the wells under study. These continuous profiles served two main purposes: enabling environmental corrections of the logging data and supporting the evaluation of petrophysical parameters. As illustrated in Figure 2, logging parameters from both wells are presented in multiple tracks: the first column shows depth; the second column displays the gamma-ray log, bit size, and caliper logs; the third column depicts continuously computed drilling fluid parameters, including mud resistivity, filtrate resistivity, and mud-cake resistivity; and the final column presents continuous logs of formation temperature and pressure. The figure demonstrates a clear increase in both temperature and pressure with depth, underscoring the critical influence of environmental factors on logging measurements.

In this context, “environment” encompasses all factors surrounding the logging tools that can alter their responses, including naturally occurring variables such as temperature, pressure, and borehole diameter, as well as operational and chemical effects from drilling fluids and hydrocarbons. Temperature fluctuations significantly affect temperature-sensitive logs, particularly resistivity measurements. Pressure changes impact the mechanical properties of the formation and drilling mud, influencing parameters such as density and acoustic travel time.

Additionally, an increased borehole diameter results in a larger drilling fluid volume surrounding the logging tool, which can attenuate tool signals. The influence of drilling mud on logging responses depends strongly on its physical and chemical properties, including mud type, composition, salt concentration, and additives such as barite or ferrobar. These factors affect multiple logging measurements, including resistivity, density, hydrogen index, gamma-ray, and acoustic travel time. Figure 3 illustrates the application of environmental corrections to gamma-ray, neutron, and density logs from Well A. Both raw and corrected logs are presented side by side within a single track, highlighting the extent of the corrections applied. Notably, neutron and gamma-ray logs exhibit more significant adjustments compared to the density log, reflecting their higher sensitivity to environmental conditions in the wellbore. This emphasizes the essential role of the pre-calculation and environmental correction process in ensuring reliable petrophysical interpretation.

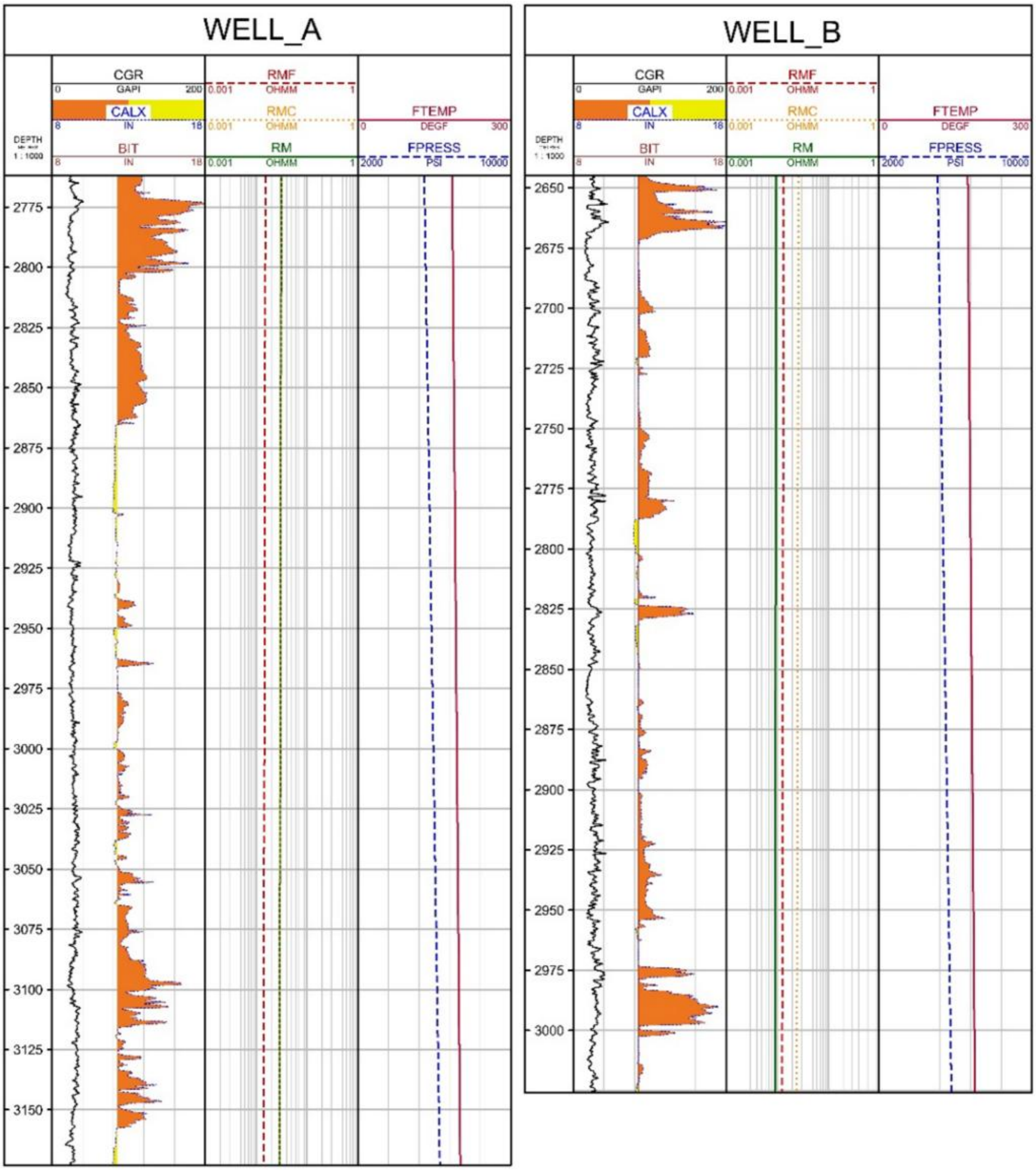


Figure 2

The pre-calculation stage, including continuous logs of temperature, pressure, mud-cake resistivity, filtrate resistivity, and mud resistivity along the reservoir interval

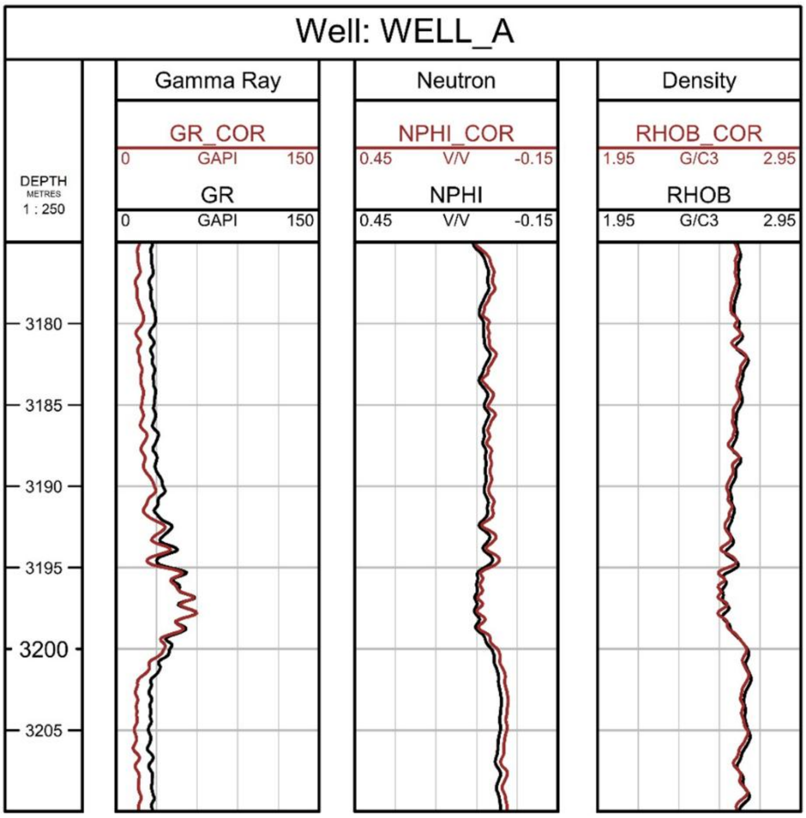


Figure 3

Corrections applied to gamma-ray, neutron, and density logs for the sample in well A

5. Petrophysical evaluation

Paradigm Geolog version 19 offers an advanced multi-well database system designed to efficiently manage extensive well datasets, setting a high standard within the industry. The integrated tools in Geolog 19 provide enhanced capabilities for intuitive data visualization, retrieval, and processing, making it well suited for large-scale petrophysical evaluations. In this study, petrophysical parameters were computed using both deterministic and probabilistic approaches. Deterministic methods produce single, definitive estimates of reservoir properties, offering straightforward interpretations. In contrast, probabilistic methods incorporate uncertainty by generating a range of possible scenarios, thereby providing a more comprehensive understanding of reservoir characteristics and their inherent variability. This dual approach ensures robustness in reservoir characterization and supports more informed decision-making during field development planning.

