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Porosity and Density Determination from Well Log Data: Machine Learning and Simulation Approaches

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ABSTRACT

Reservoir characterization is vital for petroleum exploration, largely relies on well log data analysis. Machine Learning (ML) empowers analysis of complex datasets quickly and more easily in a cost-effective way. ML allows deeper insights into reservoir properties such as porosity, permeability, water saturation, resistivity and many more. This study focuses on Reservoir characterization using ML approach (Python). Investigating reservoir behaviours involves intricate inverse problems; ML tackles this challenge. Integration of ML improves understanding, optimizing petroleum industry practices. This study used data from well logs to evaluate porosity, density, and gamma ray log. Through Petrel-based simulations, the findings were verified and validated.

1. Introduction

Reservoir characterization, especially well log data analysis plays an important role in petroleum exploration. Reservoir characterization is a process for quantitatively assigning reservoir properties, such as porosity, permeability, and fluid saturations, while recognizing geologic information and uncertainties, in spatial variability [1,2]. In essence, it is a process of identifying the petrophysical characteristics of the subsurface primarily using seismic and well-log data [3]. It is essential in determining if reservoir management and development strategies are economically successful. A significant amount of heterogeneity is sown by almost all reservoirs [4-6]. This nonlinear and heterogeneous nature of the subsurface is the major bottleneck in estimating the reservoir properties [7]. Evidently the properties that determine reservoir quality are porosity and permeability [8].

The productivity of wells in hydrocarbon-bearing reservoirs depends on Petro-physical properties which include lithology, porosity, water saturation, permeability, etc. Any method for

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characterization of a reservoir should focus on its transport and storage characteristics, such as permeability and porosity. Through the pore networks of the porous systems, they regulate the flow and directions of the reservoir fluids [9]. These properties of a reservoir are estimated using well logs data, such as gamma ray, density, neutron porosity log, photoelectric effect values, and resistivity logs. Shale is frequently found in areas with high GR values because it has a higher natural radioactivity level. Low GR values point to lithologies other than shale, such as sandstone or limestone [10]. Additionally, Low Neutron Porosity (NPHI) values imply low porosity whereas High Neutron Porosity (NPHI) values show high porosity. Higher values represent a more porous formation because this log directly measures porosity [11]. While increased porosity is associated with low bulk density or RHOB values because denser rocks have higher bulk densities. Low RHOB levels therefore indicate more porosity [12].

Geophysical well logging is a process in which a logging tool is lowered into a well and some electronic and/or radioactive signals are sent to the rock formations and subsequent responses are recorded and analysed [1].

So, from the above discussion, Reservoir characterization methods can be categorized into these types:

i. Experimental Method
   a. Core Sample Analysis
   b. Well Logs Analysis
ii. Reservoir Simulation
iii. Machine Learning Approaches

In general, experimental methods are more time consuming as well as expensive than any other methods [13]. Besides, reservoir simulation method is also too much expensive due to powerful hardware requirement. However, the principal advantage of the method is its speed, which comes from the fact that it simply post-processes the results of any technique that produces conditional probability distributions [14]. Lastly, machine learning can be a powerful tool in reservoir characterization as it allows for the analysis of large and complex datasets within very short time period which is at the same time it is cost effective too. By proper utilization of machine learning techniques, the industry can potentially gain a deeper view of reservoir properties, behaviour, and uncertainties, which will lead to more informed and optimized reservoir management decisions. In order to address bottlenecks, machine learning (ML) can be utilized to completely extract the knowledge behind such crucial data [15]. With the aid of ML, the system is able to automatically learn from and improve upon earlier data without having to be explicitly programmed.

The objectives of this research were porosity and density determination and validation of the machine learning output through simulation. Here, reservoir characterization is presented by applying a systematic ML approach and analysing the relevant research released in recent years. The results obtained in the article were also validated in this study by simulation using Petrel. Through new technology and data acquisition to processing and interpretation, the rate of success in exploration has risen up to 40%. Using prediction method more analysis can be done on it and more depths of data can be earned which is not done here.

2. Data Description

The type of data used for this research work was well log data. The version of log was CWLS log ASCII Standard Version 2.00. The range of Depth was 2000.0976 m to 2449.9824 m. In this study, data was taken in each 0.1524 m interval. It was an exploratory field. Hole Fluid type was Polymer fluid and density was about 1.09796957350526 G/C3. These data were in dot(.)las format or computer supported format (softcopy). All data digitized from hard copy log, Specific Curves and Intervals. No additional editing applied, data output as per logs. Basically, in reservoir characterization different types of data are used. The data required for reservoir characterization can vary depending on the specific objectives and the type of reservoir being studied.

In machine learning, especially in Python, the choice of data for reservoir characterization depends on the specific task and the nature of the machine learning algorithm being used. After analysing all the aspects, it was decided to work with well log data as Well logs provide continuous measurements of rock and fluid properties along the wellbore. They can be directly used as input features in machine learning algorithms. Log data can be pre-processed, normalized, and used to train models for various tasks such as lithology classification, porosity estimation, permeability prediction, and facies identification [3]. So, it was easier to extract well log data with machine learning software and working for further investigations.

When using machine learning in reservoir characterization, it is common to combine multiple data types to improve the accuracy and robustness of the models. For example, a combination of different well logs like gamma ray log, neutron porosity log, density log and more information can be used together as input features to predict reservoir properties or identify sweet spots for drilling. Well logs have high resolution along the depth.

Several key parameters are commonly present in well log data that are relevant for reservoir characterization. The specific parameters required can vary depending on the objectives of the reservoir characterization study and the properties being evaluated. The parameters that have been used in this study was gamma ray, neutron porosity, density and bulk density because for porosity measurement, the gamma ray log (GR), neutron porosity (NPHI), sonic log (DT) and bulk density (RHOB) logs should be used [3]. Main focus of this study was to calculate Porosity from (.)las file. Gamma ray was used to validate the algorithms from a previous study of same field. Bulk Density and density were evaluated as is related to porosity. The more is the density the less is the porosity.

3. Methodology

Initially the required data was selected analysing the previous research paper. After collecting the specific data, a crosscheck was done for machine learning use. For this study, data format of (.)las extension was needed, the data format was verified and sometimes it was converted as required. After finalizing file format, the data was run in Machine Learning software. In this study, PyCharm Community Edition 2023.1.1. was used.

PyCharm Community Edition 2023.1.1 is the latest iteration of the popular Integrated Development Environment (IDE) designed for Python developers. Developed by JetBrains, this version comes with a host of exciting features and enhancements that aim to streamline the coding experience. With its user-friendly interface and powerful tools, PyCharm Community Edition remains a top choice for programmers of all levels, whether they are beginners or seasoned professionals.

