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Prediction of Well Logs Data and Estimation of Petrophysical Parameters of Mishrif Formation, Nasiriya Field, South of Iraq Using Artificial Neural Network (ANN)

Abbas Kareem Abdulsahib Mohammed[1,2], Mohammed Kareem Dhaidan[3]*

[1]*Geology Department, Field Division, Ministry of Oil, Missan Oil Company, Misan, Iraq*

[2] *Mineralogy and geology Institute, Miskolc University, Hungary*

[3]*Geology Department, Field Division, Ministry of Oil, Thi-Qar Oil Company, Nasiriya, Iraq*

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Abstract

Petrophysical properties including volume of shale, porosity and water saturation are significance parameters for petroleum companies in evaluating the reservoirs and determining the hydrocarbon zones. These can be achieved through conventional petrophysical calculations from the well logs data such as gamma ray, sonic, neutron, density and deep resistivity. The well logging operations of the targeted limestone Mishrif reservoirs in Ns-X Well, Nasiriya Oilfield, south of Iraq could not be done due to some problems related to the well condition. The gamma ray log was the only recorded log through the cased borehole. Therefore, evaluating the reservoirs and estimating the perforation zones has not performed and the drilled well was abandoned. This paper presents a solution to estimate the missing open-hole logs of Mishrif Formation including sonic, neutron, density and deep resistivity using supervised Artificial Neural Network (ANN) in Petrel software (2016.2). Furthermore, the original gamma-ray log along with the predicted logs data from ANN models were processed, and the petrophysical properties including volume of shale, effective porosity and water saturation were calculated to determine the hydrocarbon zones. The ANN Mishrif Formation models recorded coefficient of determination (R^2) of 0.65, 0.77, 0.82, and 0.04 between the predicted and the tested logs data with total correlations of 0.67, 0.91, 0.84 and 0.57 for sonic, neutron, density, and resistivity logs respectively. The best possible hydrocarbon-bearing zone ranges from the depth of about 1980-2030 m in the mB1unit. The ANN provides a good accuracy and data matching in clean and non-heterogeneous formations compared to those with higher heterogeneity that contain more than one type of lithology. The Ns-X Well can, therefore, be linked to the development plans of the Nasiriya Field instead of neglect it.

Keywords: Well logs data, Artificial Neural Network; Well logs data prediction; Nasiriya Oilfield; Limestone Mishrif Formation.

*Email: muhammedkareem39@gmail.com

التنبؤ ببيانات التسجيلات البئرية وحساب الخصائص البتروفيزيائية لتكوين المشرف في حقل الناصرية، جنوب العراق، باستخدام الشبكة العصبية الاصطناعية

عباس كريم عبدالصاحب محمد[1، 2], محمد كريم ضيدان[3]*

[1] قسم الجيولوجيا, هياة الحقول, وزارة النفط, شركة نفط ميسان, ميسان, العراق

[2] قسم علم المعادن والجيولوجيا, جامعة مسكولك, هنغاريا

[3] قسم الجيولوجيا, هيأة الحقول, وزارة النفط, شركة نفط ذي قار, ذي قار, العراق

الخلاصة

تعد الخصائص البتروفيزيائية والتي تشمل حجم السجيل والمسامية والتشبع المائي واحدة من اهم الدوال المستخدمة في الشركات النفطية في تقييم المكامن النفطية وتحديد مناطق تواجد الهيدروكربون، وهذه الخصائص يمكن الحصول عليها من خلال الحسابات البتروفيزيائية التقليدية من بيانات التسجيلات البئرية مثل مجس أشعة جاما والمجس الصوتي ومجس النيوترون والكثافة ومجسات المقاومة العميقة. في البئر Ns-X في حقل الناصرية النفطي، جنوب العراق تعذرت عمليات الجس البئري لمكمن المشرف المستهدف بسبب بعض المشاكل المتعلقة بحالة البئر. وكان مجس أشعة جاما هو المجس الوحيد المسجل من خلال التجويف المبطن للبئر. لذلك ، لم يتم تنفيذ تقييم مكمن المشرف وتحديد مناطق التثقيب وتم التخلي عن البئر المحفور. تقدم هذه الورقة حلاً لتقدير التسجيلات البئرية للتجويف المفتوح المفقودة لتكوين مشرف بما في ذلك المجس الصوتي ومجس النيوترون والكثافة ومجس المقاومة العميقة باستخدام الشبكة العصبية الاصطناعية (ANN) في برنامج Petrel (2016). علاوة على ذلك ، تمت معالجة مجس أشعة جاما الأصلي جنبًا إلى جنب مع بيانات السجلات المتوقعة من نماذج ANN ، وتم حساب الخصائص البتروفيزيائية بما في ذلك حجم السجيل والمسامية الفعالة والتشبع المائي لتحديد مناطق التواجد الهيدروكربوني. سجلت نماذج الشبكة العصبية الاصطناعية ANN لتكوين المشرف معامل تحديد (R^2) 0.65 و0.77 و 0.82 و 0.04 بين بيانات التسجيلات المتوقعة والمختبرة مع ارتباطات إجمالية قدرها 0.67 و 0.91 و 0.84 و 0.57 لسجلات الصوت والنيوترون والكثافة والمقاومة على التوالى. تتراوح أفضل منطقة حاملة للهيدروكربون الممكنة من عمق 1980−2030 متر في وحدة mB1. توفر الشبكات العصبية الصناعية ANN دقة جيدة وبيانات متطابقة في التكوينات النظيفة و المتجانسة مقارنة بالتكاوين ذات التغاير العالي والتي تحتوي على أكثر من نوع واحد من الصخور. لذلك يمكن ربط البئر Ns-X بخطط تطوير حقل الناصرية بدلاً من إهماله.

Introduction

Petrophysical parameters of the reservoirs including porosity, permeability, volume of shale, water saturation and lithology identification are of concern for petroleum companies because they are essential for estimation the hydrocarbon accumulations. The well logs such as gamma-ray (GR), sonic (DT), neutron (NPHI), density (RHOB) and resistivity (ILD) are essential in calculating those parameters [1].

The well Ns-X was drilled in 2017 by Thi-Qar Oil Company (TOC) for production purposes from the Mishrif formation. However, while drilling the third hole-section (8 1/2" section) a serve mud loss has happened. Due to the well condition and some problems happened during the drilling, the well logging operations that supposed to include GR, DT, NPHI, RHOB and ILD logs were not done. Therefore, the well was cased and cemented. The GR log was the only log that successfully recorded through the cased hole. Hence, the well Ns-X was not perforated because it is difficult and highly risky to determine the best possible hydrocarbon zones within the Mishrif Formation without the full logs data set. It is common for the logging operation to be missing due to many reasons such as broken instruments, hole conditions, instrument failure, or loss of data due to inappropriate storage and incomplete logging [2]. When well logs are missing for any reasons, they can be estimated from other available log types [3].

