Carbonate Reservoirs Permeability Prediction

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Permeability is a crucial property that can be used to indicate whether a material can hold fluids or not. Predicting the permeability of carbonate reservoirs is always a challenging and expensive task while using traditional techniques. Traditional methods often demand a significant amount of time, resources, and manpower, which are sometimes beyond the limitations of under developing countries.

permeability prediction AdaBoost carbonate reservoir

1. Introduction

In a general context, the term permeability is a characteristic given to a material indicating the ease of flow of a fluid through such material [1]. In petroleum engineering, it is known as the ability of porous rocks to pass through oil and/or gas [2][3][4][5]. Notably, it is not always necessary for a porous rock to be permeable. For a rock to be permeable and for the oil and/or gas to penetrate through it, the pore spaces between the grains in the relevant rock must be connected. This implies that permeability is a measure of the ability of oil and/or gas to penetrate through a rock [6]. In this regard, one of the most widely used classification systems for carbonate rock porosity by petroleum geologists was introduced by Choquette and Pray in 1970 [7]. This classification nomenclature is available in numerous books published on carbonate classification, for instance, Tucker and Wright (1990) [8]. It has been cited as a main system for classifying porosity in carbonates.

Permeability is an essential reservoir property and a basic element of reservoir characteristics and the simulation process. This input is generally used to determine hydrocarbon production, recovery estimates, optimal well location, pressure, fluid contact classification, and so forth. More accurate predictions of reservoir permeability surely improve the overall exploration and discovery processes in the concerned area. Studies in the literature reveal that a more accurate prediction of coreless reservoir penetration is still a challenge in the oil and gas industry and needs significant concentration [3][4][5]. It is also known that an accurate estimation of the permeability rate of a target reservoir is essential for the probable oil and gas repository in that reservoir [2][3][4][5][9]. It may help in assessing the realistically achievable percentage of oil and gas, flow rate, estimation of future exploration, and the appropriate and correct design of exploration equipment.

Though permeability seems easy to realize, there exist several variables that may affect it, for example, the dynamic viscosity of the fluid, applied pressure difference, and rock/reservoir properties, such as grain size, sorting, and the pore’s throats [10][11]. Permeability can be measured in many ways [10][11]. In the beginning, it was primarily measured involving numerous parameters, such as the gamma-ray, neutron porosity, bulk density, resistance, sonic waves, spontaneous potential, well size, and/or reservoir depth. However, a standard method for determining permeability is performed using conventional core analysis (CCA) and/or the porosity permeability-relationship (PPR) while determining a non-linear relationship between porosity and permeability [11]. Though traditional well testing, core analysis, and well-log evaluation can predict the permeability of carbonate reservoirs, these conventional methods are not only costly but also time-consuming. This is because the relevant persons make multiple visits to the laboratory to test target samples and predict permeability [12]. In addition, estimating permeability in heterogeneous carbonate reservoirs are also a great challenge, which must be handled carefully to guarantee precise prediction [10][11]. As stated earlier, the permeability of a material is its capacity to allow fluids to flow through it. It is measured in the Darcy/Square-meter (Darcy/m^2), which is defined as the volume of fluid passing through a surface in the unit time under the surface pressure gradient at the point where flow passes through it [1].

ML has inevitably been used in permeability prediction and found quite promising. For instance, a study conducted in [13] employed white-box ML approach to model permeability from heterogeneous carbonate reservoirs in Iran. The algorithms are k-nearest neighbors (kNN), genetic programming (GP), and modified group modeling data handling (GMDH). The proposed study outperformed zone-specific permeability, index-based empirical, or data-driven models already investigated in the literature with R^2 values of 0.99 and 0.95 against GMDH and GP, respectively [13]. The study was organized motivated by a study by the same authors in [14], where they employed a supervised machine learning algorithm known as Extreme Gradient Boosting (XGB) on heterogeneous reservoir data to predict permeability. The output of the algorithm is a modified formation zone index (FZIM*), based on which the permeability was estimated as R^2 values of 0.97. The study further investigated the k-mean clustering algorithm to classify/categorize petrophysical rock typing (PRT) to study their properties.

Machine learning is a subfield of computer science and artificial intelligence that focuses on the development of algorithms that enable computers to learn from and make decisions or predictions based on data [15]. The main objective is to model the probable relationship between a set of observable quantities (inputs) and another set of variables related to them (outputs) [16]. Usually, all ML algorithms require large amounts of data for training and learning. This implies that collecting many of the representative training examples and saving them in a format suitable for computational purposes is an essential step [16]. In general, target data are not ready to use because they may contain irrelevant attributes, missing attributes, redundant attributes, attribute-value noise, and class-label noise. The observable quantities that are usually fed to ML algorithms are called “features”. During training, a target algorithm struggles to learn to associate these features with the desired output variables, thereby fitting the model’s parameters. This implies that features must be relevant to predict outcomes with precision [16]. This implies that pre-processing target data is an indispensable task. In this regard, several preprocessing techniques have been developed in the literature to handle various types of data. These include images, audio, text, video, and their combination. Accordingly, various techniques have been utilized to eliminate noisy and unwanted data [16]. For instance, handling missing values, normalization for numeric data and scaling, filtering, and denoising are commonly used in images [16].