In PyCharm Community Edition 2023.1.1 the data was run using a specific algorithm, which was developed for this research project specifically. The algorithm was built in such a way so that the minimum algorithm value, average value as well as maximum value can be determined at the same time for any given range. This same algorithm also enables graph plotting for the given ranges. All the work is done in frictions of seconds because it is super time efficient, which is so important in modern days. After getting results, it was validated using previous works done on same field by different methods. To validate the algorithm, after running the algorithm in PyCharm for a well log file and obtaining values of targeted parameters, the seismic file of the same well was run and modelled in Petrel software. Different parameters like GR log, NPHI, DRHO were calculated. The provided code does not include any specific Machine Learning algorithms. However, it primarily focuses on reading LAS files (a file format used in the oil and gas industry to store well log data), extracting specific curves from the data, performing basic data analysis (calculating averages), and visualizing the curves using following Python libraries:

i. lasio: This lasio library is used for reading LAS files, which are commonly used in the oil and gas industry for storing well log data.
ii. numpy: This is a fundamental library for numerical computations in Python. numpy provides support for arrays, matrices, and a wide range of mathematical operations.
iii. matplotlib: matplotlib library is used for creating visualizations in Python. It provides a range of functions for creating plots, charts, and graphs.

Petrel allows to interpret and analyse seismic data, incorporate and interpret well logs and petro physics, build geological models, build and run simulation models and incorporate production data. Actually, Petrel here was used to validate the algorithm. The values obtained from well log data using the algorithm were validated by using Petrel software modelling. The same values were found in Petrel software too. To simulate the seismic data in Petrel, the steps basically were followed are given below.

At the very first step, the seismic data were given as input in Petrel simulation software. The seismic data must be in (.)sgy format. After loading the data in Petrel, some seismic data was selected, and accurate and proper horizon were selected for 3D modelling. Then, considering all the steps a proper validated model was created. Now, a new interpretation window has opened, and log data were given as input here. From input section, well log was check marked and here some log section will be opened which were done in main well logging work. In this section the log data that is wanted to know or determine or check, should be check marked. Now, in the interpretation window, the chosen log will be shown.

Porosity calculation was done using gamma ray log. The formula or equation [16,17] for porosity using gamma ray log is given below as Eq. (1).

$$\text{Porosity} = \alpha \frac{(\varphi - \varphi \min)}{(\varphi max - \varphi min)} \tag{1}$$

where,
φ is known as gamma ray log value for specific depth,
φ min is the minimum gamma ray log value,
φ max is the maximum gamma ray log value,
α is known as Rock type value constant.

Now,
value of φ =110 GAPI; φ min =90 GAPI; φ max 145 GAPI and α is 0.6
So, Porosity is calculated 0.21.

4. Results and Discussion

After running the algorithm in machine learning, a prompt window opened and showed the keys available in the well log file. After that, it asked to choose which keys or parameters were wanted to calculate. After selecting specific parameters, the prompt asked the range we want to calculate. When we input the range of our expected range and enter the press, the prompt window shows us a graphical representation of desired parameters and at the same time minimum, maximum and average value of that Range.

For Gamma Ray value measurement, we have chosen GR log from the prompt and selected the full range. At next it showed the graphical representation and the mentioned values. Similarly, For Density log value, Bulk Density value and Neutron Porosity value measurement, we have chosen RHOB, DRHO and NPHI respectively from the prompt and selected the full range. At next it showed the graphical representations and the mentioned values of parameters.

In Figure 1, four calculated logs' output windows are shown. In Figure 1 (a) Gamma ray values have been calculated. In Figure 1 (b) RHOB or Density Log calculation has been shown. Similarly, in Figure 1 (c) and in Figure 1 (d) the Bulk Density or DRHO log and NPHI or Neutron Porosity log have been calculated respectively. For all the logs, the minimum and maximum values have been shown including Average values of the mentioned logs too.

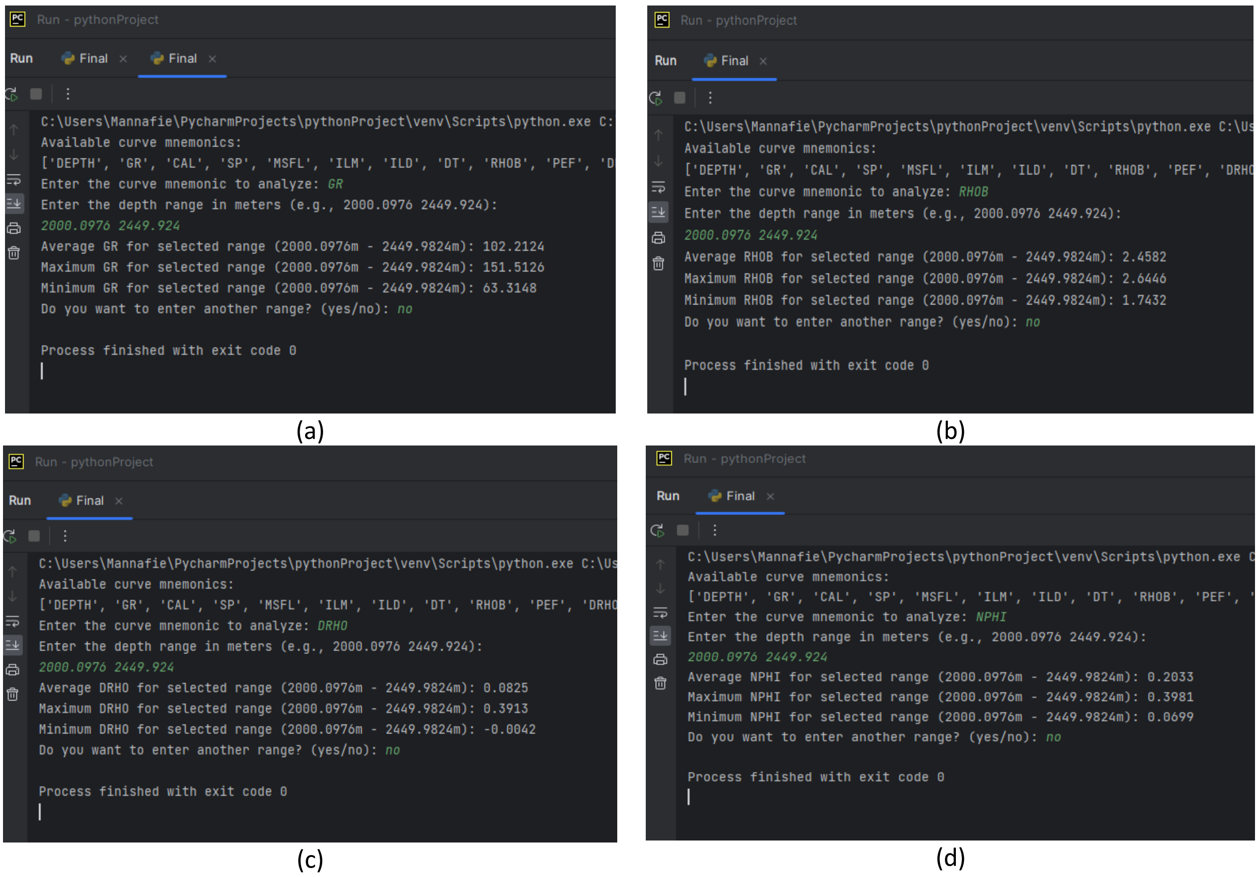


Fig. 1. Values of various logs; (a) GR log, (b) RHOB log, (c) DRHO log, and (d) NPHI log

The obtained values have been shown in Table 1 for getting a quick overview. Log values were measured for different ranges. Minimum and maximum values at the same time the average values were calculated and plotted in the graphs for proper visualization.