The prediction of the missing well logs data by using the Artificial Neural Network (ANN) models has been increasing in the last years [4, 5, 6, 7, 8]. Artificial Neural Network technique (ANN) provides a way to predict the logs data for the unlogged intervals [6, 7]. There were few studies tried to estimate the missing well logs data using artificial neural networks [9, 10, 6, 7]. They agreed that the ANN method produces an accurate estimation of the predicted logs data that are significantly matched the measured values. [6] used artificial neural networks to generate the missing intervals of well logs data in Mishrif Formation. She stated that the capability of ANN models to create the missing well logs intervals with high accuracy, it is a robust, inexpensive, and requires only sufficient data for training and memorizes the pattern. [7] used ANN to predict the missing well logs in Noor Oilfield. The results show excellent relationships between the original and the predicted logs in the Mishrif Formation. Their results were compared and the Mishrif reservoir was divided into layers based on the petrophysical properties. However, they only correlate the results of the predicted logs from the ANN models and compared it with only the training wells that involved as inputs well when releasing the ANN models. This study will consider the matching results between the predicted logs data against the training as well as the testing inputted wells.

This study aims to predict the missing well logs data including DT, NPHI, RHOB, and ILD from the GR log in the Ns-X Well using the ANN in Petrel software. The predicted logs processed and petrophysical properties including volume of shale (Vsh), effective porosity (PHIeff) and water saturation (Sw) calculated, and the results correlated and compared with the adjacent drilled wells in Nasiriya Oilfield to determine the best hydrocarbon zones.

Study Area

Nasiriya Oilfield located in the Thi-Qar Province, about 38 km northwest of Nasiriya city (Figure 1). The Nasiriya Oilfield lies on the stable shelf, Mesopotamian Basin, Euphrates subzone [11]. The field was discovered by the National Oil Company in 1973. The past survey showed that there was a shallow convex enclosure towards the northwest. (INOC) from 1978 to 1988, five exploration wells were drilled. It was observed through the drilled wells that the oil is accumulated in three main reservoirs, Mishrif, Nahr Umr, and Yamama formations.

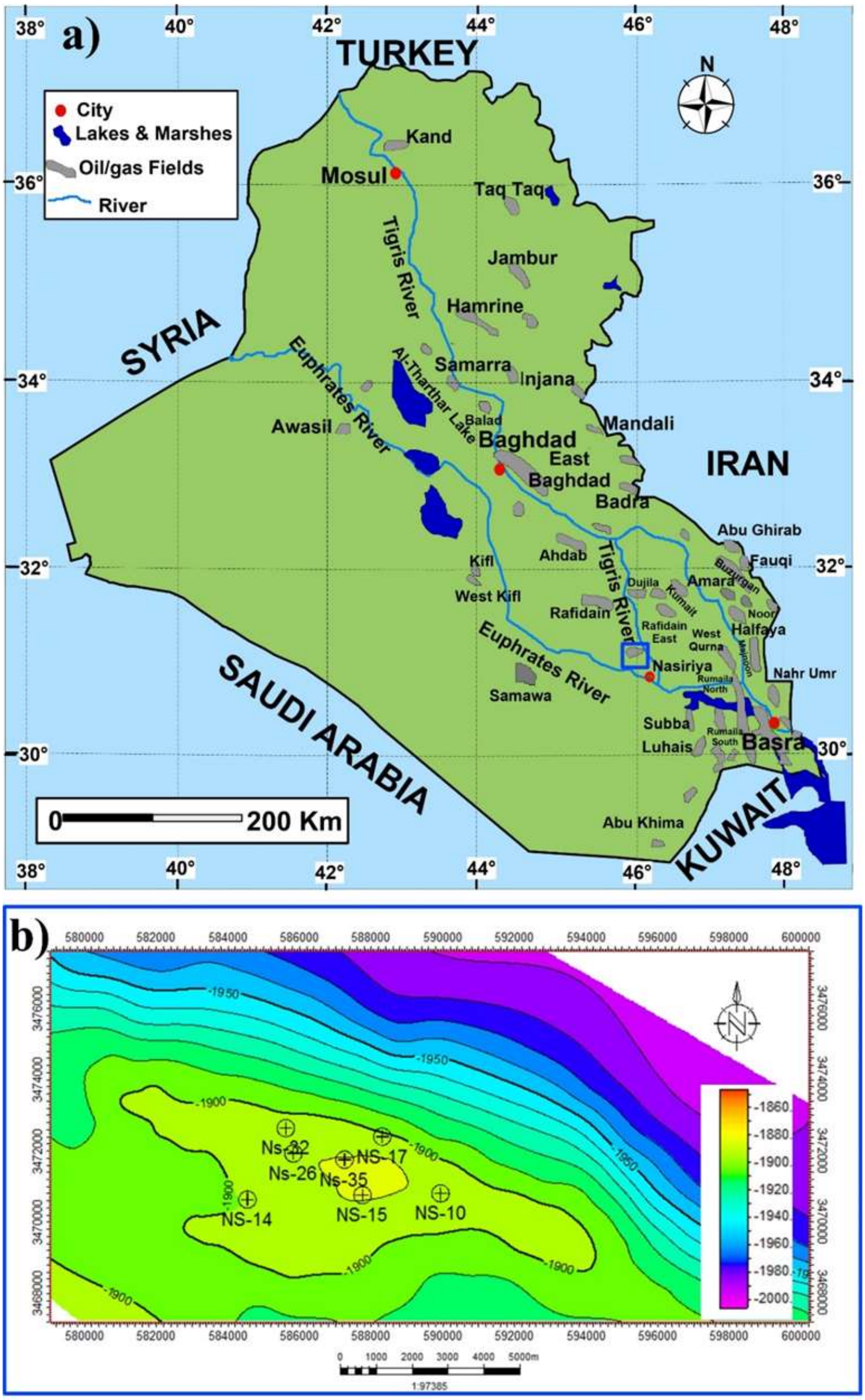


Figure 1: a, Iraqi map showing most oil and gas fields, the blue rectangle refers to the Nasiriya Oilfield of this study (adapted from [7]). b, Mishrif Formation structural map of the Nasiriya Oilfield

The Mishrif Formation (Cenomanian–Early Turonian age) is the main carbonate reservoirs in the middle, southern Iraq and throughout the Middle East. It is equivalent to the upper part of Sarvak reservoirs in Iran and the Natih Formation in Oman [12]. In southern Iraq, The

Mishrif Formation consists of the main rudist-bearing reservoir in many oilfields such as Zubair, West Qurna and Nasiriya [13]. The Mishrif Formation contains up to 40% of Cretaceous oil reserves in Iraq, and approximately 30% of the total Iraqi oil reserves [11, 13]. The main Mishrif reservoir layers consist of bioclastic and peloidal facies of shoal and shelf margin facies [11]. In the Nasiriya Oilfield, the Mishrif Formation gradationally overlies the Rumaila Formations and unconformably underlies the Kifl Formation (Figure 2).