2. Artificial Neural Network (ANN)

Akande et al. [12] used ANN while generalizing the performance and predictive capability of ANN by implementing an innovative correlation-based feature extraction technique. They used their data, which was gathered from five distinct wells located in the Middle Eastern region and obtained an improvement in the coefficient of correlation using the ANN correlation-based technique with 93.76%. Abusurra [17] used ANN while developing a new method to predict the vertical and horizontal stress for Marcellus shale well drilled in the County of Monongalia, West Virginia. The data used is from the drilling surface calibration measurements combined with the recorded well logging data over time. Such data have been used to predict an average correlation coefficient of 87.5%.

Al-Khalifah et al. [18] compared the effectiveness of using ANN and GA to predict the permeability of tight carbonate rocks. This work also compared different ML approaches with seven traditional equations to predict permeability. It was experimentally observed that the genetic algorithm technique was more useful while gaining more insight into which parameters control predicted permeability. The dataset consisted of 130 samples derived from the Portland Formation. Ahrimankosh et al. [19] also used an ANN-based technique to predict permeability using log-data in the Hydraulic Flow Units (HFUs). HFU is a permeability estimation method that depends on the flow-zone indicator (FZI). The data samples were collected from different areas of the Iranian heterogeneous carbonate reservoir. ANN was developed for FZI prediction, and variables with the highest correlation with the target were selected for input variables. The resultant model exhibited 98.72% accuracy and an average absolute error of 9.8%. Moreover, the authors developed ANN-based models for permeability prediction without using FZI. Though this model successfully predicted permeability with 98.17% accuracy and an average absolute error less than 10.9%, the use of the FZI data point and ANN was relatively better.

Ursula and Parra [20] involved ANN while estimating the reservoir’s properties for two applications having two different datasets gathered from south-eastern Florida and northeast Texas, US. While the first application used the multi-attributes from surface seismic data with well-log permeability and porosity, the second one only used the well-log data. The results obtained were a correlation of 90.6% for the first application and 76.5% for the second one. Mohebbi et al. [21] endeavored to improve the performance of the current methods in one of Iran’s heterogeneous oil fields to predict permeability based on drilling log-data, thereby zoning the reservoir based on geological characteristics and subsequent data classification. Th results obtained from logging wells with ANNs were compared with the permeability measured in core analysis experiments. The corresponding compatibility of the results confirmed the validation of the proposed method. The upper part of the different zones was successfully extended to the entire reservoir using the kriging method. The overall success of trained networks demonstrated the effectiveness of the analysis of variance technique for reservoir zoning. Successful results of trained networks for different regions are good reasons for the compatibility of rivers with geological types and lithological properties of the deposits. For Zone 21, the network performed better, with R^2 values of 0.94, 0.89, and 0.85 for the training, testing, and cross-validation data, respectively. The scheme was also promising in terms of other figures of merit.

3. Support Vector Machines (SVM)

Akande et al. [12] applied an improved SVM model while predicting the permeability of carbonate reservoirs. The dataset used was obtained from some of the Middle East oil and gas wells. The result of this improved SVM model is promising, as it achieved 97% accuracy on this dataset. Gholami et al. [22] also applied the SVM model while predicting the permeability of hydrocarbon reservoirs using a dataset of three gas wells located in the Southern Pars field. It was experimentally observed that the SVM model was suitable for permeability prediction, which was relatively better than the general regression neural network. This model achieved 97% accuracy on this dataset. A study conducted by Al-Anazi and Gates [23] showed that SVM was the best version of the Electrical Text platform followed by PNN. In addition, SVM exhibited better performance compared with other contemporary methods.

4. Other Contemporary ML Models

Gu et al. [24] used a hybrid of the SVR and particle swarm optimization (PSO) with deep learning (DL) to enhance the SVR's computational ability. Method validation data were recorded from three wells located at the LULA oil field. From the validation data, two experiments were designed. Experimental results showed that the proposed method can predict better results than the SVRs and PSO-SVRs if used individually. This implies that this hybrid model is more effective for predicting permeability when processing real-world data. Compared to traditional regression methods, SVR is more efficient in solving a nonlinear fit problem due to the advantage of the main function. PSO can dramatically improve SVR computing capabilities, as PSO works to supply an optimal initial parameter setting for SVR. Mehdi et al. [5] used the Gaussian process regression model, which is a state-of-the-art ML algorithm, to estimate the permeability of carbonate reservoirs. It showed the supremacy of the proposed GPR strategies over some contemporary schemes. The validity of the used database and reliability of the GPR version changed into additional illustration through making use of outlier analysis. It changed and found that the irreducible water saturation has the very best and bad effect on permeability estimation. Finally, it is shown that GPR provides the highest precision with a mean relative error of (MMRE) and an adjusted R-squared of 38% and 0.98, respectively.