5.1. Deterministic method

The deterministic petrophysical method, which predates probabilistic approaches, involves the sequential calculation of key reservoir parameters such as total mineral volume, shale volume, porosity, and fluid saturation. A primary advantage of this method is its reliance on a single, well-defined solution with fixed analytical parameters, providing a straightforward and transparent interpretation framework. However, this approach has notable limitations. It typically depends on a limited set of electrical logs, where cumulative random errors from measurements often exceed the number of available logs, reducing overall reliability. As a result, deterministic interpretations tend to be less robust and of lower quality. For example, in gas-bearing zones, porosity calculations often assume water saturation in the underlying equations, neglecting the presence of hydrocarbons. This simplification undermines accurate reservoir characterization. Moreover, when neutron or density logs are involved, significant differences in tool responses to water and gas introduce additional uncertainty in porosity estimates. The deterministic method generally relies on simplified models that exclude data from zones with weak tool responses. Each analytical step focuses on a single formation property, usually derived from one or two logging tools. For instance, gamma-ray log responses primarily indicate shale volume but may be skewed by radioactive minerals such as dolomite or feldspar, as well as effects from drilling mud filtrates or potassium chloride–based muds, which are not accounted for. These factors can lead to misinterpretation of lithology and reservoir quality.

5.2. Probabilistic method

Mayer and Sibbit (1980) introduced a novel approach to reservoir petrophysical interpretation that moves beyond reliance on individual electrical logs to estimate specific parameters. Instead, their method simultaneously integrates all available log data by solving systems of simultaneous equations. This allows for the iterative calculation and refinement of unknown reservoir quantities, such as fluid volumes and mineral fractions, yielding statistically more probable and accurate results. Importantly, this approach enables the incorporation of expert judgment regarding the presence or absence of particular minerals and fluids, thereby enhancing model reliability and flexibility.

The fundamental principle of probabilistic petrophysical analysis is the alignment of measured well-log data with petrophysical models and interpretive functions. Complex multi-mineral models are constructed by using all accessible logs concurrently, forming simultaneous equations to resolve the unknown volumes of reservoir constituents. Optimal performance requires a comprehensive suite of well logs, enabling robust characterization. Grounded in statistics and probability theory, the probabilistic method expresses results as likelihood distributions, with the solution of highest probability accepted as the best estimate. This framework quantitatively evaluates the confidence and quality of interpretations, in contrast to the deterministic method's single-point estimates. Furthermore, it emphasizes continuous validation of model predictions against measured data throughout the evaluation process.

Rather than interpreting isolated petrophysical responses, the probabilistic approach considers the collective behavior of well logs over the entire logged interval. Each electrical log response is predicted as a function of the total volumes of minerals and fluids influencing the measurement. These volumes are iteratively adjusted to minimize discrepancies between observed and predicted log responses within a defined tolerance. For example, the formation density log (ρ_H) response is modeled as follows:

$$\rho_H = \rho_{oil}V_{oil} + \rho_{matrix}V_{matrix} + \rho_{quartz}V_{quartz} + \rho_{dolomite}V_{dolomite} + \rho_{water}V_{water} \tag{1}$$

In this equation, V and ρ represent the volume fractions and densities of the respective constituents. Although multiple combinations of mineral volumes can satisfy the equation, selecting geologically plausible solutions ensures close agreement between modeled and measured density values. The method was further refined through the application of specific linear response equations. While these adjustments initially tended to slightly overestimate instrument readings, subsequent simplifications of Sibbit and Mayer's equations using multiple logs demonstrated minimal impact on overall accuracy. The rise of computational power has since greatly advanced reservoir characterization, enabling more sophisticated probabilistic evaluations.

In 1990, Cannon and Coates emphasized that optimal petrophysical models must integrate electrical logs alongside other data sources (e.g., core analysis, X-ray diffraction) to improve accuracy, as electrical logs alone are insufficient. Compared to deterministic methods, the probabilistic approach offers several key advantages:

- **Reduced error propagation:** Unlike the sequential deterministic approach, where errors accumulate, the probabilistic method incorporates correlations between measured and predicted values, minimizing cumulative errors.
- **Integration of diverse data:** It enables the inclusion of additional geological and petrophysical data, improving interpretative accuracy.
- **Quantitative uncertainty assessment:** Probabilistic results include confidence metrics, validating the reliability of calculations.
- **Incorporation of expert judgment:** Model parameters and design reflect interpreter knowledge, with accuracy statistically quantified.

Given these advantages, this study adopts the probabilistic petrophysical method to calculate reservoir parameters, ensuring a robust and statistically grounded interpretation. In the petrophysical model for the Sarvak reservoir, conductivity logs (derived from formation resistivity logs), neutron, density, gamma-ray, acoustic, and photoelectric logs were considered, along with fixed parameters such as temperature, pressure, mud-filtrate resistivity, and Archie parameters. Based on previous field studies, the Archie parameters m, n, and a were set to 2, 2.1, and 1, respectively, with a formation water resistivity of 0.018 Ω·m.

5.3. NMR processing

In reservoir studies, increasing both the quantity and quality of available data reduces uncertainty and enhances the precision of petrophysical evaluations. This, in turn, supports more effective planning for identifying and exploiting productive zones, directly impacting production costs and the overall economic viability of the reservoir. Typically, petrophysical parameter estimation within well sequences relies primarily on conventional wireline logs, as these are routinely acquired across all wells in a field. However, in strategically selected key wells, supplementary data—such as core samples and advanced logging techniques, including NMR logging—are obtained alongside traditional logs (Golsanami et al., 2021; Rezaee, 2022).

This enriched dataset allows for more accurate identification of productive layers and improved estimation of hydrocarbon volumes, thereby aiding the delineation of economically optimal zones based on hydrocarbon-to-water saturation ratios. By integrating outputs from specialized tools such as NMR logs in key wells, petrophysical evaluations in other wells can be significantly enhanced through the generalization of sensitive NMR-derived parameters. NMR log interpretation provides critical insights into reservoir rock and fluid properties, including porosity, permeability, and fluid volume fractions, which are often difficult to quantify precisely from conventional logs alone (Coates et al., 1999; Yao et al., 2010; Yan et al., 2021).

This section presents the estimation of key petrophysical parameters derived from NMR data interpretation and investigates their relationships with parameters obtained from conventional logs. These relationships are then used to optimize the petrophysical characterization of the target reservoir. Specifically, NMR tool outputs in wells where NMR data are available substantially improve reservoir petrophysical assessments. Among the principal NMR-derived parameters considered are total porosity (PHIT), effective porosity (PHIE), clay-bound water volume (CBW), irreducible water saturation (SWir), and bound fluid volume (BFV). It should be noted that BFV is defined as the sum of CBW and irreducible water volumes (BVI).