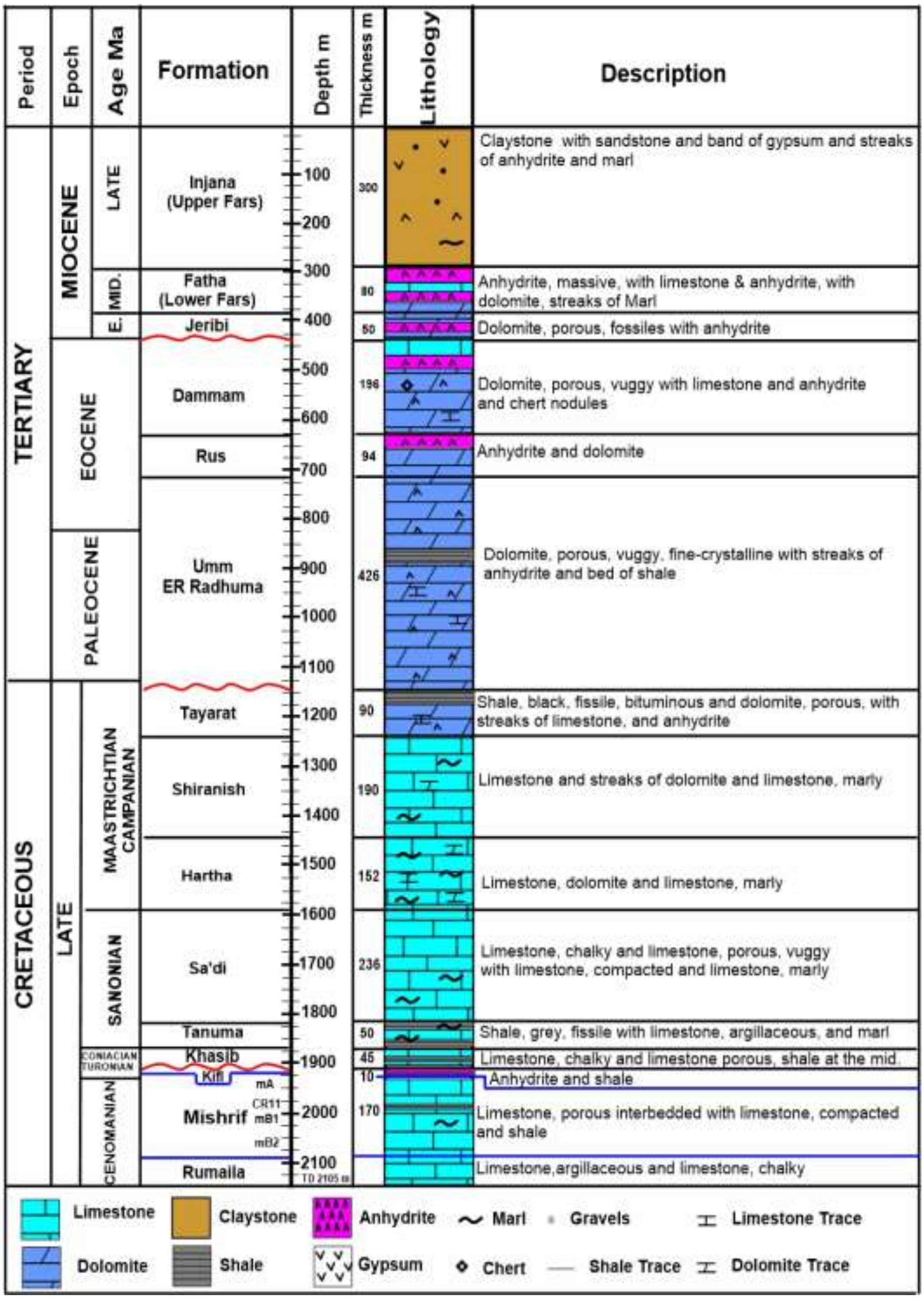


Figure 2: A general stratigraphic column of the Nasiriya Oilfield (complied from different Thi-Qar Oil Company reports), the Mishrif Formation, the interest of this study is bounded by blue color.

The formation is divided into several members (mA, CR11, mB1, mB2) with a total thickness of about 168m, the main oil horizon is the lower part of the formation (mB1). [12] analyzed the geochemical properties of the Mishrif Formation of the Nasiriya Oilfield, they found that the Mishrif source rocks are the carbonate sediments of the Jurassic Surgelu Formation.

Methods

Six wells have been chosen in the Nasiriya Field. These wells are surrounding the targeted Ns-X Well, these are Ns-10, Ns-14, Ns-15, Ns-17, Ns-26 and Ns-32 (Figure 1), each well contains GR, DT, NPHI, RHOB and ILD logs while the Ns-X Well which contains only GR.
ANN in Petrel software was used to generate the missing logs data of the Ns-X Well. ANN is computer-based algorithms inspired by the way of biological neural networks, such as the brain, process information [14, 15]. The concept was first introduced by McCulloch and Pitts in (1943). To date, the artificial neural network is being used to solve a wide variety of scientific, engineering, and medical problems.

ANN is comparable to biological systems, and it consists of input layer, hidden layers, and output layers. Therefore, as in biological systems, the network function is determined to a great extent by the connections between elements [14, 15]. A characteristic feature of a neural network is that it learns by an example. Therefore, the network must be provided with a training of input data as well as response data. In terms of learning features, artificial neural networks can be roughly categorized into two types: supervised and unsupervised (Petrel help centre). Figure 3 illustrates the process at which the ANN models were built in this study.