Table 1
Obtained Values of Required Parameters

Name of Log	Range (m)	MAX	MIN	AVERAGE
GR	2000.0976 - 2449.924	151.51 GAPI	63.314 GAPI	102.21 GAPI
GR	2400.5600 - 2447.500	151.51 GAPI	63.934 GAPI	101.93 GAPI
GR	2427.600 - 2443.5000	151.51 GAPI	76.221 GAPI	120.03 GAPI
RHOB	2000.0976 - 2449.924	2.6446 G/C3	1.7432 G/C3	2.452 G/C3
DRHO	2000.0976 - 2449.924	0.3913 G/C3	-0.0042 G/C3	0.0825 G/C3
NPHI	2000.0976 - 2449.924	0.3991	0.0699	0.2033

Here Figure 2 represents the Gamma ray log. In the Graph Maximum Value is 151.5126 GAPI, whereas, Minimum value is 63.314 GAPI and Average value is 102.2124 GAPI. Moreover, in this graph, it is seen that at the start the gamma ray log is very low and from 2000m to around 2030m the gamma ray log value is comparatively lower. In fact, after 2310m Gamma ray reading is seen so much fluctuating. And after 2400m the value suddenly goes up and suddenly goes down. Dramatically it suddenly goes up again. Basically, it indicates different layers of lithology zone.

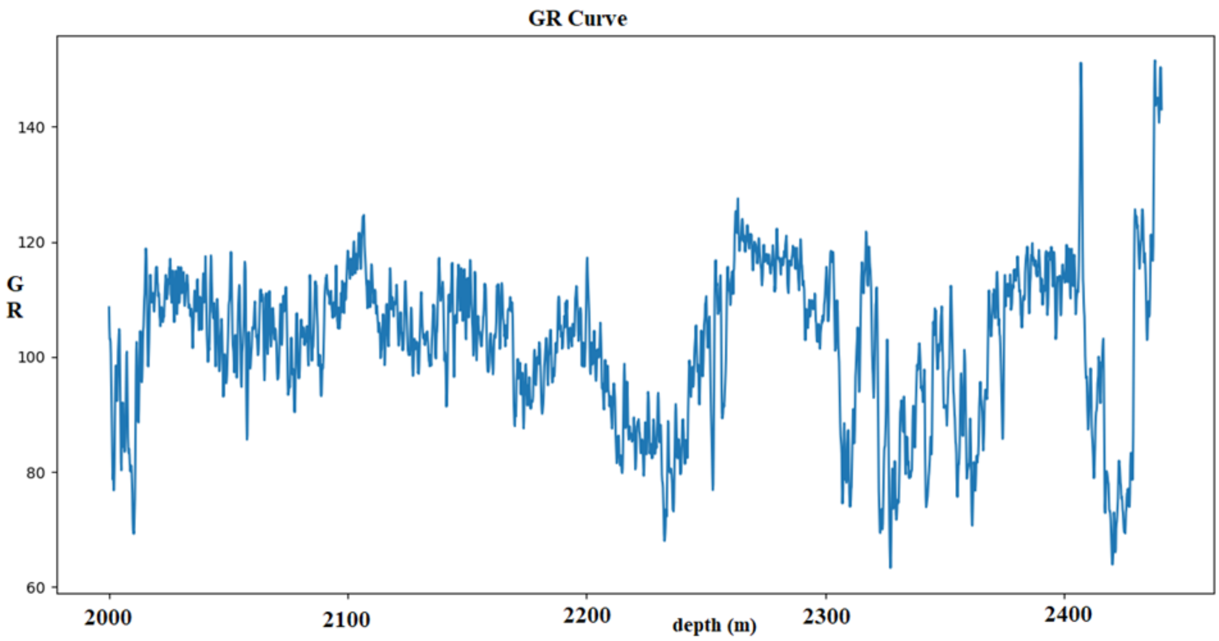


Fig. 2. Gamma Ray Log

When gamma ray readings are high, it typically indicates the presence of radioactive materials in the formations. These materials can include shales and clay-rich rocks, which tend to have higher levels of naturally occurring radioactive elements like uranium and thorium [18]. High gamma ray readings can also suggest the presence of certain mineral deposits. Conversely, when gamma ray readings are low, it often suggests that the formations are composed of non-radioactive materials, such as sandstones or limestone. These rocks usually have lower levels of naturally occurring radioactive elements, leading to reduced gamma ray emissions [19].

In Figure 3 of Neutron Porosity Log, it is seen at starting the porosity value for a specific range is very high, but then the level seems constant. At the very end, around 2310m suddenly the porosity value started to change drastically. Which is the same as gamma ray values. So, it can be optimized that there's a relationship between gamma ray and porosity value. Here, the Maximum Value of porosity is 0.3991 and minimum value is 0.0699. Whereas Average porosity value is 0.2033.

