IJEIT
The International Journal of Engineering and Information Technology
journal homepage:www.ijeit.misuratau.edu.ly
MISURATA UNIVERSITY

Permeability Prediction from Well Log Data Using Artificial Neural Networks: A Case Study of the Hawaz Formation in D-Field, Libya

Saleh J. Arwini
Faculty of Engineering
University of Tripoli, Libya
S.Arwini@uot.edu.ly

Abstract — **Permeability is an important parameter in the characterization of any hydrocarbon reservoir. Yet, despite its vital importance, it is one of the most difficult and controversial petrophysical properties to calculate accurately due to nonlinearity and uncertainty in the dataset. Formation permeability is often measured in the laboratory from cores or evaluated from well test data. Core analysis and well test data, however, are only available from a few wells in a field, while the majority of wells are logged. The aim of this paper is to design an artificial neural network (ANN) model to predict formation permeability using a dataset from the Hawaz Formation in the D-field NC-186 concession, East Murzuq Basin, Libya. In this study, a back-propagation neural network (BP-ANN) model was built using the Python programming language. A total of 950 core horizontal permeability measurements and their corresponding well log data were collected from four wells to build the model. Traditional statistical analysis of the porosity/permeability relationship in cored well data yielded no reliable correlations for predicting permeability in uncored wells with R^2 less than 15%. A supervised BP-ANN model was trained successfully and was successfully able to predict the permeability of the formations. Despite the presence of high reservoir heterogeneity, the permeability profile predicted by the ANN model using well log data agrees well with core permeability, which clarifies the applicability of this method.**

Index Terms: **formation permeability; artificial neural network; Python; well log data.**

I. INTRODUCTION

Reservoir characterization is a very important domain of petroleum engineering. One of the essential parameters for defining an accurate reservoir model is the permeability distribution. Permeability is often evaluated using cores extracted from wells or pressure transient tests conducted on the wells. However, due to the high cost associated with those procedures, cores and well tests are available from a limited number of wells in a reservoir, while geophysical logs are commonly available from most, if not all, of the wells. Therefore, the evaluation of permeability from well log data is an important step to reduce cost while keeping reservoir modeling within acceptable accuracy [1].

Received 06 Jan, 2024 ; Revised 27 Mar, 2024 ; Accepted 01 May , 2024.
Available online 08 Jul , 2024

In some intervals or wells, the core is not on hand to be tested; therefore, estimation of permeability should be performed based on other types of data [2]. A poroperm cross-plot for a clean sandstone and a carbonate is shown in Figure 1. It is clear from this figure that the permeability of the sandstone is extremely well controlled by the porosity, as seen in Figure (1a), whereas the carbonate has a more diffuse cloud, indicating that porosity has an influence, but there are other major factors controlling the permeability. In the case of carbonates, there can be high porosities that do not give rise to high permeabilities because the connectivity of the vugs that make up the pore spaces is poorly connected [3]. As shown in Figure 1b, the complexity of carbonated rock pore spaces is always a source of concern.

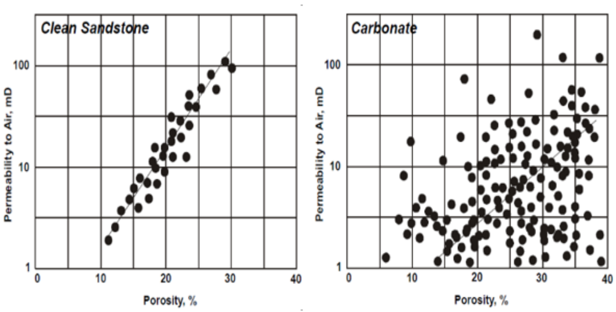

Figure 1. Typical Permeability-porosity relationship for (a) Clean sandstone and (b) Carbonate formations [4].

Because core permeability data are available in the majority of exploration and development wells, statistical methods have become a more versatile solution for this problem domain. Therefore, regression is widely used as a statistical method in searching for relationships between core permeability and well log parameters [5, 6]. This parametric method requires the assumption and satisfaction of multinomial behaviour and linearity. It is a model-based technique, and hence it must be applied with caution. Details of the uses and abuses of statistical methods in geosciences can be found in the literature [7, 8].

Besides traditional or statistical methods, Artificial Intelligence (AI) techniques such as artificial neural networks (ANN) have become increasingly popular in the petroleum industry. Previous studies [9–13] have successfully demonstrated that obtaining reliable permeability values from geophysical log data using Artificial Neural Networks is possible. Since the mid-1980s, when mathematicians made several significant advances, artificial neural networks have made a strong comeback. ANN is a biologically inspired, massively parallel, distributed information system that mimics the human brain regarding the pattern recognition, learning, and memorization processes of those patterns [14]. Figure 2 shows a fundamental representation of an artificial neuron.

This paper presents a nonparametric model to predict reservoir permeability from conventional well log data using an artificial neural network (ANN). The ANN technique is demonstrated with an application to the Hawaz Formation in the D-field NC-186 concession, East Murzuq basin, Libya.

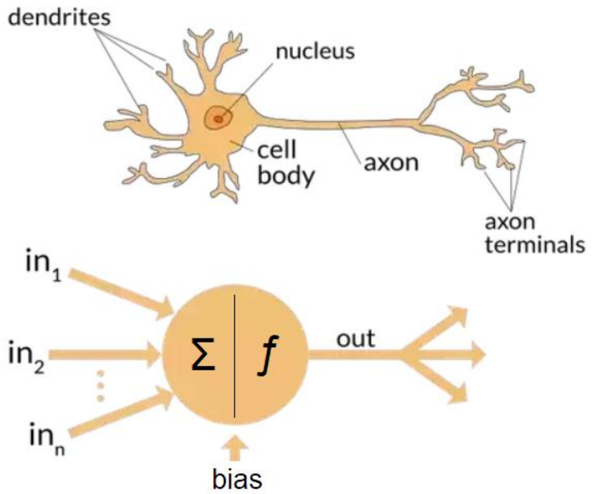

Figure 2. Similarity between a biological neuron and an artificial neuron [15].