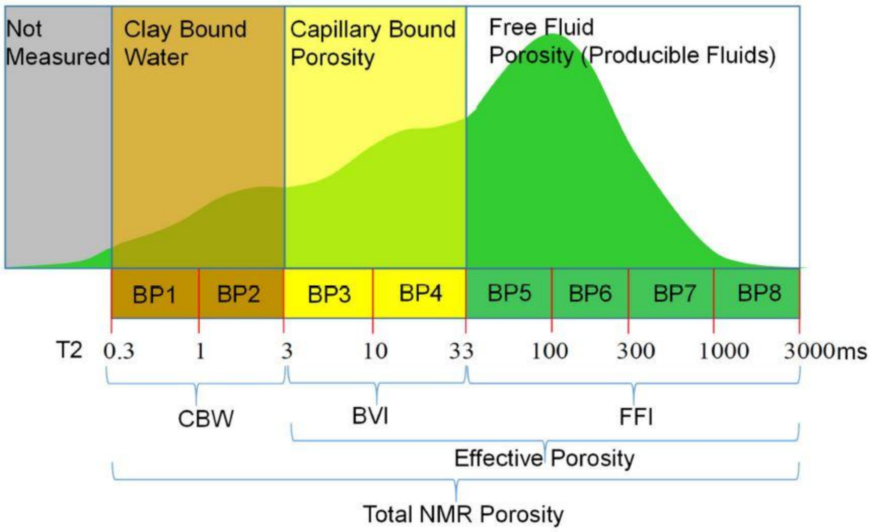


Figure 4

Schematic T_2 relaxation time distribution diagram showing the separation of different fluid volumes and their associated petrophysical parameters (Rezaee, 2022)

By dividing the area under the T_2 distribution curve into eight discrete bins (Figure 4), fluid volumes and associated petrophysical parameters can be calculated using established relationships derived from the relaxation time data.

$$CBW = \sum_{i=1}^{2} Bin_i \tag{2}$$

$$BVI = \sum_{i=3}^{4} Bin_i \tag{3}$$

$$BFV = \sum_{i=1}^{4} Bin_i = CBW + BVI \tag{4}$$

$$FFI = \sum_{i=5}^{8} Bin_i \tag{5}$$

$$PHIE = \sum_{i=3}^{8} Bin_i = BVI + FFI \tag{6}$$

$$PHIT = \sum_{i=1}^{8} Bin_i = BFV + FFI \tag{7}$$

Incorporating outputs from NMR interpretation significantly strengthens petrophysical models by improving the accuracy of parameter estimation. Moreover, extrapolating NMR-derived outputs to wells lacking direct NMR measurements through machine learning or clustering methods markedly enhances the overall reliability of petrophysical evaluations across the entire field. In this study, NMR log data were available for Well A, and the corresponding outputs were calculated. Figure 5 presents the results of the NMR log interpretation in Well A.

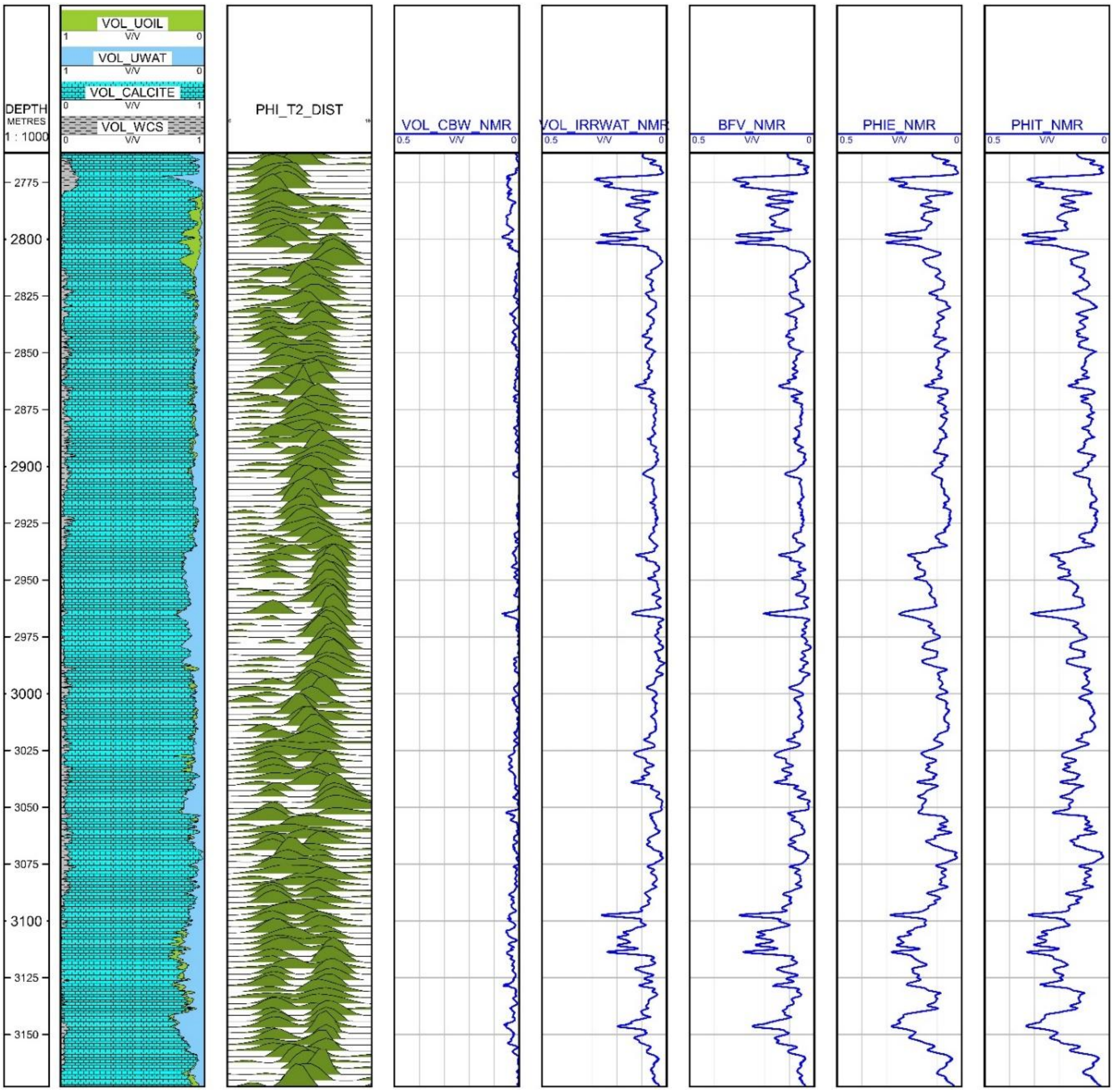


Figure 5

NMR log processing and interpretation results for well A

6. Results and discussion

6.1. Estimation of NMR outputs

Clustering methods represent a widely used approach for estimating log data in the oil industry. These techniques are broadly categorized into supervised (observer-dependent) and unsupervised (observer-independent) methods. Supervised approaches include backpropagation neural networks (BPNN) and fuzzy logic, whereas unsupervised methods encompass self-organizing maps (SOM), ascending hierarchical classification (AHC), dynamic clustering (D-C), and multi-resolution graph-based clustering . Among these, the MRGC method has demonstrated superior effectiveness in identifying electrical facies within carbonate reservoirs. This approach overcomes several limitations common to other clustering techniques, such as the requirement for prior knowledge of the number of clusters, sensitivity to initial parameter selection, and concerns regarding result reliability.

The MRGC algorithm is particularly adept at analyzing complex datasets, naturally classifying groups with varying shapes, sizes, and densities, making it highly suitable for reservoir characterization. Accordingly, the MRGC clustering method was employed in this study to estimate NMR tool outputs in a neighboring well where direct NMR data were unavailable. The input dataset for the MRGC model comprised conventional logs, including gamma-ray (CGR), acoustic transit time (DT), density (RHOB), neutron porosity (NPHI), and photoelectric factor (PEF). The targeted NMR parameters for estimation included total porosity , effective porosity , clay-bound water volume , irreducible water saturation , and bound fluid volume . Figure 6 presents the frequency distributions of both input logs and estimated NMR parameters, while Figure 7 shows cross-plots comparing the input logs with the corresponding estimated values. Analysis of these plots reveals strong correlations between several input and estimated parameters, although some relationships are comparatively weaker.