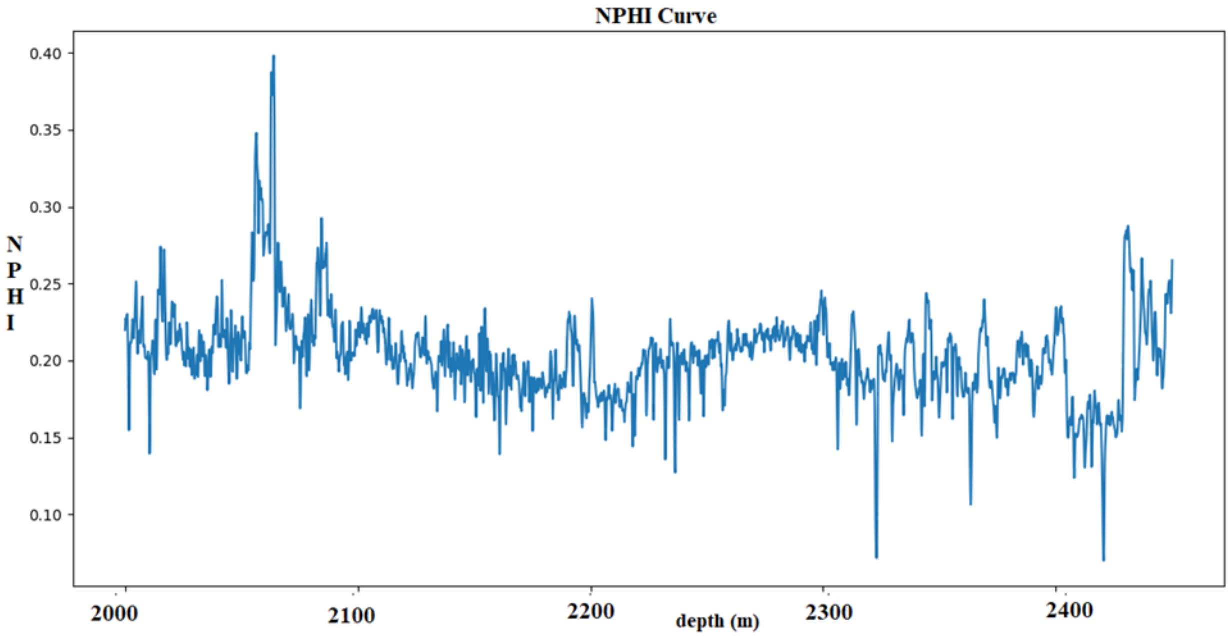


Fig. 3. Neutron Porosity Log

The density log graph or Figure 4 represents almost the opposite of Neutron porosity log. Because the denser the rock mass the lower the porosity Here, the Maximum Value is 2.6446 G/C3. Minimum value is 1.7432 G/C3 and Average value is 2.452 G/C3

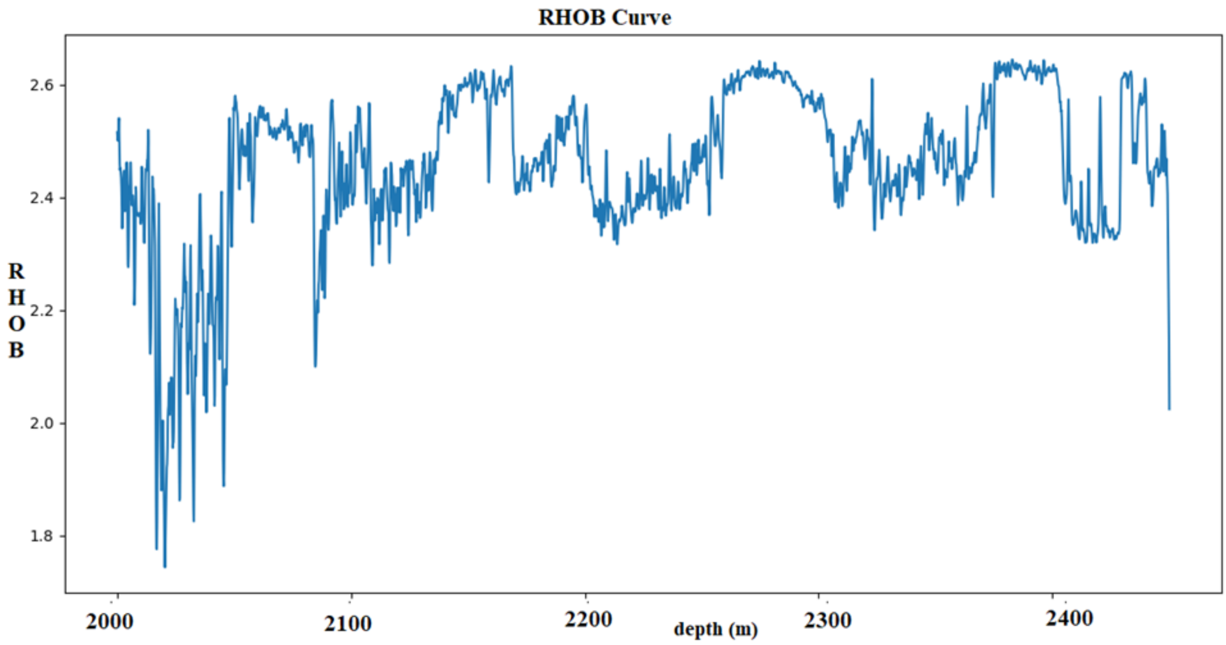


Fig. 4. Density Log

In well logging, when the density is higher than expected, it may indicate the presence of denser materials in the subsurface, such as rocks with high mineral content or the presence of fluids with higher densities, like brine or drilling mud [19]. On the other hand, when the density is lower than anticipated, it could indicate the presence of less dense materials, such as porous rocks or fluids with lower densities, like hydrocarbons or gas [12]. Interpreting density measurements in well logging helps geoscientists and engineers understand the composition of the subsurface and can provide valuable information for determining the type of formations and potential resources present in a well [20].

Now, In Figure 5 the Bulk Density Log representing graph has been shown. The Maximum Value of bulk density is 0.3913 G/C3 but the Minimum value is negative, and it is -0.0042 G/C3. Average value is 0.0825 G/C3. When the bulk density is higher in well logging, it generally indicates that the subsurface material being logged is denser and more compact. On the other hand, when the bulk density is lower in well logging, it suggests that the subsurface material is less dense and more porous [21-25]. So, it can be identified from the graph that though the initial zone in around 2000m to 2150m is more compact or non-porous zone but the depth down below 2150m is more porous. Because from that depth the bulk density values seem constant and lower than initial values.