II. CASE STUDY: NC186-D OIL FIELD

A. RESERVOIR DESCRIPTION

The Murzuq basin, located in SW Libya, is one of the most important basins on the North African Platform (Figure 3). The NC-186 concession is situated in the southwest of Libya in the Sahara Desert near the village of Ubari, some 720 km from the Mediterranean Sea [16]. The NC-186 is Operated by Akakus Oil Operations It is located east of the NC186 block and consists of a complete Hawaz section with an upper and lower Hawaz, as shown in Figure 4. At the edge of the field, the upper Hawaz appears partially eroded and is overlain by the Mamuniyat and Melez Shuqran Fm. The Hawaz formation was discovered by the exploration well D-01 in November 2001, which was drilled in the crest of the structure.

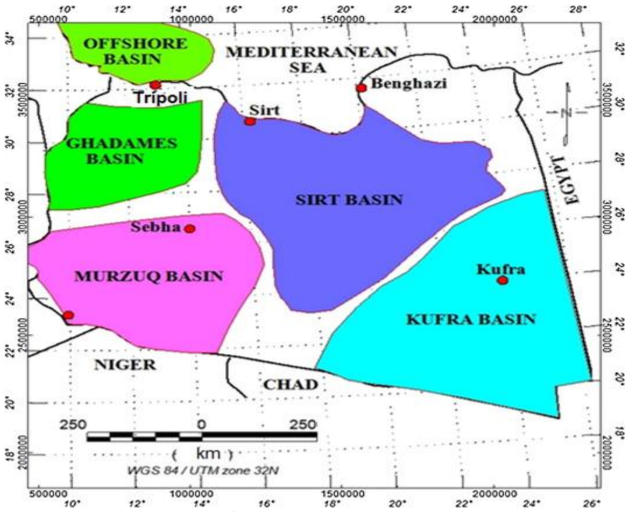

Figure 3. Location map of Libya showing the main sedimentary basins [16].

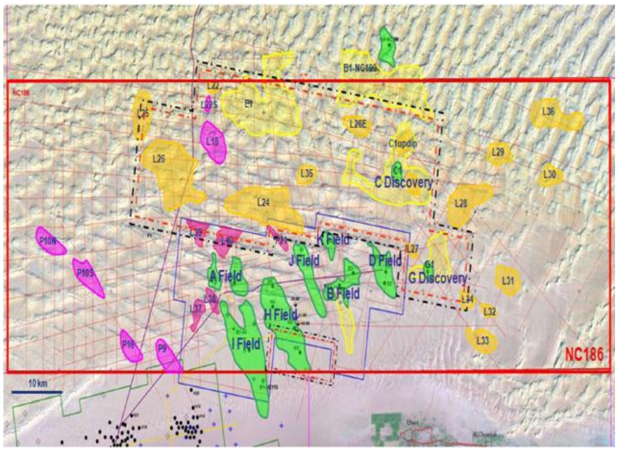

Figure 4. Location of the NC-186 concession including D oil field [16].

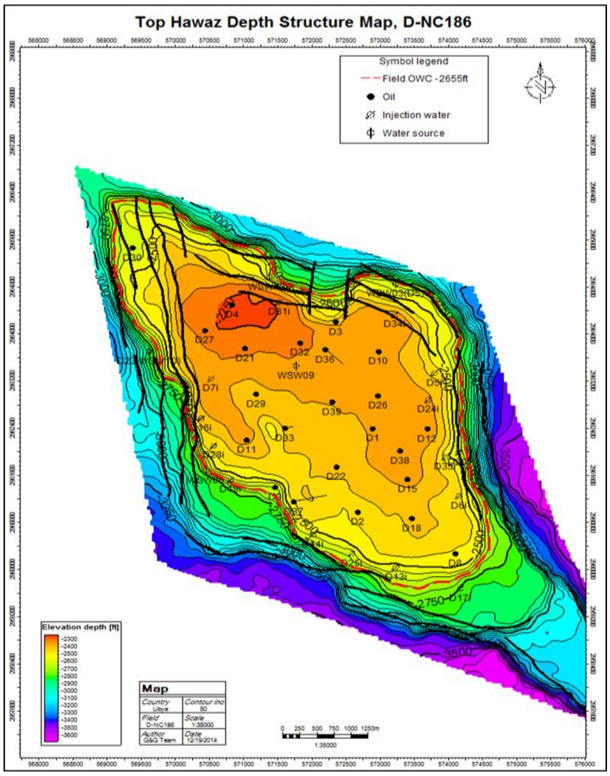

Figure 5. Structural map of D-field with current well locations [17].

B. Porosity-Permeability crossplot

It has been convenient to plot core permeability versus core porosity for several wells and generate a correlation to estimate formation permeability in wells for which cores are not available. For homogeneous reservoirs, this method may prove adequate. As the degree of reservoir heterogeneity increases, such a correlation loses its reliability. In this study, a wide range of porosity and permeability was selected from four wells in D Field, and they show a wide range of distribution as seen in Figure 6. A scatter plot of the logarithmic permeability versus the porosity for all the cores used in this study is shown in Figure 7. Conventional statistical analysis of the porosity/permeability relationship from the cored well data did not reveal any reliable correlations that could be used to predict permeability in uncored wells.