Taking advantage of MRGC's objective determination of the optimal cluster number, the model identified twelve distinct clusters as the most representative classification based on the relationships between input logs and estimated NMR outputs. Figure 8 illustrates the spatial distribution of these clusters, alongside the frequency distributions of input and estimated data within each category.

The estimation process began by calculating the NMR outputs for Well A, where both actual NMR measurements and predicted values were available. This comparison enabled a robust assessment of the MRGC model's predictive accuracy. After successful validation, the trained MRGC model was applied to neighboring wells lacking NMR logs, allowing for the reliable prediction of NMR parameters in these wells. Figure 9 compares the estimated NMR logs against the actual measurements in Well A, demonstrating close agreement and thus validating the model's performance. Additionally, statistical evaluation of estimation accuracy was conducted via cross-plots between observed and predicted values, as shown in Figure 10, further confirming the robustness of the MRGC-based estimation.

6.2. Estimation of NMR outputs in neighboring wells

The training and validation of the MRGC model in Well A demonstrated highly accurate estimation of NMR outputs across all targeted parameters. This strong performance confirms the robustness of the model in capturing the complex relationships between conventional well log data and NMR-derived petrophysical properties. Building on this validated foundation, it is feasible to extend the MRGC model's application to neighboring wells lacking direct NMR measurements, thereby broadening its practical utility. In this study, the MRGC model—trained using the comprehensive log dataset from Well A, which included gamma-ray (CGR), acoustic transit time (DT), density (RHOB), neutron porosity (NPHI), and photoelectric factor (PEF)—was applied to Well B, a neighboring well without direct NMR data. By inputting the conventional log data from Well B into the pre-trained MRGC model, key NMR parameters, including total porosity , effective porosity , clay-bound water volume , irreducible water saturation , and bound fluid volume , were predicted with high confidence.