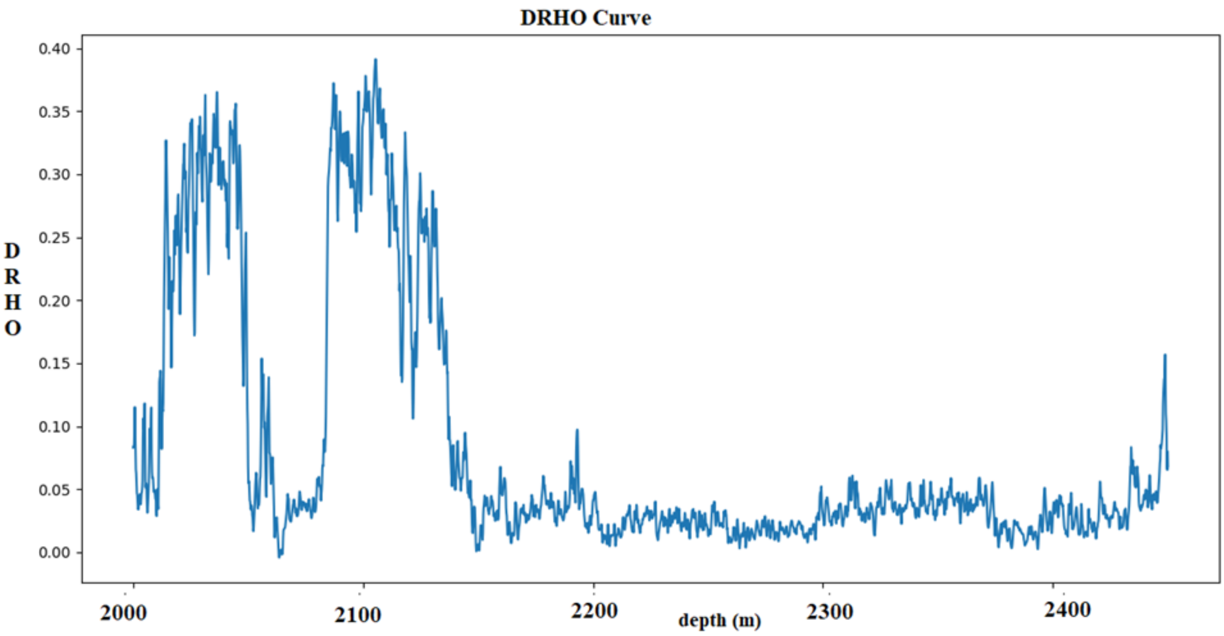
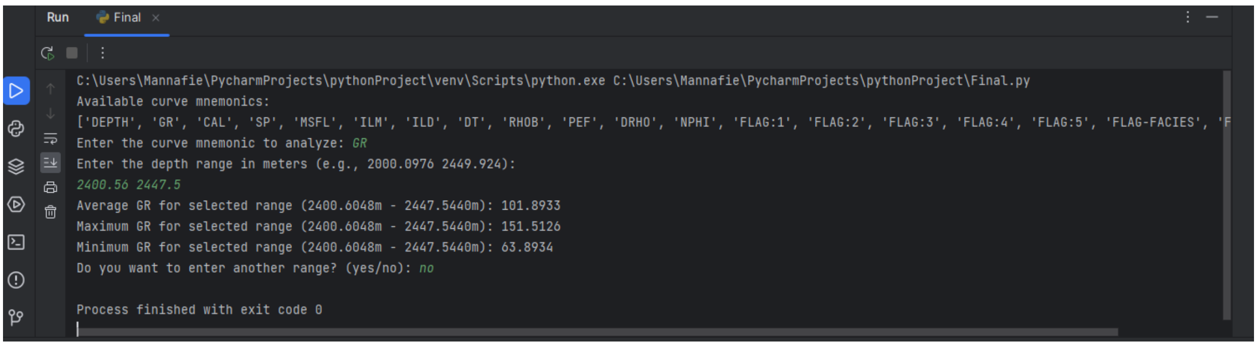


Fig. 5. Bulk Density Log

Now, for more detail's representation of graph, the range should be shortened. And using this algorithm, the shortening process is simpler and easier. By shortening the range of expectations in input variables it can be easily executed. For example, for the given input range of 2400.56m - 2447.5m, the following data and graphical representation is shown.

At this stage, Figure 6 represents the range shortening process for GR log. And Figure 7 represents the shortened but detail graph of gamma ray log.



```
C:\Users\Mannafie\PycharmProjects\pythonProject\venv\Scripts\python.exe C:\Users\Mannafie\PycharmProjects\pythonProject\Final.py
Available curve mnemonics:
['DEPTH', 'GR', 'CAL', 'SP', 'MSFL', 'ILM', 'ILD', 'DT', 'RHOB', 'PEF', 'DRHO', 'NPHI', 'FLAG:1', 'FLAG:2', 'FLAG:3', 'FLAG:4', 'FLAG:5', 'FLAG-FACIES', 'F
Enter the curve mnemonic to analyze: GR
Enter the depth range in meters (e.g., 2000.0976 2449.924):
2400.56 2447.5
Average GR for selected range (2400.6048m - 2447.5440m): 101.8933
Maximum GR for selected range (2400.6048m - 2447.5440m): 151.5126
Minimum GR for selected range (2400.6048m - 2447.5440m): 63.8934
Do you want to enter another range? (yes/no): no

Process finished with exit code 0
```

Fig. 6. Values of GR log

From the graph, the graph became more detailed and can easily be visualized than before. Now, for another given input range of 2427.6m - 2443.5m, the following data and graphical representation is shown below using same algorithm.

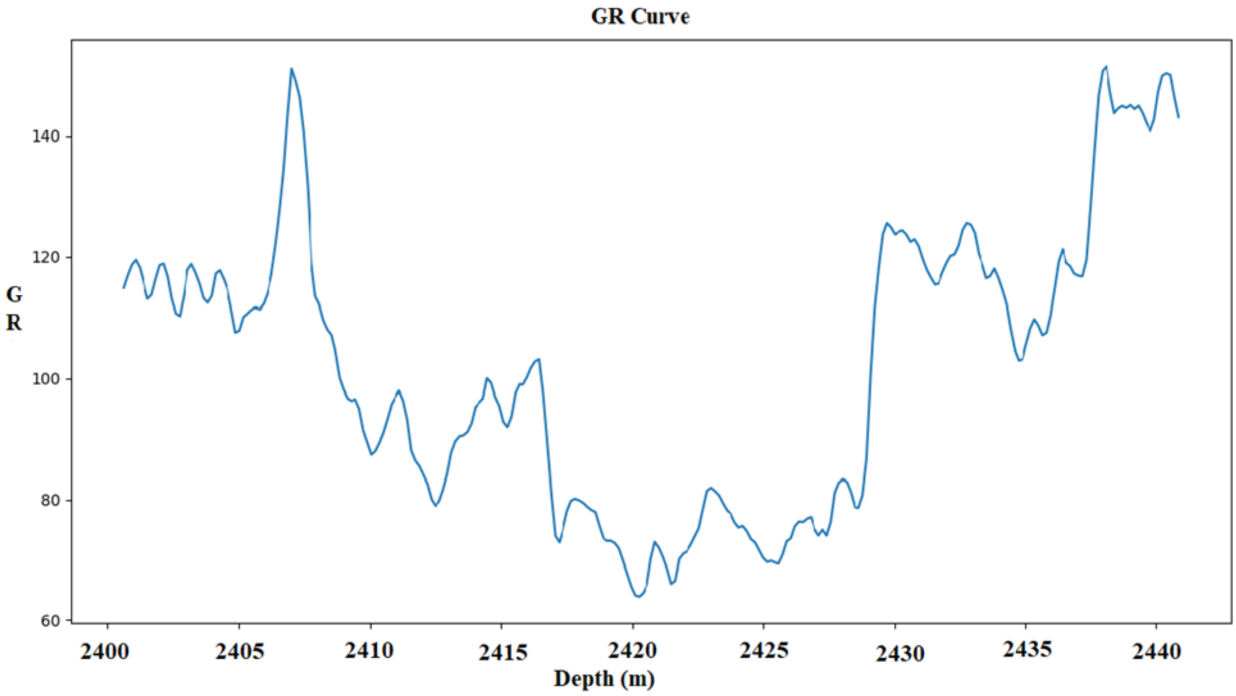


Fig. 7. Gamma Ray Log

Here, again Figure 8 represents a more detailed GR log extraction input given procedure.