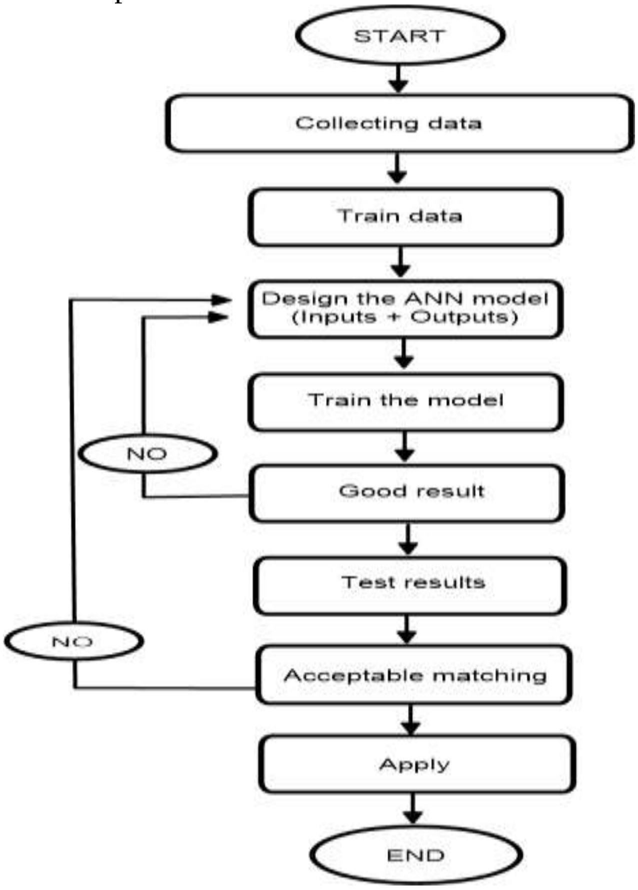


Figure 3*:* A flow chart illustrating the process made for ANN models in this study

In this study the supervised neural networks were used to estimate the missing logs in Ns-X Well, the supervised neural network is the most common method for neural network solutions. When output (target) data is present, this data together with the input data is used to optimize the weights required. Using the RMS (root mean square) of this error to ensure that the solution achieves the best possible fit for all the data. The training data were split into two data sets; one being used for the training and the other used to calculate the error that helps to prevent overtraining.

The Neural network model prediction accuracy was evaluated by using root mean squared error (RMSE) and correlation of determination (R^2) (Table 1).

Table 1: The error statistics for the experiments in ANN models

Predicted log	**Static errors**	
	RMSE	**R^2**
Sonic DT	2.36	0.82
Neutron NPHI	1.02	0.92
Density RHOB	0.02	0.86
Deep resistivity ILD	10.55	0.31

After achieving the highest correlation by controlling the input data (GR log, depth, and the involved wells), the ANN of DT log was built, the results were tested and the DT of the Ns-X Well was generated (Figure 3). The generated DT log was then added as to the input data and the NPHI log was generated by repeating the same above steps. Similarly, the RHOB and ILD logs were predicted.

To check the data validation, the predicted well logs data were processed and the Vsh, PHIeff and Sw were calculated, and correlated to the other wells [16]:

$$PHI_{total} = \left(\frac{PHI_D + PHI_N}{2}\right) \quad (1)$$

Where the PHI_{total} is the total porosity (fraction), PHI_D is the porosity derived density (fraction), and the PHI_N is the Neutron porosity (fraction).

Density derived porosity was calculated [17]:

$$PHI_D = \left(\frac{\rho_{ma} - \rho_b}{\rho_{ma} - \rho_{fl}}\right) \quad (2)$$

Where ρ_{ma} is the matrix density which assumed to be quartz (2.71 g/cm^3). ρ_b is the log density reading, and ρ_{fl} is the fluid density which assumed to be oil (0.9 g/cm^3), The total porosity then corrected from the shale effect.

$$PHI_{eff.} = (PHI_{total}) - Vsh(PHI_{total}) \quad (3)$$

Where $PHI_{eff.}$ is the effective porosity and Vsh is the volume of shale (fraction).

Vsh was obtained using Larionov's equation for the old sediments:

$$Vsh = 0.33(2^{2\times GRI} - 1) \quad (4)$$

Where GRI (Gamma Ray Index) calculated using the gamma ray logs [18]:

$$GRI = \frac{\text{GRlog} - \text{GRsand}}{\text{GRshale} - \text{GRsand}} \quad (5)$$

Where GR_{log} is the gamma ray log reading, GR_{sand} is the gamma ray reading in the sand (the lowest gamma ray reading), and GR_{shale} is the gamma ray reading in the shale (the highest reading).

Water saturation was then calculated using Archie's (1942) equation [19]:

$$Sw = \left(\frac{a*Rw}{Rt*(PHI_{eff.})^m}\right)^{1/n} \quad (6)$$

Where Sw is water saturation (fraction), a, m and n are constant values, assumed to be 1, 2 and 2 respectively, Rw is the formation water resistivity, Rt is the reading of the deep resistivity log.

Results and Discussion

1- The Gamma-Ray Data Correlation

Before releasing the models, it is important to correlate and compare the GR logs in the Ns-X and the GR of the other selected wells that used as training wells (training data). The results show that the GR logs behave similarly in the Ns-X Well compared to Ns-14, Ns-17, Ns-26, and Ns-32 wells (Figure 4).