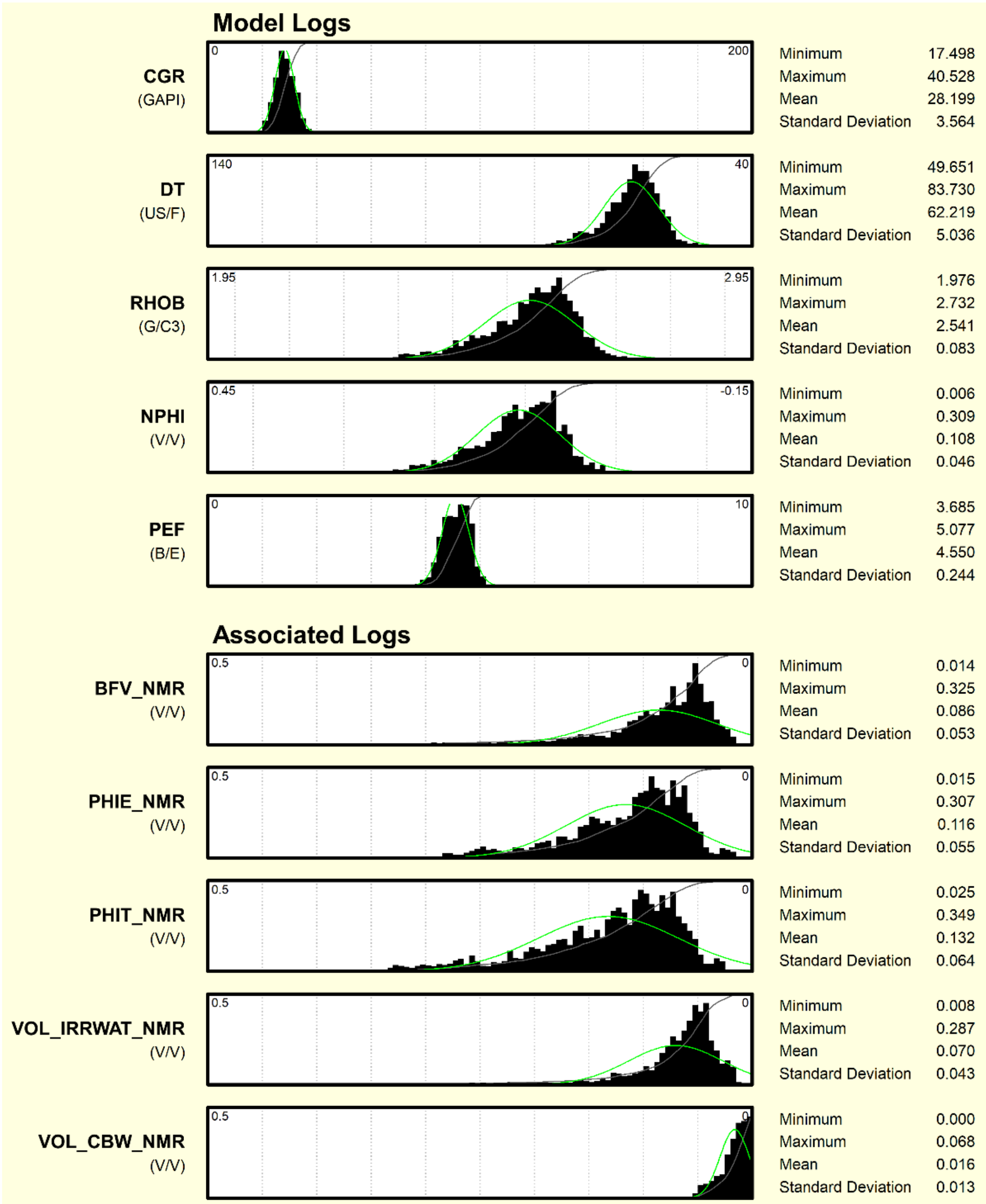


Figure 6

Logs used as input for the MRGC clustering model

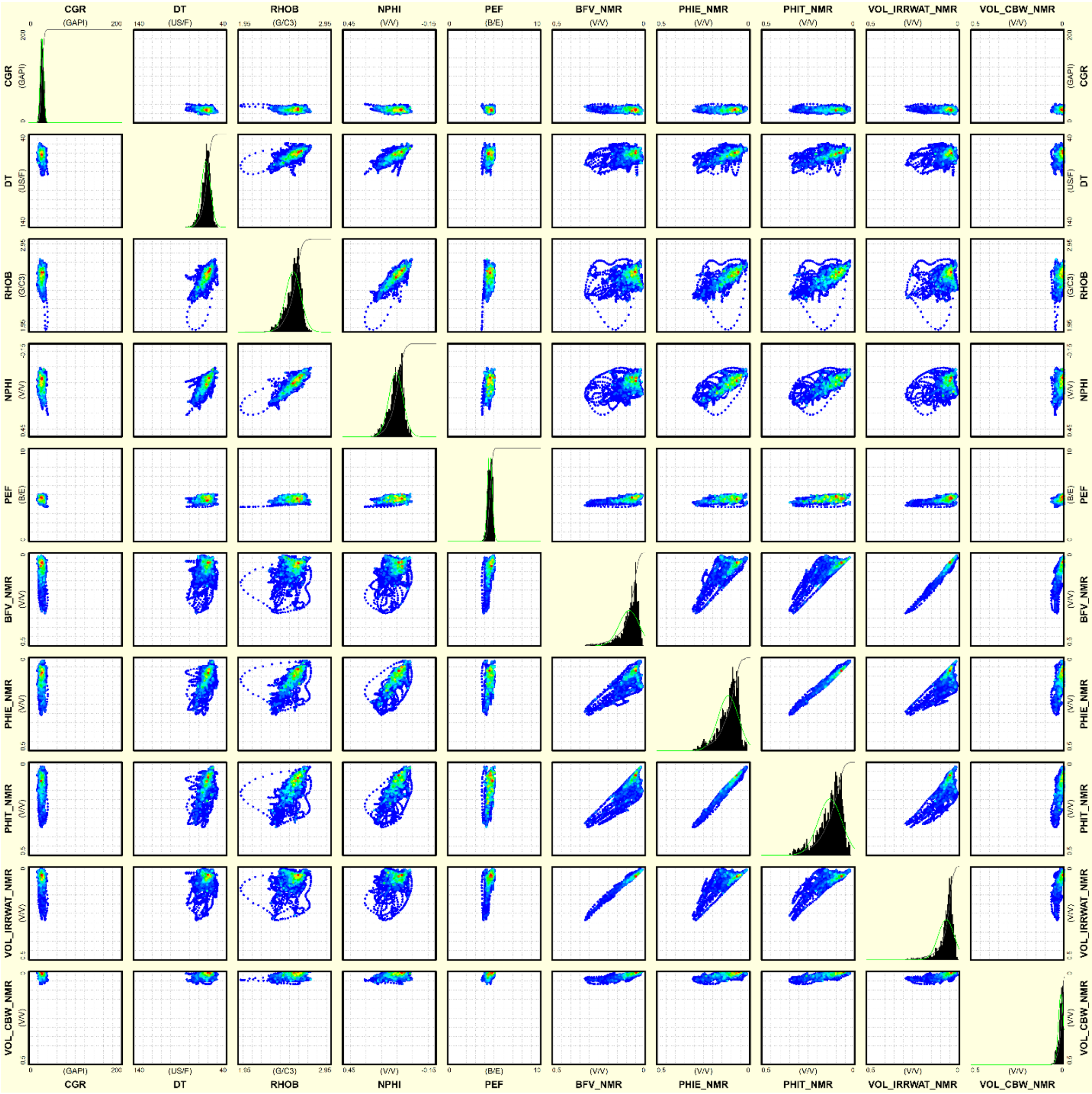
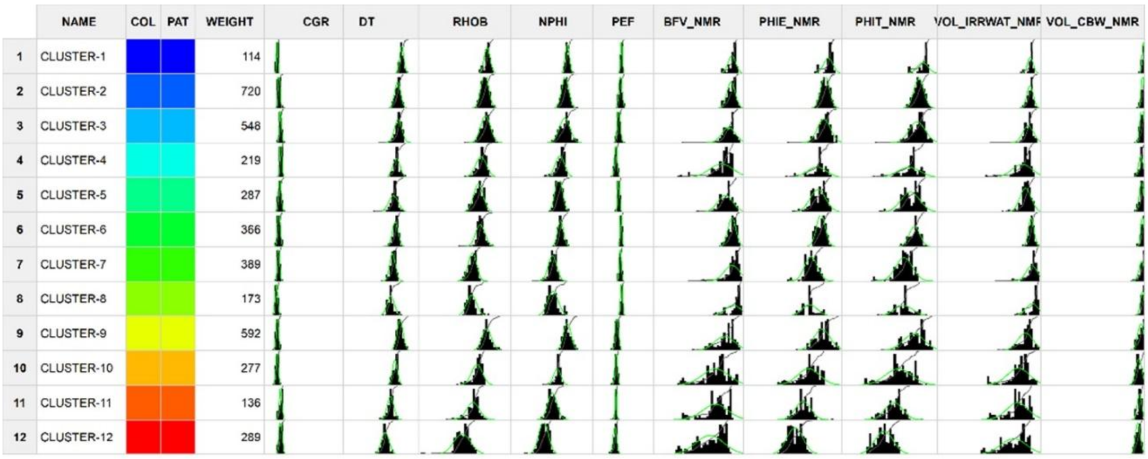


Figure 7

Cross-plots illustrating relationships among input variables



	NAME	COL	PAT	WEIGHT	CGR	DT	RHOB	NPHI	PEF	BFV_NMR	PHIE_NMR	PHIT_NMR	VOL_IRRWAT_NMR	VOL_CBW_NMR
1	CLUSTER-1			114										
2	CLUSTER-2			720										
3	CLUSTER-3			548										
4	CLUSTER-4			219										
5	CLUSTER-5			287										
6	CLUSTER-6			366										
7	CLUSTER-7			389										
8	CLUSTER-8			173										
9	CLUSTER-9			592										
10	CLUSTER-10			277										
11	CLUSTER-11			136										
12	CLUSTER-12			289										

Figure 8

Optimal number of clusters in the MRGC model

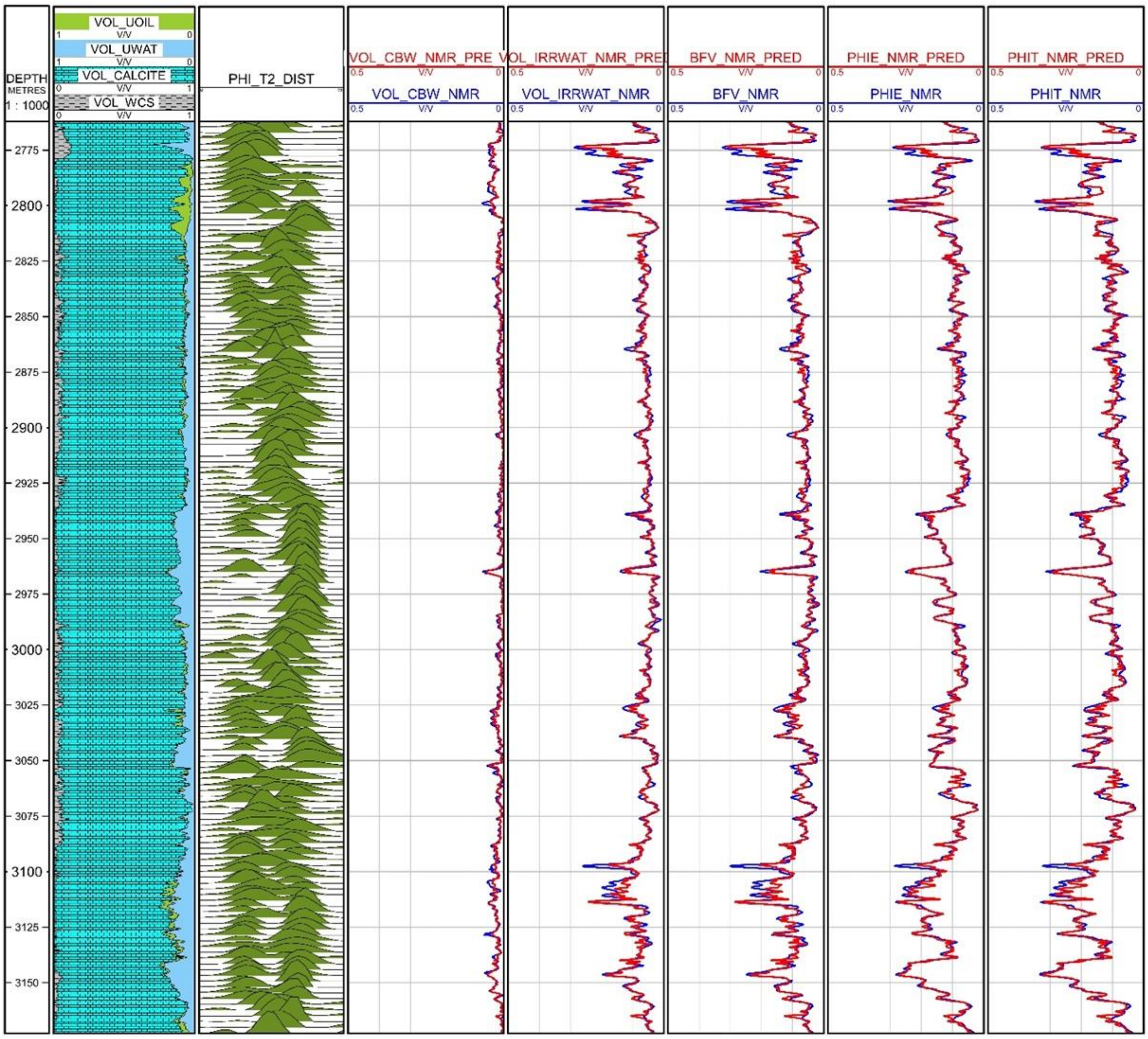


Figure 9

Comparison of NMR log estimates generated by the MRGC algorithm with actual NMR logs in well A

This approach enables the estimation of detailed reservoir petrophysical properties that traditionally require costly and time-intensive direct NMR measurements. Reliably inferring NMR parameters from conventional logs markedly improves petrophysical evaluations, particularly in fields where comprehensive logging suites are not consistently available across all wells.