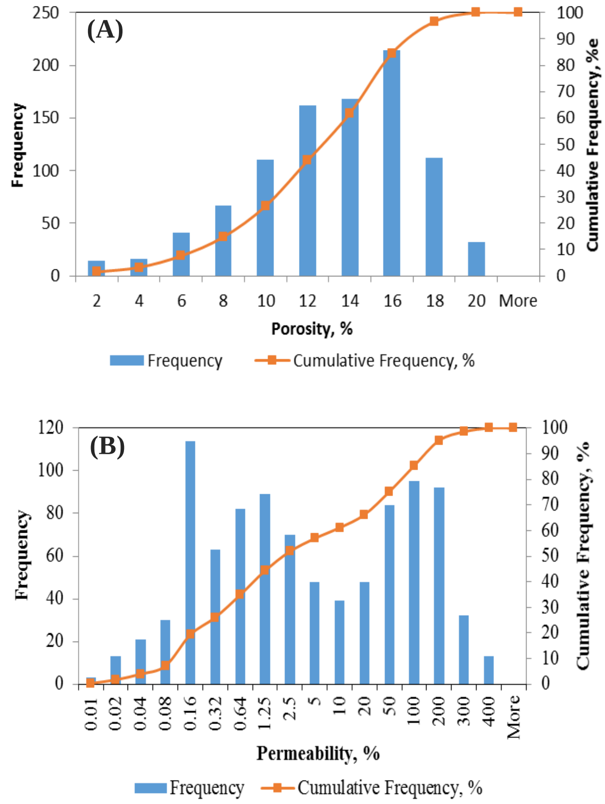

Figure 6. Histograms displaying the distribution of porosity **(A)** and permeability **(B)** values used in this study.

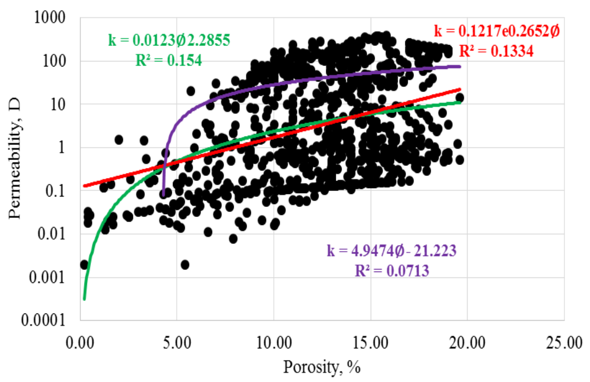

Figure 7. Permeability-Porosity Cross Plot for Three Wells.

III. NEURAL NETWORK MODEL DESIGN AND DEVELOPMENT

A. Data Description

The data presented in this investigation have been collected from four wells covering a wide area of the reservoir. The names of the wells are D1, D2, D3, D10, and D30; of these, the D30 well is used as a blind-test well to assess the proposed prediction model. Before conducting any type of analysis on the well log responses or core data, all data were carefully inspected for depth compatibility. Data shifting has been performed wherever necessary to assure that all values are appropriately adjusted to the same depth. A total of 950 core horizontal permeability measurements and their corresponding well log data were collected from four wells. The commonly used well logs include gamma ray (GR), bulk density log (RHOB), compressional sonic log (DT), effective porosity (PHIE), and deep induction log (ILD). Appendix A shows show logs for wells D1, D2, D3 and D10 respectively. The basic statistics of input and output variables (well logs and permeability data, respectively) are summarized in Table 1.

Table 1. Input (Well log data) and output (Core Permeability) data statistics.

	Deep Resis., ***Ohm.m***	**DT**	**Gamma Ray** ***°API***	**PHIE** ***fraction***	**RHOB** ***g/cc***	**Core perm.** ***md***
Mean	150.19	74.13	47.55	0.1248	2.432	27.24
SD	154.39	4.82	18.49	0.0382	0.051	48.04
Min	12.85	61.46	18.03	0.0009	2.29	0.11
Max	768.49	87.20	108.28	0.2039	2.58	209.42

B. DATA PREPARATION

The data should be normalized before being fed into the ANN model. Normalizing the data generally speeds up learning and leads to faster convergence. A common normalization technique is Min-Max scaling, which puts the data within the range [-1, +1]. The following equation is used in this study:

$$X_{norm} = 2 \times \frac{X - X_{min}}{X_{max} - X_{min}} - 1 \qquad \text{(Eq. 1)}$$

A logarithmic scale has been used instead of the absolute value of the target variable (K). After normalizing the data to the range [-1, +1], it is divided into three parts: training (70% of the data), validation (15%), and testing (15%). Figure 8 shows the pie chart and illustrates how the data is being split.

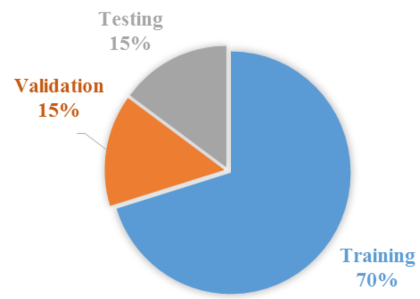

Figure 8. Pie chart shows percent of Training, Validation and Testing data used.

C. Network Training

In this study, Back Propagation Neural Network BP-ANN model was built using the Python programming language, as it is the most widely used and powerful language for deep learning and machine learning projects [18–21]. A typical BP-ANN is composed of three layers: input, hidden, and output layers. Each layer is made of a number of processing elements, or neurons. Each neuron is connected to each neuron in the preceding layer by a simple weighted link. The BP-ANN requires the use of training patterns, and involves a forward-propagation step followed by a backward propagation step. The forward propagation step sends an input signal through the neurons at each layer, resulting in the calculation of an output value. BP-ANN uses the following mathematical function:

$$y = \left[b_0 + \sum_{j=1}^{n_2} b_j f_j \left(w_{oi} + \sum_{i=1}^{n_1} w_{ij} x_i \right) \right] \quad \text{(Eq. 2)}$$

where y is the output variable, x_i are the input variables, b and w are the connection weights, n_1 is the dimension of the input vector, and n_2 is the number of hidden neurons. The objective of the neural network is to obtain optimal weights to give the best value for the neuron (node of the dependent variable) of the output layer [18]. In this work, a process of trial and error is used to design an optimally performing network. The network architecture that has been designed consists of:

- input layer: five input neurons (GR, ILD, RHOB, DT, and PHIE)
- 1st hidden layer: 35 neurons
- 2nd hidden layer: 20 neurons
- Output layer: one neuron (log core permeability)

The Levenberg-Marquardt training-back propagation algorithm was used in this project, with hyperbolic tangent (Tanh) as the activation function. This algorithm is easy to understand mathematics-wise, and training is time-efficient, especially in data fitting and function approximation problems. A sketch of the architecture of the designed neural network is drawn in Figure 9.