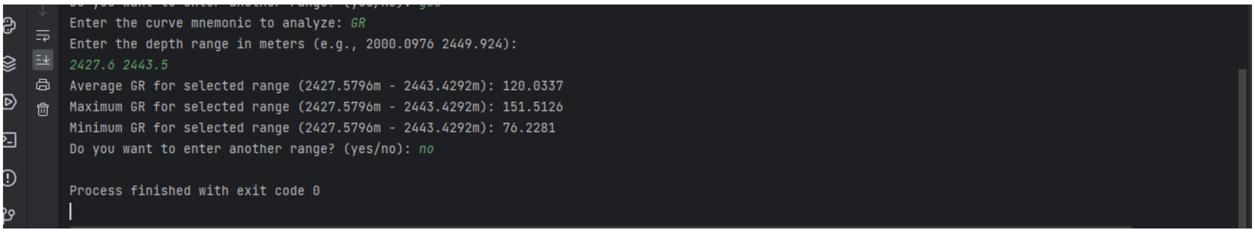


Fig. 8. Values of GR log

And Figure 9 is the output graph of gamma ray log. The Maximum Value is 151.5126 GAPI. The minimum value is 76.221 GAPI and average value is 120.0337 GAPI.

In Figure 9 it is seen that the graph became even more detailed as the Range was shortened using input variables.

To validate the algorithm, the seismic file of the same well was run in Petrel. And using Petrel software different parameters like GR log, NPHI, DRHO were obtained and visualized. The data features simulated in Pycharm are similar to Petrel. From the analysis of Petrel, it can be visualized, which is the interested zone for this study, the maximum gamma ray value is around 151.30 GAPI. Which is shown in Figure 10 (b). The depth of maximum gamma ray value is in the range of 2400m – 2440m. For a more detailed view a zoomed version of the image is given in Figure 10 (c).

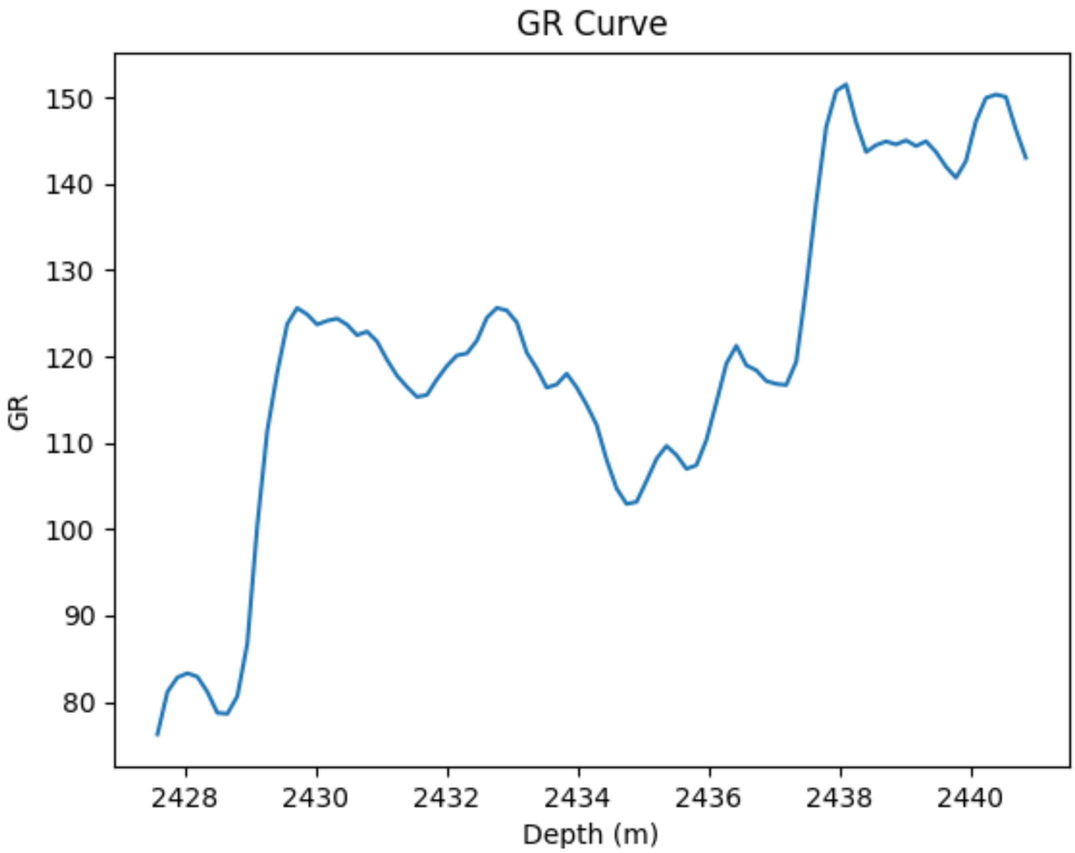
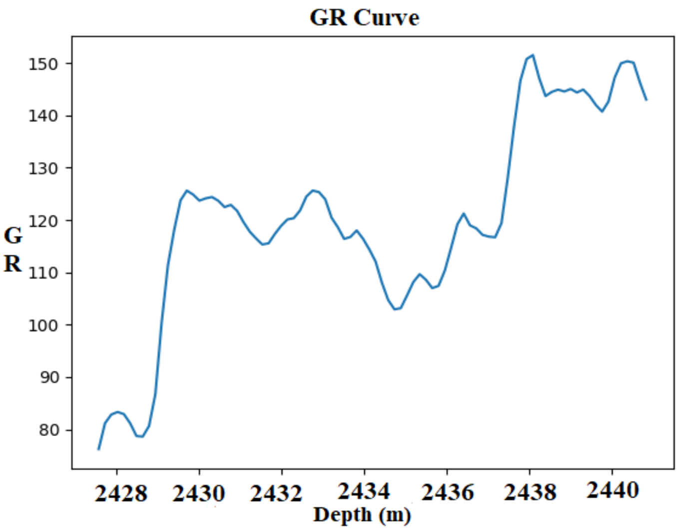