Figure 11 illustrates the Sarvak reservoir interval in Well B, highlighting the distribution of estimated NMR parameters throughout the reservoir section. These predicted profiles provide valuable insights into the reservoir’s pore structure and fluid saturations, thereby enhancing reservoir characterization. This information supports more informed decision-making in reservoir management and development planning.

In summary, the successful application of the MRGC model to estimate NMR outputs in adjacent wells demonstrates its effectiveness in generalizing across similar reservoir environments. The method provides an efficient and reliable tool for augmenting petrophysical analysis in wells with incomplete datasets, ultimately facilitating improved reservoir evaluation and optimization.

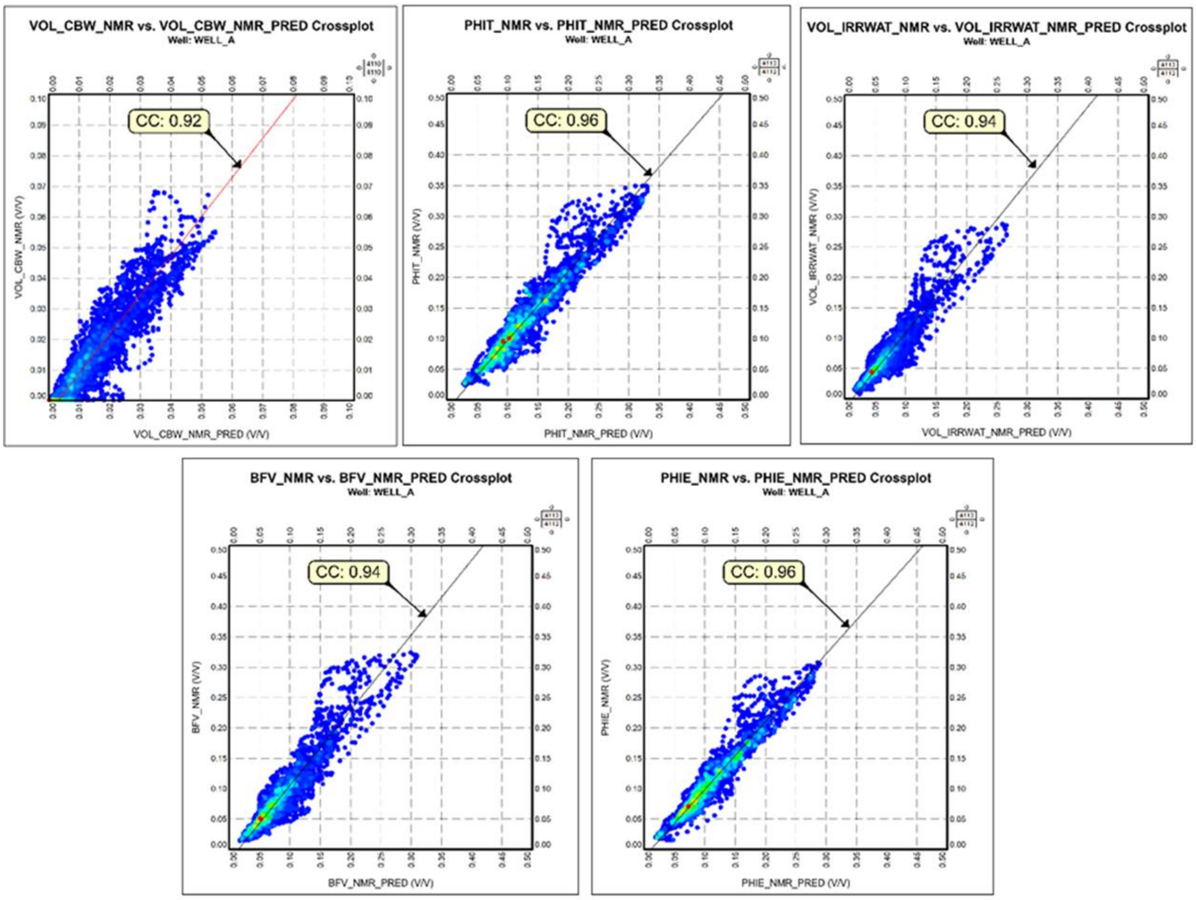


Figure 10

Cross-plots comparing actual and estimated NMR outputs

6.3. Optimal petrophysical model

To enhance the accuracy and reliability of petrophysical evaluations, outputs obtained from NMR logging were integrated into the petrophysical modeling workflow. Incorporating NMR-derived parameters into the petrophysical model enables a more detailed and nuanced characterization of reservoir rock and fluid properties, which is crucial for improving reservoir description and subsequent production forecasting. The accompanying figure illustrates the integration of several key NMR output parameters—such as total porosity , effective porosity , clay-bound water volume , irreducible water saturation , and bound fluid volume —into the petrophysical evaluation framework.

Traditionally, petrophysical models rely on a single form of porosity, typically total or effective porosity, due to limitations in data availability or modeling approaches. However, the inclusion of multiple porosity types and related fluid parameters derived from NMR data provides a more comprehensive understanding of pore space distribution, fluid typing, and saturation levels. This refined petrophysical model was applied to reservoir sequences in Wells A and B, which were selected based on their representativeness and the availability of comprehensive data.