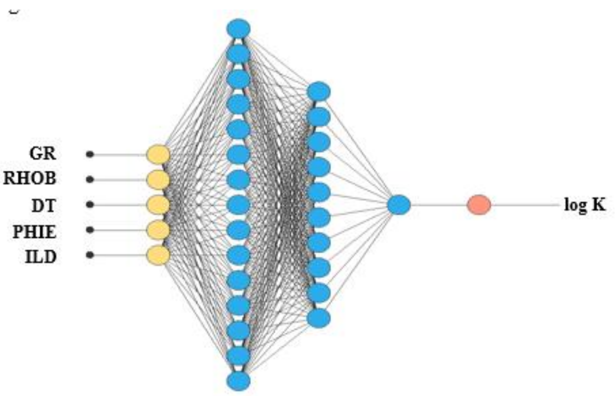

Figure 9. Designed Neural Network model.

When training a neural network, there comes a point where the network should no longer be trained to avoid overfitting; consequently, the best parameters are to be selected that prevent overfitting and yield a good generalized model. The network training is done in two steps: forward propagation (training) and backward propagation (error minimization through weight alteration). Figure 10 shows the mean squared error (MSE) as a function of epoch, where epoch defines the number of times that the learning algorithm will work through the entire training dataset to obtain the error training curve of the used algorithm.

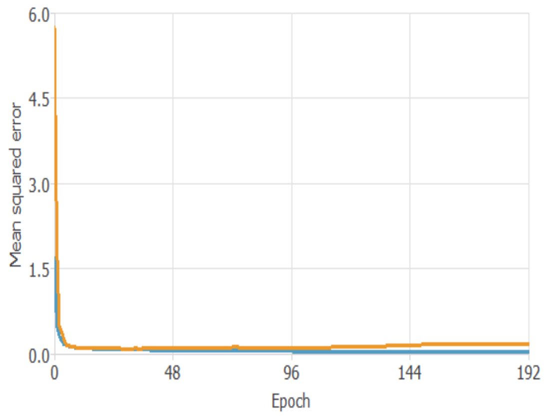

Figure 10. Levenberg Marquardt technique error history.

IV. RESULTS AND DISCUSSION

A back-propagation neural network is trained with all the available data from four wells (D1 to D3 and D10), including the measured permeability from cores. This is the "learning" process, during which the network recognizes the pattern of permeability distribution and "adapts" itself in order to be able to predict that pattern. By trial and error, network training led to the following results, as shown in Table 2, and the performances showing the initial and final MSE.

Table 2. Summary of the performance of the datasets used

MSE	Training	Validation	Testing
Initial MSE	1.6853	5.758	6.58
Final MSE	0.0231	0.1	0.12

Despite the presence of high reservoir heterogeneity, the performance of the ANN model yielded a good match with a correlation coefficient (R^2) of 95%, as shown in Figure 11. After the model is trained successfully, it is then applied to the testing dataset, also called the "unseen dataset," as shown in Figure 12. The model yielded a correlation coefficient of 90%, which indicates a good generalization of the model that was trained. Except for a few points, the good agreement between predicted and measured values is obvious.

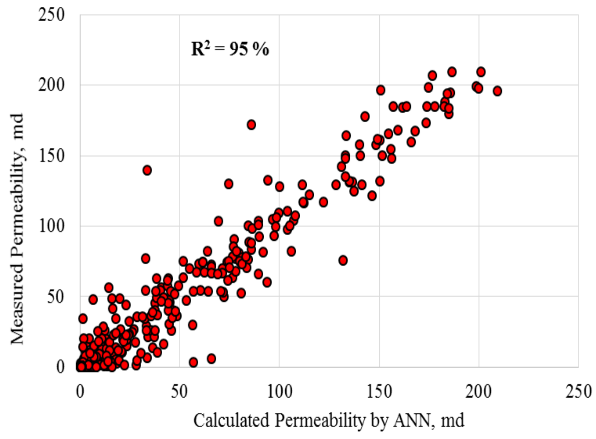

Figure 11. Training Dataset Performance.

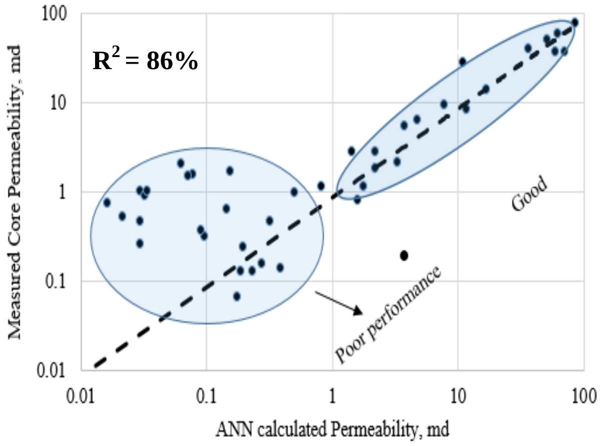

Figure 13. A crossplot of measured permeability versus predicted permeability using the trained BP-ANN for well D30.

With these promising results, permeability was predicted for the rest of the uncored wells in the reservoir. The trained BP-ANN is applied to the data set from Well D30 as a completely independent test. Figure 13 illustrates the performance of the ANN model on a dataset that was not used for either training or testing. It is clear from that ANN model that it provides a very good fit to the measured permeability data, with a correlation coefficient R^2 of 86%. The model, however, performs poorly at k $\leqslant$ 1 millidarcy (nonreservoir). The principal reason why some of the extreme points do not match may be that, during training, the BP-ANN did not receive enough information to acquire the ability to predict very low values at some intervals. Or, the dataset has some pretty small outliers or widely varying ranges between features. Moreover, although the systematic shift of 4.5 m between well log and core sample depths has been removed, small random shifts in depth between the two values still exist.