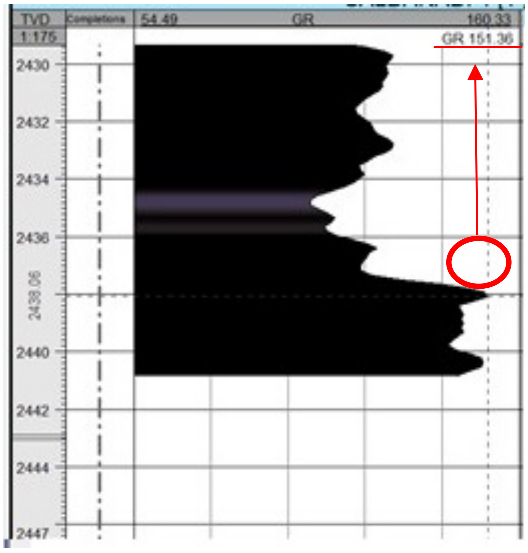
Fig. 9. Gamma Ray Log

From Figure 10 (a) of this study it is seen that the maximum value is 151.5126 GAPI and it was found in around 2438m. Moreover, by correlating with multiple logs like bulk density and porosity, it is seen there are definite connections between the log's variables. So, the outcomes are perfect and trustworthy, which ensures the validity of our machine learning algorithms. So, basically Figure 10 is the representation of the validity of this study.

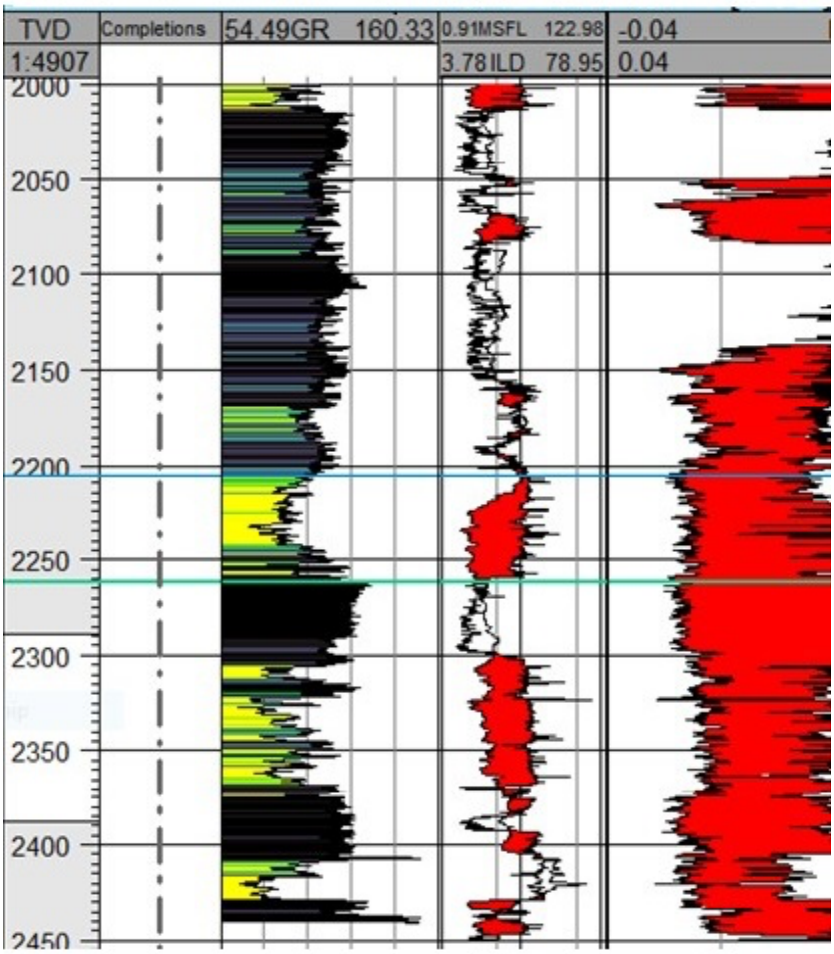
Moreover, it was calculated that the value of porosity using gamma ray was 0.21 and by using algorithm it was found 0.2033. The simple variation that is seen here is because of uncertainties and constant variables. Those are ignorable. Finally, it can be said the algorithm is well and simple enough to measure any well log data, especially gamma ray log, porosity, and density.



(a) GR Curve obtained using Machine Learning Algorithm



(b) GR Curve obtained using Petrel



(c) Detailed form of GR Curve obtained using Petrel

Fig. 10. Validation Images for Comparison

5. Conclusions

Reservoir characterization is a heavily data-driven problem, which integrates seismic, logging and core analysis data to improve the understanding of subsurface properties such as porosity, saturation, permeability and pressure–volume–temperature. Reservoir characterization for petroleum exploration heavily depends on well log data analysis, where Machine Learning (ML) plays a key role. In this study, porosity was determined using Machine learning algorithms. Then the values were validated using calculation by gamma ray log and Petrel simulation. ML enables efficient analysis of complex datasets, offering deeper insights into properties like porosity, permeability, and more. This study employs Python and an ML approach to enhance reservoir understanding and optimizing petroleum industry practices. Future works can be done on permeability, as the properties that determine reservoir quality are porosity and permeability. Moreover, by using petrel a proper 3D Model can be prepared for proper visualization. In this study the porosity was calculated, so by calculation of permeability and using prediction method more analysis can be done on it by correlating. Through new technology and data acquisition to processing and interpretation, the rate of success in exploration has risen up to 40%.

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References
[1] Okon, Anietie N., Steve E. Adewole, and Emmanuel M. Uguma. "Artificial neural network model for reservoir petrophysical properties: porosity, permeability and water saturation prediction." *Modeling Earth Systems and Environment* 7, no. 4 (2021): 2373-2390. https://doi.org/10.1007/s40808-020-01012-4

[2] Anifowose, Fatai Adesina, Jane Labadin, and Abdulazeez Abdulraheem. "Hybrid intelligent systems in petroleum reservoir characterization and modeling: the journey so far and the challenges ahead." *Journal of Petroleum Exploration and Production Technology* 7 (2017): 251-263. https://doi.org/10.1007/s13202-016-0257-3

[3] Chaki, Soumi, Aurobinda Routray, and William K. Mohanty. "Well-log and seismic data integration for reservoir characterization: A signal processing and machine-learning perspective." *IEEE Signal Processing Magazine* 35, no. 2 (2018): 72-81. https://doi.org/10.1109/MSP.2017.2776602