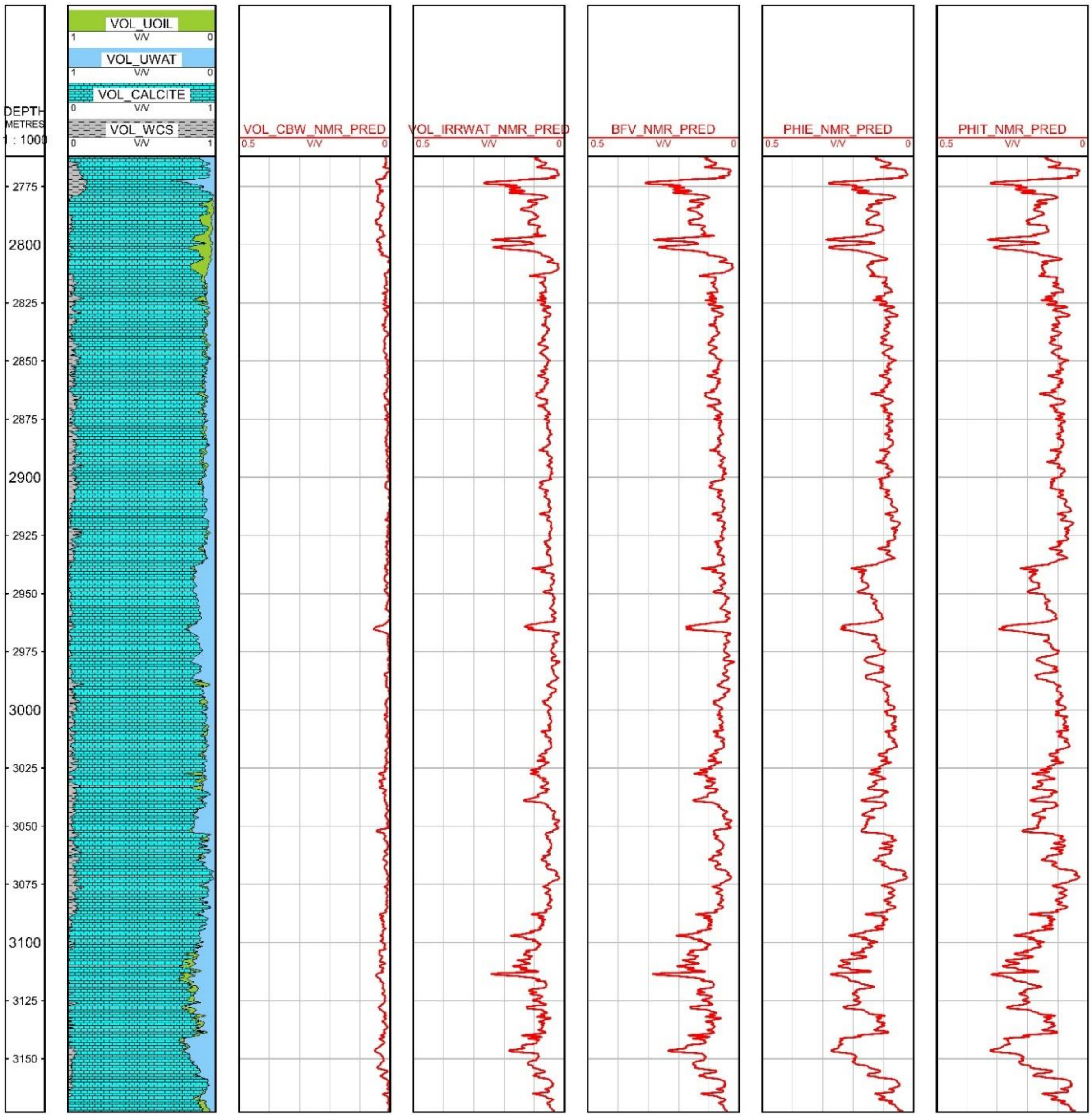


Figure 11

Estimated NMR outputs by the MRGC algorithm in well B, where NMR log data were unavailable

Figure 12 presents comparative visualizations of conventional petrophysical evaluations—based solely on standard logs such as gamma ray, density, neutron, and resistivity—and the optimized models incorporating NMR outputs. Although overall petrophysical parameter estimates appear similar across the entire reservoir interval, a marked improvement is evident within the productive zones of the Sarvak reservoir sequence. In particular, well A exhibits a notable difference in the estimated thickness of the productive interval when comparing conventional and optimized petrophysical interpretations. The conventional approach, relying only on traditional logs, may underestimate or overestimate productive zone thickness due to limited fluid typing and porosity discrimination. In contrast, the optimized petrophysical model enriched with NMR data more effectively captures pore-scale heterogeneities and fluid distributions, resulting in a refined and more accurate delineation of the productive zones. This improvement in defining productive thickness carries significant implications for reservoir management, including enhanced estimation of hydrocarbon volumes, more targeted completion strategies, and optimized production planning. In summary, integrating NMR-derived outputs into petrophysical modeling represents a substantial advancement in reservoir characterization. By providing additional constraints and higher-resolution data on rock and fluid properties, this approach increases the precision of petrophysical assessments and ultimately enables more informed decision-making in reservoir development and exploitation.

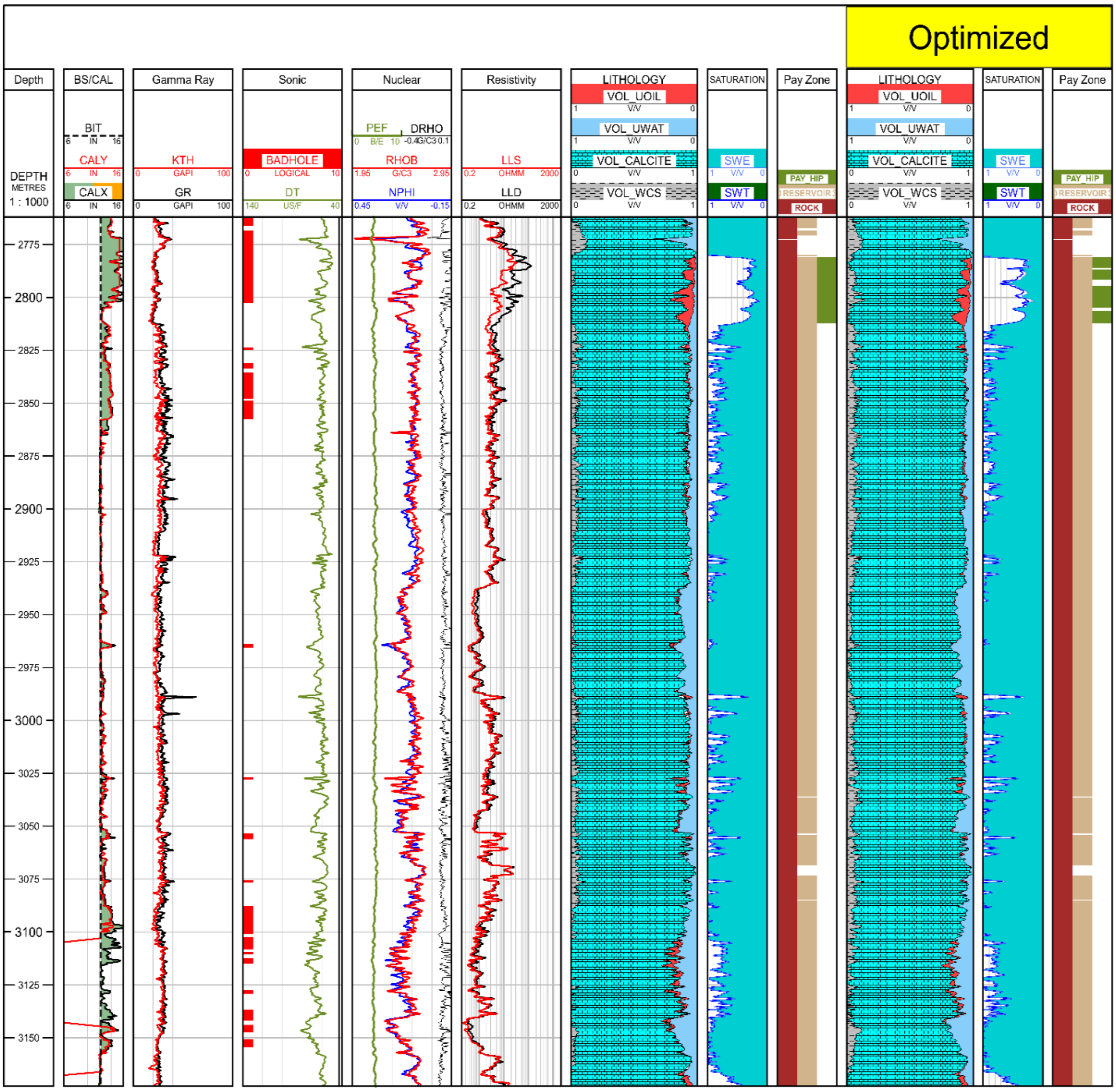


Figure 12

Optimized petrophysical evaluation of the Sarvak reservoir in well A using NMR outputs

Drilling core porosity data were employed to verify and validate the results of the petrophysical evaluation. Figure 13 illustrates the correlation between the total porosity obtained from the petrophysical evaluation and the total porosity measured from the drilling core analysis (CORE_PR). A strong correlation of approximately 92% is observed. Specifically, Figure 13 demonstrates a 92% agreement between porosity derived from core data analysis and porosity obtained from the petrophysical evaluation in Well A. Consequently, by utilizing the estimated NMR log outputs from Well A, the petrophysical evaluation in Well B was also optimized, as shown in Figure 14.