According to these results, the author believes that the prediction of permeability could be improved if the data were divided into several sections based on suitable classification techniques such as the Flow Zone Indicator [22] or the Global Hydraulic Element [23]. Then the permeability in each sector could be estimated based on a separate network.

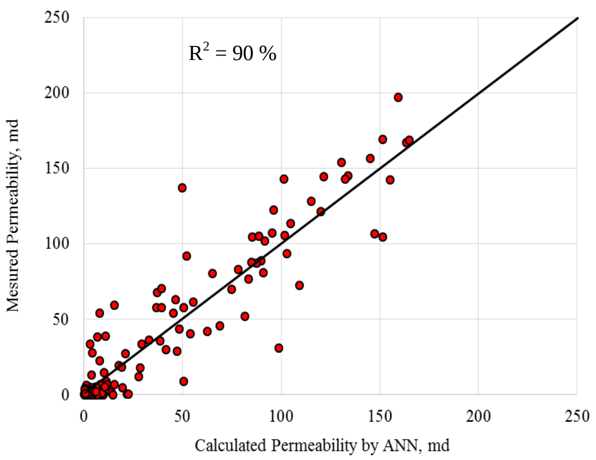

Figure 12. Testing Dataset Performance.

V. CONCLUSIONS

Based on this study, the following conclusions were drawn:

[1] The Hawaz formation in the Murzuq basin (D Field) is a very complex and heterogeneous carbonate reservoir.

[2] Traditional statistical analysis of the porosity/permeability relationship from the cored well data did not reveal any reliable correlations that could be used to predict permeability in uncored wells.

[3] ANN was successfully developed, and the permeability profile predicted by the ANN model using logging data agrees well with core permeability, which clarifies the applicability of this technique.

[4] It is recommended to classify reservoirs into different zones based on suitable techniques to overcome the extreme reservoir heterogeneity, then apply ANN for each zone. Also, the inclusion of data with sufficient geographic, environmental, diagenetic, and geochronological diversity will lead to a more widely applicable ANN permeability model.

ACKNOWLEDGMENT

The author wishes to thank the Libyan Oil Corporation (NOC) and Akakus Oil Operations for providing the data necessary to complete this work. Also, special thanks to Eng. Abdurrauf A. Elshomakhi for his assistance and time to code ANN in the Python programming language to accomplish this work.

REFERENCES

[1] Lim, J.S., and Kim, J. "Reservoir porosity and permeability estimation from well log using fuzzy logic and neural networks," paper SPE 88476, Asia Pacific Oil and Gas Conference, Perth, Australia, October 18–20, 2004.

[2] Tiab, D. "Advances in Petrophysics," Vol. 1-Flow Units. Lecture Notes Manual, University of Oklahoma, 2000.

[3] Glover, P. "Petrophysics Permeability, Petrophysics MSc Course Notes," University of Aberdeen, UK, 2014.

[4] Arwini, S., "Porosity-Permeability Relationship of Libyan Carbonate Reservoir in Defa Oil Field," *World Academics Journal of Engineering Sciences* (WAJES), Vol.7, Issue No. 2, pp. 1-5, June, 2020.

[5] Wendt, W. A., Sakurai, S., and Nelson, P. H., "Permeability Prediction from Well logs Using Multiple Regression," *Reservoir Characterization: Academic Press, Inc*., Orlando, Florida, pp. 181-222, 1985.

[6] Mohaghegh, S., Balan, B., and Ameri, S., "State-of-the-Art in Permeability Determination from Well Log Data: Part2 – Verification, Accurate Permeability Predictions, the Touch-Stone of all Models, SPE 30979, Presented at the SPE Eastern Regional Conference and Exhibition, held in Morgantown, West Virginia, September 17-21, 1995.

[7] Size, W.B., "Use and Abuse of Statistical Methods in the Earth Sciences," Oxford University Press, New York, 1987.

[8] Davis, J C., "Statistics and Data Analysis in Geology," John Wiley, New York, 1990.

[9] Shokir, E. M. EL-M., "Neural Network, Neural Network Determines Shaly-Sand Hydrocarbon Saturation," *Oil & Gas Journal*, pp. 37-41, April 23, 2001.

[10] Shibli, S. A.R., Wong, P. M., Huang, Y., and Maignan, M., "Applications of AI-Based Techniques for Spatial Prediction," Third Annual Conference of the IAMG, Proceedings: Part 2, pp. 675–680, 1997.

[11] Wong, P. M., Taggart, I. J., and Jian, F. X., "A Critical Comparison of Neural Networks and Discriminate Analysis in Lithofacies, Porosity and Permeability Predications," *Journal of Petroleum Geology*, Vol. 18, No. 2, pp. 191-206, 1995.

[12] Wong, P. M., Tamhane, D., and Wange, L., "A Neural Network Approach to Knowledge-Based Well Interpolation: A Case Study of a Fluvial Sandstone Reservoir," *Journal of Petroleum Geology*, Vol. 20, No. 3, pp. 363–372, 1997.

[13] Singh, S. "Permeability prediction using artificial neural network (ANN): A case study of Uinta Basin," Paper (SPE-99286-STU) presented at the SPE Annual Technical Conference and Exhibition, Dallas, Texas, October 2005.

[14] Buschow, K.H.J., Cahn, R.W., Flemings, M.C. et al. "Encyclopedia of Materials: Science and Technology," Elsevier, 2001.

[15] Nagyfi. R. "The differences between Artificial and Biological Neural Networks," 2018, [Online]. Available: https://towardsdatascience.com/the-differences-between-artificial-and-biological-neural-networks-a8b46db828b7, (accessed August 1, 2023).