[4] Rahman, Md Tauhidur, Berihun Mamo Negash, Muhammad Moniruzzaman, Ato Kwamena Quainoo, Cornelius B. Bavoh, and Eswaran Padmanabhan. "An overview on the potential application of ionic liquids in shale stabilization processes." *Journal of Natural Gas Science and Engineering* 81 (2020): 103480. https://doi.org/10.1016/j.jngse.2020.103480

[5] Rahman, Md Tauhidur, Berihun Mamo Negash, Alamin Idris, Mohammad Islam Miah, and Kallol Biswas. "Experimental and COSMO-RS simulation studies on the effects of polyatomic anions on clay swelling." *ACS omega* 6, no. 40 (2021): 26519-26532. https://doi.org/10.1021/acsomega.1c03786

[6] Rahman, Md Tauhidur, Berihun Mamo Negash, David Kwaku Danso, Alamin Idris, Ahmed Abdulla Elryes, and Ibrahim Adamu Umar. "Effects of imidazolium-and ammonium-based ionic liquids on clay swelling: experimental and simulation approach." *Journal of Petroleum Exploration and Production Technology* (2021): 1-13. https://doi.org/10.1007/s13202-021-01410-z

[7] Alfarraj, Motaz, and Ghassan AlRegib. "Petrophysical property estimation from seismic data using recurrent neural networks." In *SEG Technical Program Expanded Abstracts 2018*, pp. 2141-2146. Society of Exploration Geophysicists, 2018. https://doi.org/10.1190/segam2018-2995752.1

[8] Nwankwo, C. N., J. Anyanwu, and S. A. Ugwu. "Integration of seismic and well log data for petrophysical modeling of sandstone hydrocarbon reservoir in Niger Delta." *Sci Afr* 13, no. 1 (2014): 186-199.

[9] Dullien, Francis AL. *Porous media: fluid transport and pore structure*. Academic press, 2012.

[10] Nazeer, Adeel, Shabeer Ahmed Abbasi, and Sarfraz Hussain Solangi. "Sedimentary facies interpretation of Gamma Ray (GR) log as basic well logs in Central and Lower Indus Basin of Pakistan." *Geodesy and Geodynamics* 7, no. 6 (2016): 432-443. https://doi.org/10.1016/j.geog.2016.06.006
[11] Khan, Natasha, and Khaista Rehman. "Application of fuzzy logic and neural networks for porosity analysis using well log data: an example from the Chanda Oil Field, Northwest Pakistan." *Earth Science Informatics* 14, no. 4 (2021): 2183-2199. https://doi.org/10.1007/s12145-021-00679-2
[12] Gowida, Ahmed, Salaheldin Elkatatny, and Abdulazeez Abdulraheem. "Application of artificial neural network to predict formation bulk density while drilling." *Petrophysics* 60, no. 05 (2019): 660-674. https://doi.org/10.30632/PJV60N5-2019a9
[13] Ahmadi, Mohammad Ali, Sohrab Zendehboudi, Ali Lohi, Ali Elkamel, and Ioannis Chatzis. "Reservoir permeability prediction by neural networks combined with hybrid genetic algorithm and particle swarm optimization." *Geophysical Prospecting* 61, no. 3 (2013): 582-598. https://doi.org/10.1111/j.1365-2478.2012.01080.x
[14] Srivastava, R. M. "Reservoir characterization with probability field simulation." In *SPE Annual Technical Conference and Exhibition?*, pp. SPE-24753. SPE, 1992. https://doi.org/10.2523/24753-MS
[15] Wang, Hai, and Shengnan Chen. "Insights into the Application of Machine Learning in Reservoir Engineering: Current Developments and Future Trends." *Energies* 16, no. 3 (2023): 1392. https://doi.org/10.3390/en16031392
[16] Harms, J. C., and P. W. Choquette. "Geologic evaluation of a gamma-ray porosity device." In *SPWLA Annual Logging Symposium*, pp. SPWLA-1965. SPWLA, 1965.
[17] Pires, Luiz F., and André B. Pereira. "Gamma-ray attenuation to evaluate soil porosity: an analysis of methods." *The Scientific World Journal* 2014 (2014). https://doi.org/10.1155/2014/723041
[18] Xiao, Lizhi, and Kui Li. "Characteristics of the nuclear magnetic resonance logging response in fracture oil and gas reservoirs." *New Journal of Physics* 13, no. 4 (2011): 045003. https://doi.org/10.1088/1367-2630/13/4/045003
[19] Li, Yong, Shijia Chen, Xiangjun Liu, Bingyan Wu, Jingyue Zhang, Xin He, Feisheng Mou, and Liyuan Luo. "Study on the logging response characteristics and the quantitative identification method of solid bitumen at different thermal evolution stages." *Fuel* 316 (2022): 123424. https://doi.org/10.1016/j.fuel.2022.123424
[20] Ellis, Darwin V., and Julian M. Singer. *Well logging for earth scientists*. Vol. 692. Dordrecht: Springer, 2007. https://doi.org/10.1007/978-1-4020-4602-5
[21] Xin-hu, L. I., Luo Jie, and Liu Dong. "Lithology Identification Methods Contrast Based on Support Vector Machines at Different Well Logging Parameters Set." In *2010 International Conference on Computational and Information Sciences*. 2007.
[22] Nordin, Mariam Firdhaus Mad, Nurin Zulaikha Zulfadhly, Norrashidah Mokhtar, Nurul'Uyun Ahmad, Pauziah Muhamad, Yvan Gariépy, and GS Vijaya Raghavan. "Comparison of Chemical Composition and Antioxidant Activity of Extracted Zingiberaceae Rhizome using Subcritical Water Extraction." *Journal of Research in Nanoscience and Nanotechnology* 8, no. 1 (2023): 13-22. https://doi.org/10.37934/jrnn.8.1.1322
[23] Rebhi, Redha, Younes Menni, Giulio Lorenzini, and Hijaz Ahmad. "Forced-convection heat transfer in solar collectors and heat exchangers: a review." *Journal of Advanced Research in Applied Sciences and Engineering Technology* 26, no. 3 (2022): 1-15. https://doi.org/10.37934/araset.26.3.115
[24] Yacob, Noraishah Shafiqah, and Hassan Mohamed. "Investigation of palm oil wastes characteristics for co-firing with coal." *Journal of Advanced Research in Applied Sciences and Engineering Technology* 23, no. 1 (2021): 34-42. https://doi.org/10.37934/araset.23.1.3442
[25] Mansor, Muliani, Nurfatehah Wahyuny Che Jusoh, Azran Mohd Zainoodin, Khairunnisa Mohd Pa'ad, and Shinya Yamanaka. "The Effects of Calcination Temperature of Nickel Supported on Candle Soot towards Ethanol Oxidation Reaction (EOR)." *Journal of Research in Nanoscience and Nanotechnology* 8, no. 1 (2023): 23-30.