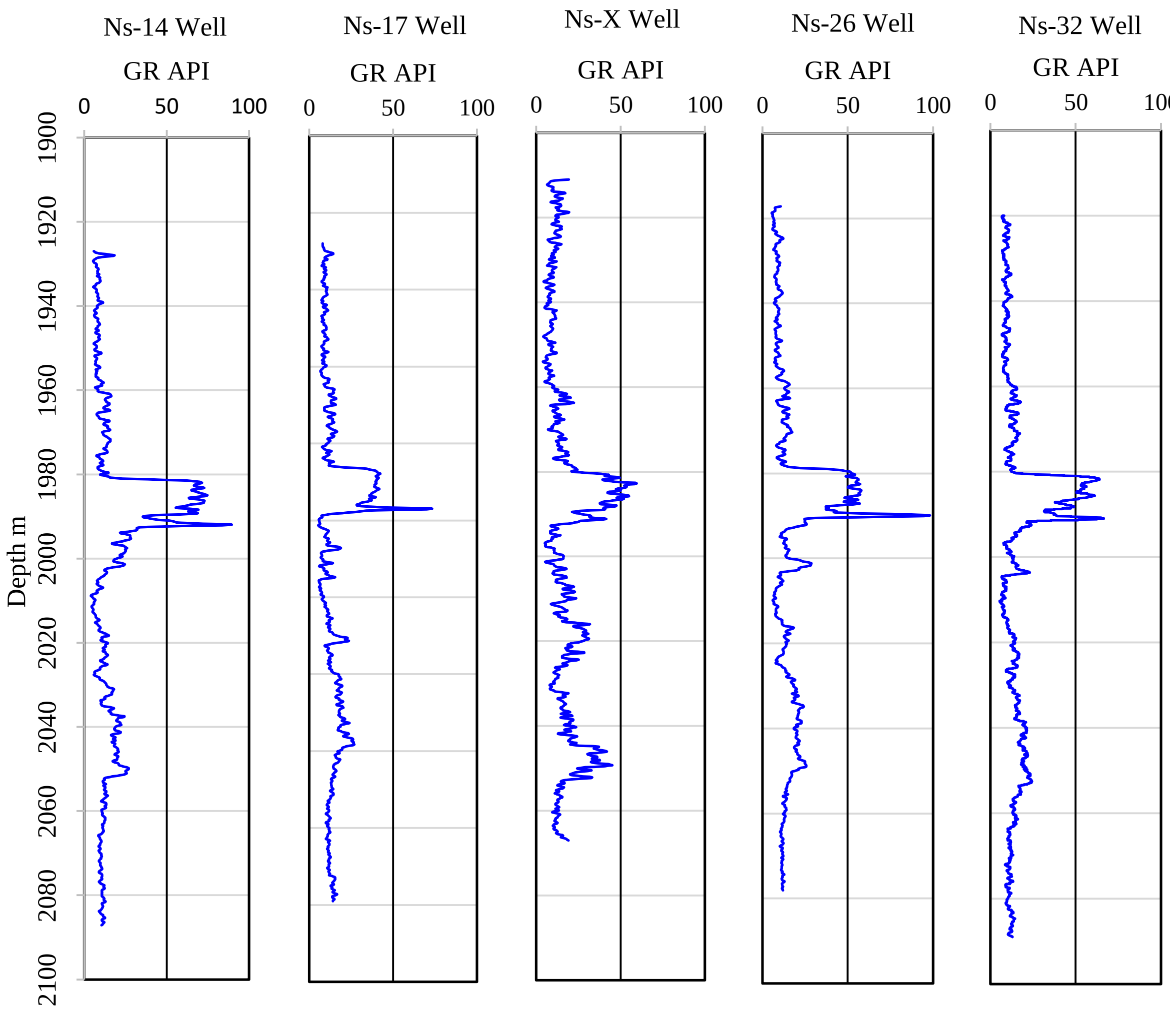


Figure 4: Wells cross section shows the GR log in each selected well in Mishrif Formation

Sonic Log Prediction

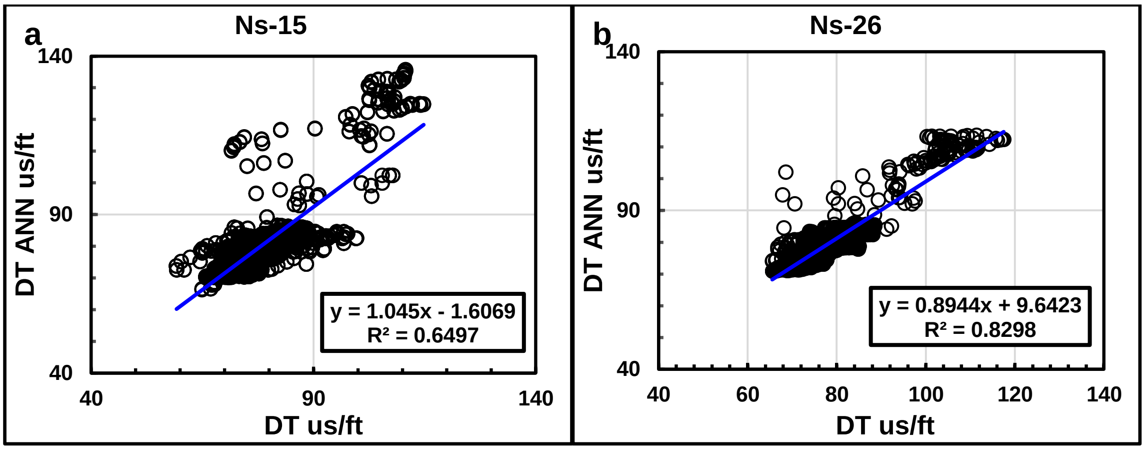
The first model built was to predict the sonic log by training the inputs data (GR logs and depth as they are existing in the targeted Ns-X Well and the DT as the output (as showing in the process in Figure 3). Choosing the wells in each ANN model was selective each time to obtain the possible highest overall correlation. In the ANN of DT model, the wells Ns-14, Ns-17, Ns-26 and Ns-32 have shown the highest correlation (0.674) (Table 2), while the wells

Ns-10 and Ns-15 left for test data. The selected input wells are almost surrounding the Ns-X Well (Figure 1b).

Table 2: The inputs wells and logs, and the total correlation for each training ANN model

ANN models (output)	Selected training wells No.	Inputs selected logs	Total correlation (Fraction)
DT (us/ft)	Ns-14, Ns-17, Ns-26, Ns-32	GR and Depth	0.674
NPHI (%)	Ns-14, Ns-17, Ns-26	GR and predicted DT	0.914
RHOB (gm/cc)	Ns-14, Ns-17, Ns-26	GR, predicted DT and predicted NPHI	0.849
ILD (ohm.m)	Ns-14, Ns-17, Ns-26	GR, predicted DT, predicted NPHI and predicted RHOB	0.575

The maximum number of iterations was set (20) this will make the algorithm stop at this number even if an adequate result has not been reached to avoid overtraining of the model, and the error limit was set 10%. The correlation coefficient R^2 is 0.64 (Figure 5a). However, this relationship was much higher when cross plotted the predicted DT and the original DT lo of one of the wells involved in the ANN DT model (Ns-26 Well) (Figure 5b). Plotting the original and the predicted sonic log of the testing well (Ns-15) shows good matching between the logs (Figure 6a). It was expected that the relationships are low, particularly in the CR11 unit due to the lithology variation that includes fissile shale beds (Figure 2), and these beds caused many washouts in the borehole and that is observed from the caliper log. Therefore, logs' responses highly possible to be affected in the CR11 unit leading to a decrease in the coefficient of determinations. This can be seen in Figure 5a. Where, the CR11 unit has the highest GR and DT readings (at depth 1970-1980). Hence, Lithology variation within the same modelled bed can reduce the coefficient of determination of the ANN models. This was also found by Mohammed et al. (2020). Therefore, it can be states that the ANN can provide higher accuracy and data matching in less heterogeneous formations (such as clean limestone formation with smoothed wellbore) since the washouts in the wellbore can negatively reduce the accuracy of the well logs.