[16] Mohamed, A. K. Selim, E.I, Kashlaf, A. "Integration of seismic interpretation and petrophysical studies on Hawaz Formation in J-field NC-186 concession, Northwest Murzuq basin, Libya," *NRIAG Journal of Astronomy and Geophysics*, Elsevier, Vol. 5, pp. 334–350, 2016.

[17] AOO, "Field Development Plan: D-field NC-186 concession," Akakus Oil Operations, Tripoli, Libya, 2020.

[18] Layton, R. "Learning Data Mining with Python," Packet Publishing Ltd.: Birmingham, UK, 2015.

[19] Python, "Python Software Foundation," Python Language Reference, Version 2.7. [Online]. Available: http://www.python.org. (accessed January 20, 2023).

[20] van Rossum, G. "Python tutorial," Technical Report CS-R9526, Centrum voor Wiskunde en Informatica (CWI), Amsterdam, May 1995.

[21] Al-Otaibi, Mohammed Abdullah, Abdullah, Eassa, and Sherif Mahmoud Hanafy. "Prediction of Permeability from Logging Data Using Artificial Intelligence Neural Networks." Paper presented at the SPE Western Regional Meeting, Anchorage, Alaska, USA, May 2023. doi: https://doi.org/10.2118/213036-MS

[22] Amafule, J.O., Altunbay, M. Tiab, D., Kersey, D.G. and Keelan, DR. "Enhanced reservoir description: Using core and log data to identify hydraulic (flow) units and predict permeability in uncored intervals/wells," Proceedings of the 68th SPE Annual Technical Conference and Exhibition, , Houston, Texas, Society of Petroleum Engineers, pp. 205-220. October 3-6, 1993

[23] Corbett, P. W. M., Ellabad, Y., Mohammed, K. R., and Pososyaev, A. "Global hydraulic elements-elementary petrophysics for reduced reservoir modelling," Paper presented at 65th EAGE Conference and Exhibition, Stavanger, Norway, June 2-8, 2003.