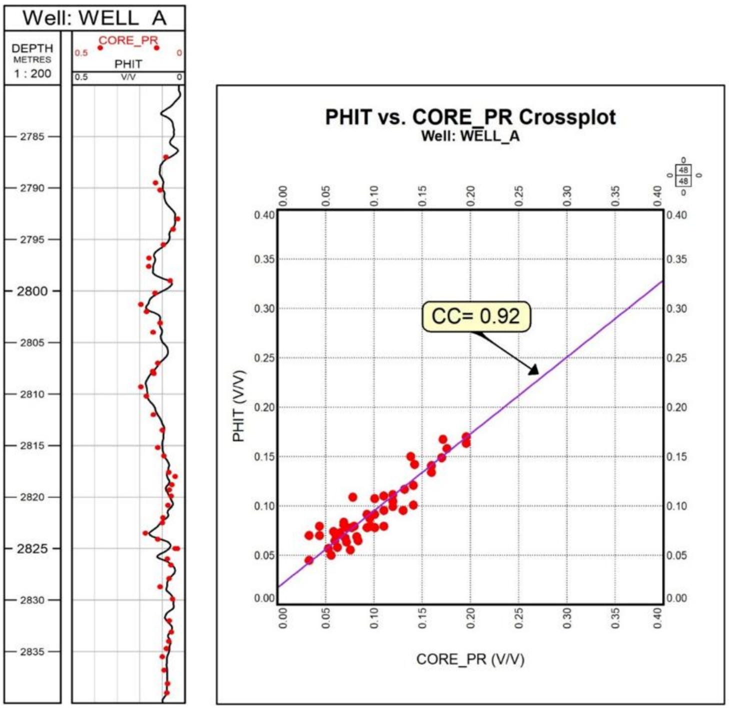


Figure 13

Core porosity compared with porosity from petrophysical evaluation results

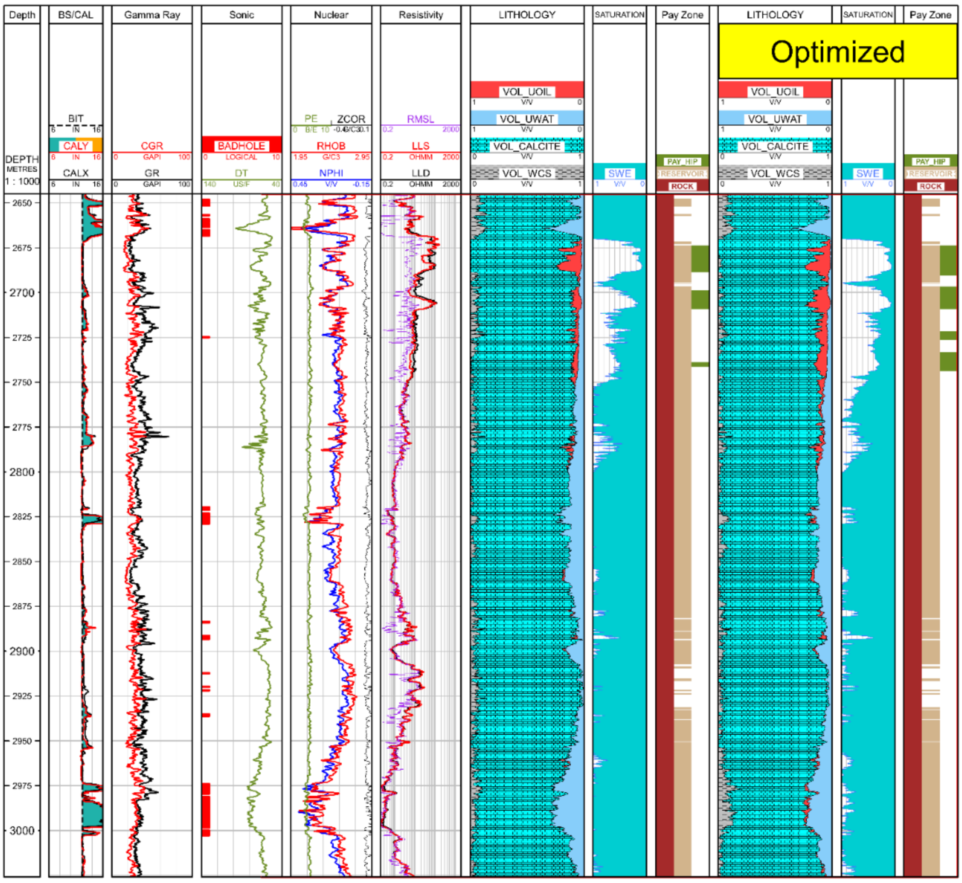


Figure 14

Optimized petrophysical evaluation of the Sarvak reservoir in well B using NMR-derived outputs from the MRGC algorithm

7. Conclusions

This study aimed to enhance the petrophysical evaluation of the Sarvak reservoir in a southwestern oil field in Iran by integrating conventional well logs with NMR data. The key findings are summarized as follows:

- Lithological analysis using neutron-density cross-plots, validated by geophysical well log (GWL) data, confirmed that the Sarvak reservoir in the two studied wells predominantly consists of limestone with minor clay content.
- Petrophysical parameters for the Sarvak formation in wells A and B were estimated using a probabilistic approach based on conventional logs. Average total porosity, effective porosity, shale volume, and water saturation were approximately 10.7%, 10.2%, 3.2%, and 85% in well A, and 12.2%, 11.8%, 3.6%, and 84% in well B, respectively.
- Productive zones were delineated using cutoff thresholds of 5% porosity, 50% water saturation, and 15% shale volume. This identified productive intervals of 31 m out of 411 m in well A and 30 m out of 380 m in well B, corresponding to productive-to-non-productive thickness ratios of 0.075 and 0.078, respectively.
- NMR (MRIL) analysis in well A, performed using an L1L2 inversion technique, defined T2 relaxation cutoff times of 3 ms and 95 ms to differentiate bound clay water , bulk free volume , and free fluid volume, consistent with the characteristics of carbonate reservoirs.
- NMR results highlighted intervals with substantial free fluid volumes that exhibited low resistivity on conventional logs, indicating water presence and identifying non-productive zones.
- Key NMR-derived outputs—PHIT, PHIE, CBW, SWir, and BFV—were estimated in well A using the MRGC method. Following validation of this approach, these parameters were predicted in adjacent well B, which lacked direct NMR measurements. Incorporation of these parameters into the probabilistic petrophysical model significantly improved reservoir characterization and productive zone identification.
- A strong correlation between irreducible water saturation and reservoir porosity enabled the derivation of an empirical relationship for estimating SWir in neighboring wells, demonstrating the feasibility of indirectly predicting NMR-derived parameters using conventional logs.
- The refined productive zones identified through this integrated approach exhibited reduced water production compared with zones defined by conventional logs alone, indicating the potential for improved reservoir management and enhanced hydrocarbon recovery.

In summary, integrating NMR-derived outputs within a probabilistic petrophysical framework provides a robust methodology for enhanced reservoir evaluation. This approach improves fluid discrimination, porosity characterization, and productive zone delineation, thereby supporting more informed and effective reservoir management decisions.

Nomenclature

AHC	Ascending hierarchical classification
AI	Artificial intelligence
BFV	Bound fluid volume
BPNN	Backpropagation neural networks

BVI	Irreducible water volume
CBW	Clay-bound water volume
CGR	Gamma-ray
D-C	Dynamic clustering
DT	Acoustic transit time
ML	Machine learning
MRGC	Multi-resolution graph-based clustering
NMR	Nuclear magnetic resonance
NPHI	Neutron porosity
PEF	Photoelectric factor
PHIE	Effective porosity
PHIT	Total porosity
RHOB	Density
SOM	Self-organizing maps
SWir	Irreducible water saturation

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