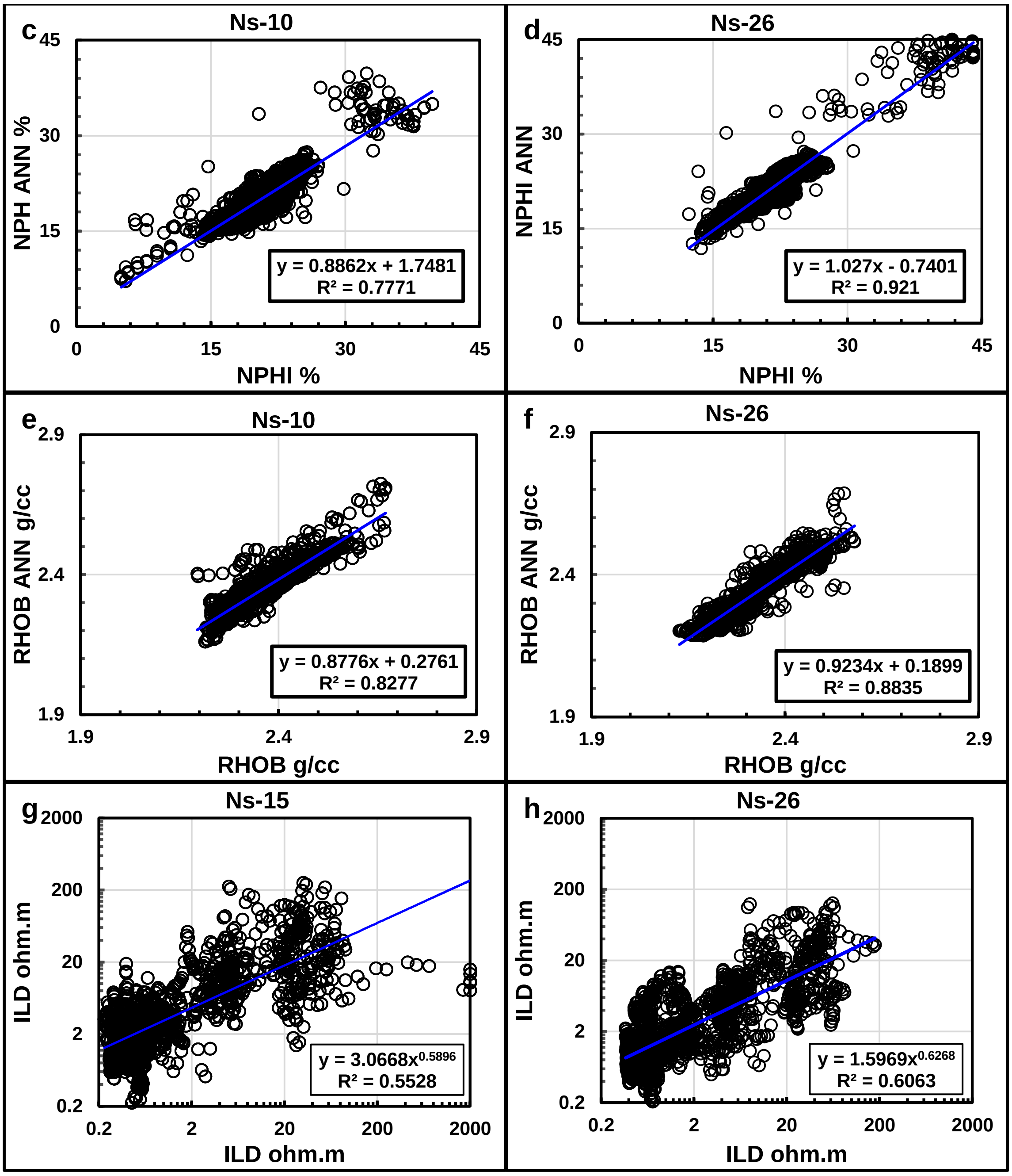


Figure 5: Cross plots of the original and predicted logs data for each shown well. The **a**, **c**, **d** and **g** are the original versus the predicted logs of the testing wells, while the **b**, **d**, **f** and **h** are the original versus the predicted logs for one of the training wells (Ns-26 Well)

Neutron Log Prediction

This model was built to predict the neutron log by inserting the GR and DT logs as inputs and Ns-14, Ns-17, and Ns-26 wells as the participated wells (Table 2).