APPENDIX A: WELL LOGS DATA

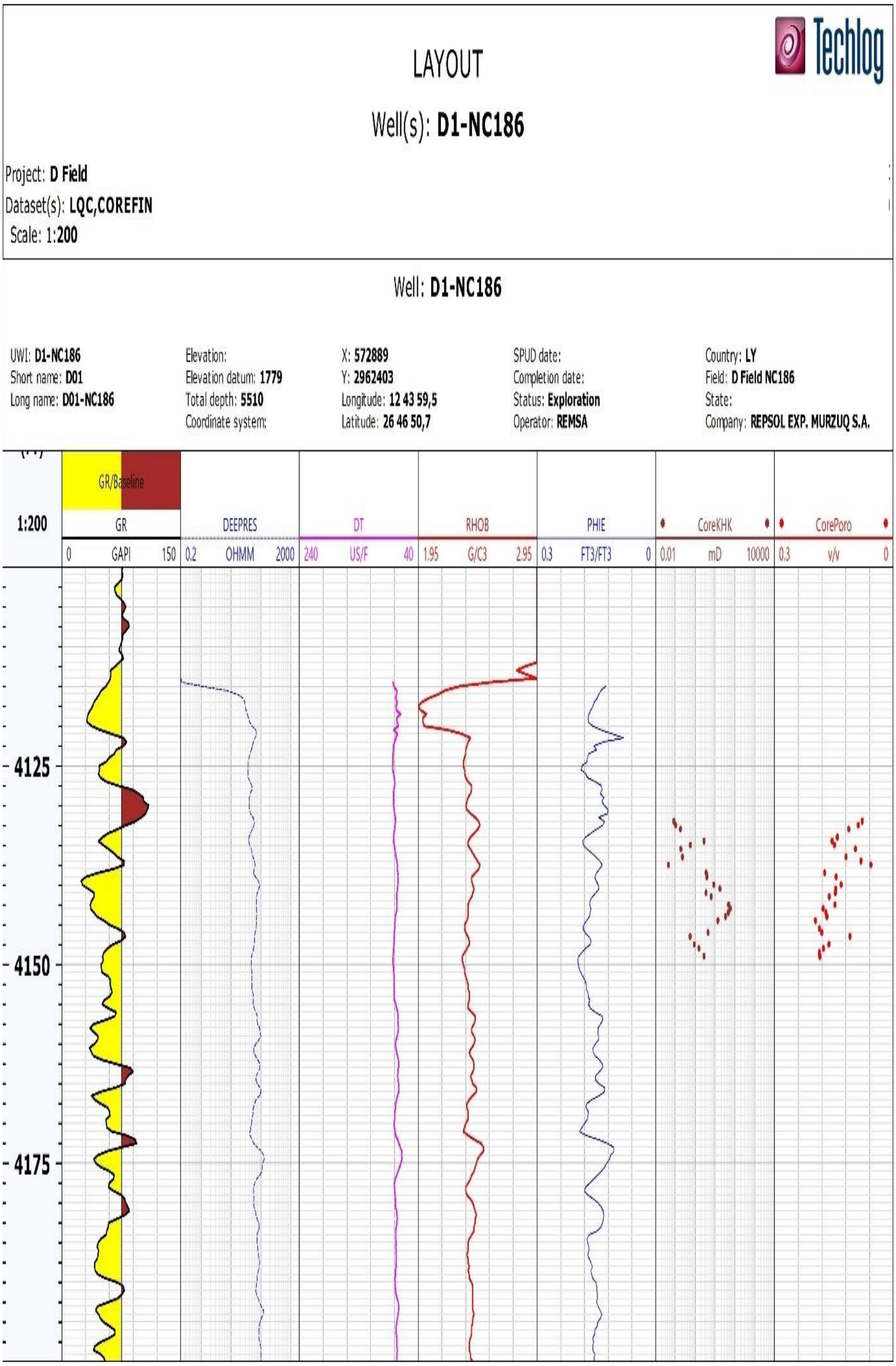

Figure A.1. Well logs D1

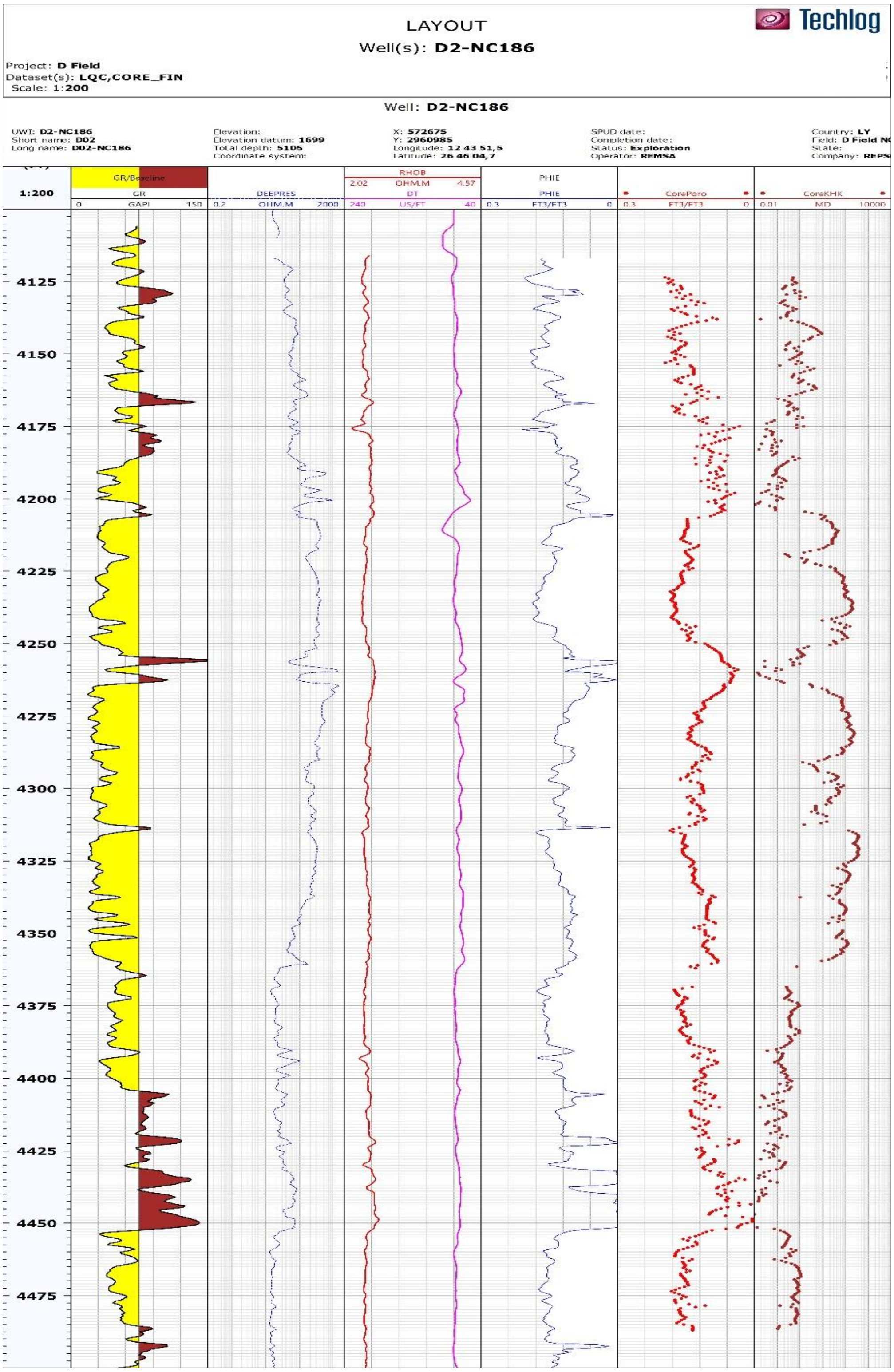