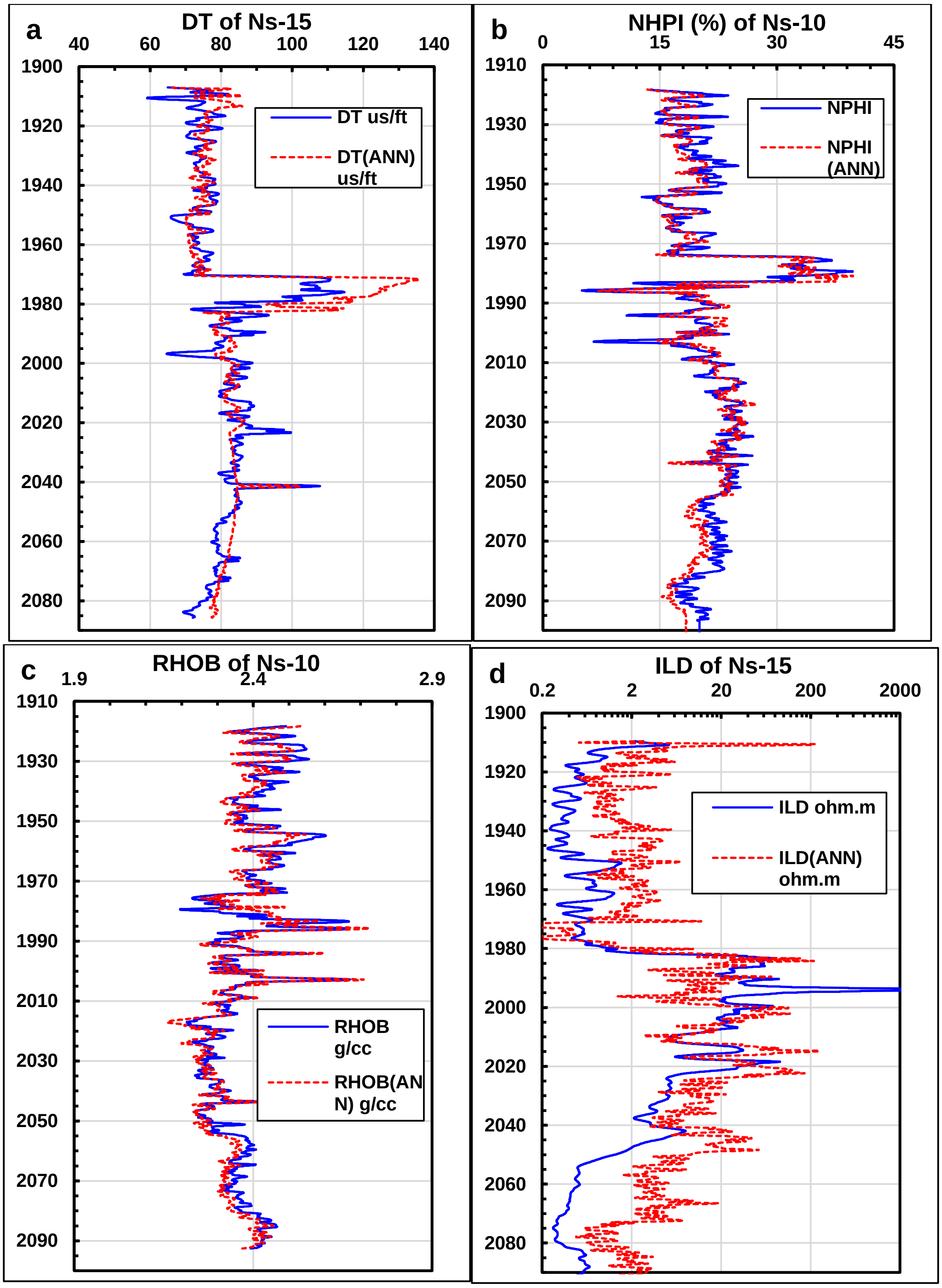


Figure 6: Plots of the original and the predicted logs against the depth of each DT, NPHI, RHOB, and ILD logs **a**, **b**, **c**, and **d** respectively for each shown testing well

The NPHI ANN model shows a good coefficient of determination reaching 0.77 for the testing data (Figure 5c). However, this remains excellent correlation and reaches 0.92 in the case of the training data (Figure 5d). The model was then applied to the Ns-X Well (the neutron porosity log was estimated and added to the next ANN of the RHOB as explained in the method section). Excellent matching between the original and the predicted NPHI log record of the testing well (Ns-10) (Figure 6b).

Density log Prediction

The supervised model based on GR, the predicted DT, and the predicted NPHI logs as input data were used to generate the RHOB log. The total correlation of the RHOB ANN model recorded 0.84 (Table 2). The correlation coefficient (R^2) of the original and the predicted RHOB log of the testing well (Ns-10) is 0.827, and 0.88 for the training well data (Well Ns-26). Excellent matching between the original and the predicted RHOB log recorded for the testing well (Ns-10) (Figure 6c). The model was applied to the Ns-X Well to estimate the density log.

Deep Resistivity Log Prediction

The ANN ILD model shown 0.57 which is the lowest correlation obtained in this study (Table 2). However, the coefficient of determination R^2 recorded low values for the testing well that was Ns-15 and for the training well (Ns-26) (Figure 5g and h). There is relatively poor matching between the predicted and the original ILD log of the testing well Ns-15 (Figure 6d). A possible explanation of that is that the Mishrif Formation in Nasiriya Oilfield is interbedded of porous and compacted limestone units, these compacted limestones can act as high resistance layers, therefore, the resistivity can have high readings through these layers. Furthermore, ANN method in Petrel that used in this study used the original data range of the data logs unlike other software such as MATLAP that can normalize the inputs logs data. Moreover, the resistivity logs are sensitive to the presence of fluids and therefore, can be influenced by the type of the fluid (gas, oil and water). These reasons might reduce the ANN of ILD log coefficient of determination (R^2) and the overall matching between the original and the predicted logs. Therefore, dealing with the resistivity logs that generated from the ANN models must be carefully treated. This confirms the finding of [7].

Predicted Data Validation

Ensuring that the predicted data are acceptable and accurate, the predicted density and neutron log of the targeted X Well cross-plotted in the Neutron-Density cross plot to check the lithology (Figure 7). Most of the data points fall on the limestone line, while some minor data points fall on the dolomite line. It is; therefore, neutron and density data are accurate and capable to be involved in the well evaluation.

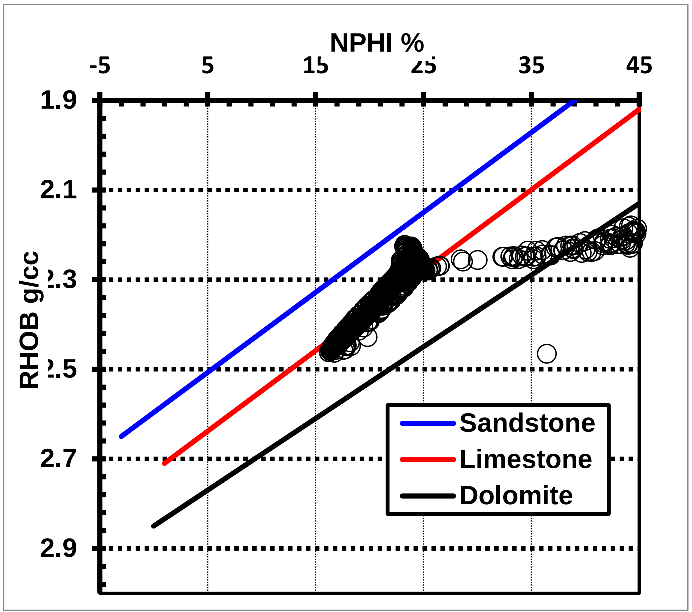


Figure -7 Neutron-density cross plot of the predicted neutron and density logs of Ns-X Well (the standards lines are from Baker Hughes interpretation charts) illustrating the predicted logs data validation

The applied Computer Process Interpretation (CPI) and through the well correlation (Figure 7 and 8), it is obvious that the logs data of the Ns-X Well correlate well with the adjacent wells. It is now trustily possible to evaluate the petrophysical properties of the Ns-X Well and dividing the Mishrif Formation into its units (mA, CR11, mB1 and mB2) (Figure 7). In contrast to Ns-14 Well and Ns-17 Well, some high readings in GR log in the main reservoir unit (mB1) can be observed (Figure 8) Where, the Vsh has shown some shaly beds (Vsh calculated directly from the GR log is a mirror of the GR log). This can be due to that the GR log was logged through the cased borehole which might affect the log readings.