Figure A.2. Well logs D2

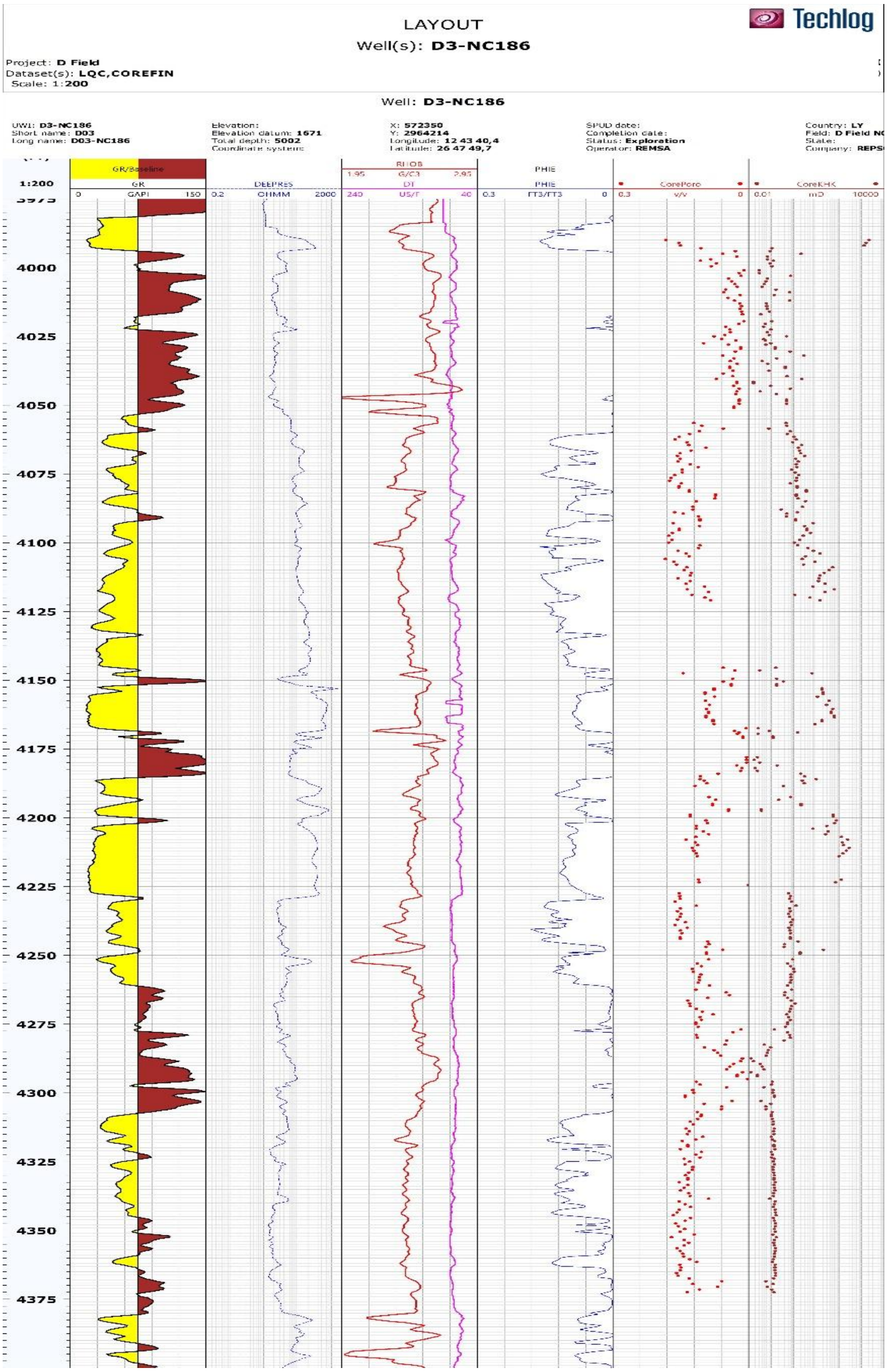

Figure A.3. Well logs D3

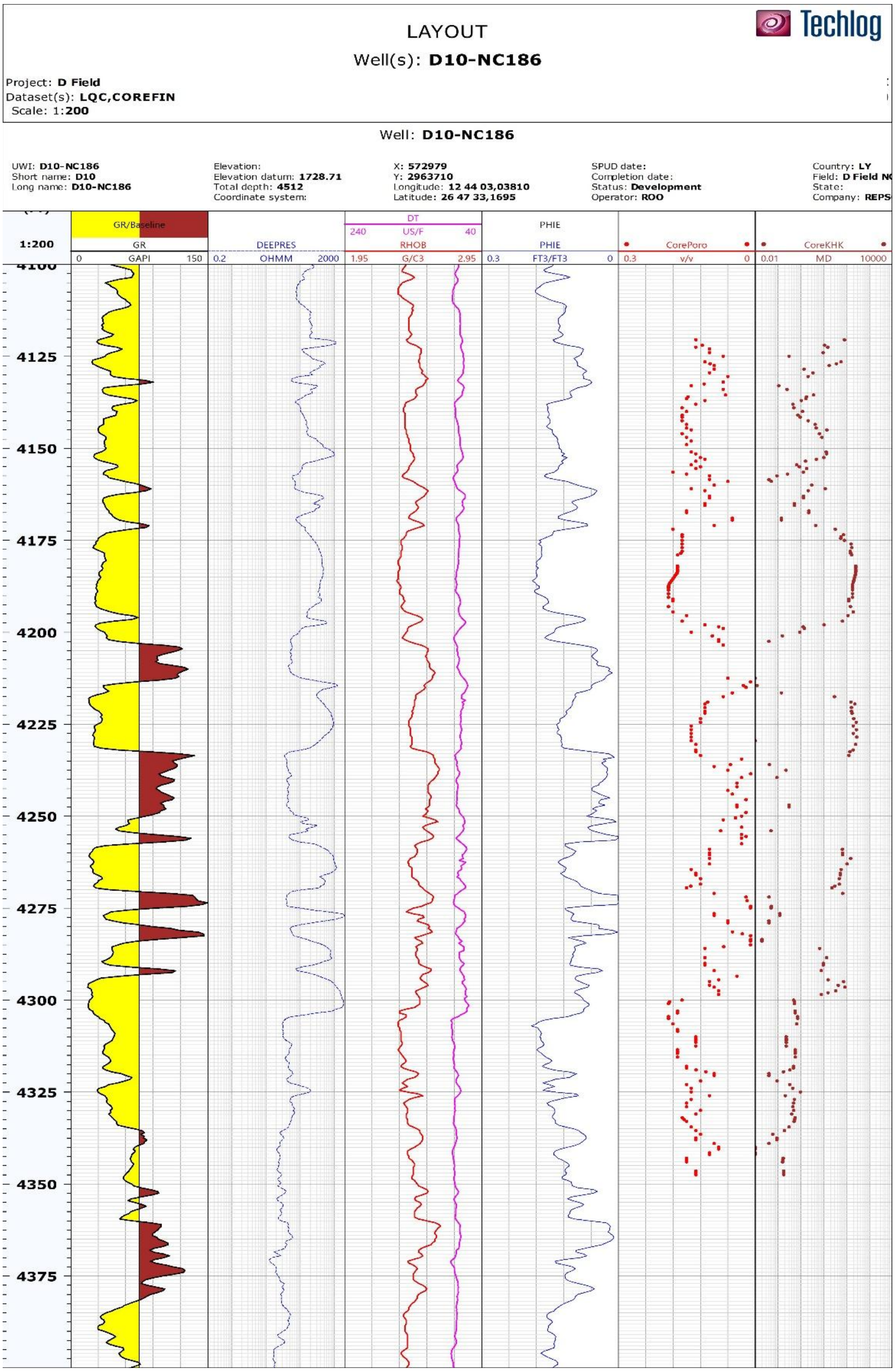

Figure A.4. Well logs D10