ANN recommended in the less heterogeneous formations with low lithological variation. Current results presented in this paper are applicable to the study field only. However future work is needed to be correlate the predicted logs with the cased hole logs than can be operated through the cased hole of Ns-X or any well with the same condition to investigate the accuracy of ANN estimated models. This would be an interesting area of research with the potential of further reducing the cost of oil companies if there are any missing logs data. It is further recommended to divide the targeted formation into different facies (from core/cuttings samples or from electro-facies that can be obtained from well logs data) to be inserted as input data of ANN to enhance the accuracy of predicted logs.

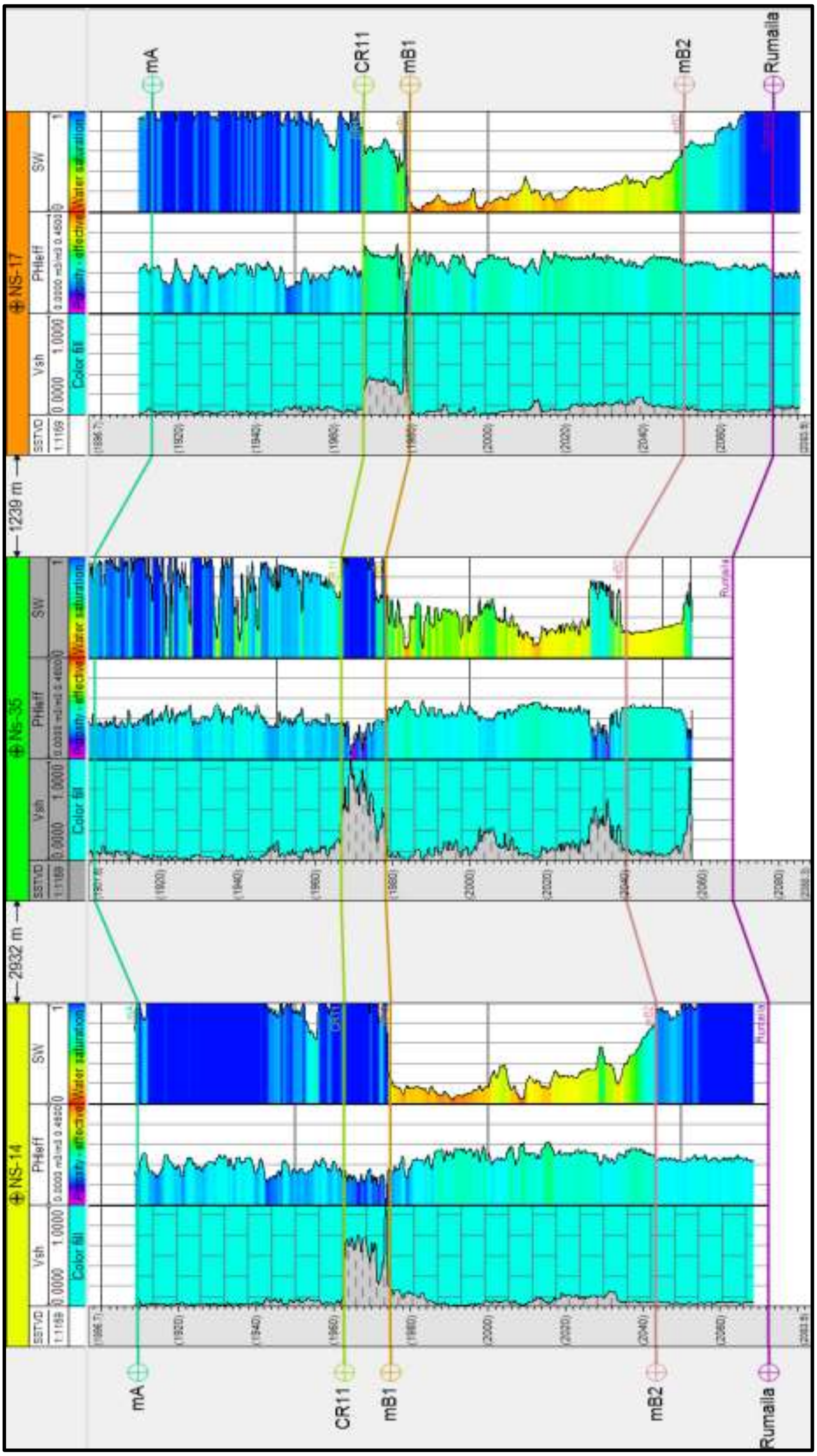


Figure 8: A well cross section showing the petrophysical correlation of Mishrif Formation, between the Ns-14, Ns-X and Ns-17 wells. The interval from 1990 to 2030 m in Ns-X Well has low Vsh (clean), high porosity and low GR, and it is well correlated with other wells

Conclusions

The well logging operations of the targeted limestone Mishrif reservoirs in Ns-X Well, Nasiriya Oilfield, south of Iraq could not be done due to some problems related to the well condition. The only log was recorded is the GR through the cased hole. ANN technique used to predict the missing DT, NPHI, RHOB, and ILD logs data for the limestone Mishrif Formation in Nasiriya Oilfield, south of Iraq. The original GR log and the predicted logs were then interpreted to evaluate the Mishrif reservoir. The predicted NPHI and RHOB logs are matched and correlated excellently with the original logs of the testing and the training wells data, DT recorded a lower correlation, while ILD showed less matching. Hence, dealing with the resistivity logs that generated from the ANN models must be carefully treated. Therefore, the predicted logs used to evaluate the Ns-X Well. The mB1 reservoir units of the Mishrif Formation in the Nasiriya field shown good petrophysical properties with a low Vsh, PHIeff, and low Sw. While the CR11 has shale beds and recorded the lowest petrophysical properties. The best possible hydrocarbon-bearing zone ranges from 1980-2040 m in the mB1 unit. The ANN technique can be used to generate the unlogged intervals because it provides an inexpensive way, shorter time than the well logging operations with good accuracy, particularly, in clean and less lithological varied formations (less heterogenous formations).

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