Salaheldin et al. [11] used three different models, ANN, SVM, and ANFIS, while predicting the permeability of heterogeneous carbonate reservoirs. "Adaptive neuro-fuzzy inference system (ANFIS) is the combination of the neural network and fuzzy logic". ANFIS can take advantage of the two AI techniques mentioned above on a single platform. The data used in this study had 1500 actual well's log-data measurements. The data were used to construct and test mathematical equations for permeability prediction. In addition, they used a new term called the mobility index, which can be effective in predicting permeability. The term mobility index is derived from the mobile oil saturation that has occurred due to the penetration of drilling fluid seeps. The accuracy achieved in this study was 95%, with an RMSE less than 28%.

References

1. Darcy, H. Les Fontaines Publiques de la Ville de Dijon: Exposition et Application des Principes à Suivre et des Formules à Employer Dans les Questions de Distribution d'eau; Victor Dalmont: Paris, France, 1856.
2. Olatunji, S.; Selamat, A.; Raheem, A. Improved sensitivity based linear learning method for permeability prediction of carbonate reservoir using interval type-2 fuzzy logic system. Appl. Soft Comput. 2014, 14, 144–155.
3. Xu, P.; Zhou, H.; Liu, X.; Chen, L.; Xiong, C.; Lyu, F.; Zhou, J.; Liu, J. Permeability prediction using logging data in a heterogeneous carbonate reservoir: A new self-adaptive predictor. Geoenergy Sci. Eng. 2023, 224, 211635.
4. Sheykhinasab, A.; Mohseni, A.A.; Barahooie Bahari, A.; Naruei, E.; Davoodi, S.; Aghaz, A.; Mehrad, M. Prediction of permeability of highly heterogeneous hydrocarbon reservoir from conventional petrophysical logs using optimized data-driven algorithms. J. Pet. Explor. Prod. Technol. 2023, 13, 661–689.
5. Mahdaviara, M.; Rostami, A.; Keivanimehr, F.; Shahbazi, K. Accurate determination of permeability in carbonate reservoirs using Gaussian Process Regression. J. Pet. Sci. Eng. 2021, 196, 107807.
6. Ayan, C.; Hafez, H.; Hurst, S.; Kuchuk, F.; O'Callaghan, A.; Peffer, J.; Pop, J.; Zeybek, M. Characterizing Permeability with Formation Testers. Oilfield Rev. 2001, 13, 2–23.
7. Choquette, P.W.; Pray, L.C. Geologic Nomenclature and Classification of Porosity in Sedimentary Carbonates1. AAPG Bull. 1970, 54, 207–250.
8. Carbonate Sedimentology. Available online: https://onlinelibrary.wiley.com/doi/book/10.1002/9781444314175 (accessed on 30 June 2023).
9. Li, S.; Liu, M.; Hanaor, D.; Gan, Y. Dynamics of Viscous Entrapped Saturated Zones in Partially Wetted Porous Media. Transp. Porous Media 2018, 125, 193–210.
10. Akande, K.; Owolabi, T.; Olatunji, S. Investigating the effect of correlation-based feature selection on the performance of support vector machines in reservoir characterization. J. Nat. Gas Sci. Eng. 2015, 22, 515–522.
11. Elkatatny, S.; Mahmoud, M.; Tariq, Z.; Abdulraheem, A. New insights into the prediction of heterogeneous carbonate reservoir permeability from well logs using artificial intelligence network. Neural Comput. Appl. 2018, 30, 2673–2683.
12. Akande, K.O.; Owolabi, T.O.; Olatunji, S.O. Investigating the effect of correlation-based feature selection on the performance of neural network in reservoir characterization. J. Nat. Gas Sci. Eng. 2015, 27, 98–108.

13. Zhao, L.; Guo, Y.; Mohammadian, E.; Hadavimoghaddam, F.; Jafari, M.; Kheirollahi, M.; Rozhenko, A.; Liu, B. Modeling Permeability Using Advanced White-Box Machine Learning Technique: Application to a Heterogeneous Carbonate Reservoir. ACS Omega 2023, 8, 22922–22933.
14. Mohammadian, E.; Kheirollahi, M.; Liu, B.; Ostadhassan, M.; Sabet, M. A case study of petrophysical rock typing and permeability prediction using machine learning in a heterogenous carbonate reservoir in Iran. Sci. Rep. 2022, 12, 4505.
15. Mitchell, T. Machine Learning; McGraw-Hill Education: New York, NY, USA, 1997; Volume 1.
16. Baştanlar, Y.; Ozuysal, M. Introduction to machine learning. Methods Mol. Biol. 2014, 1107, 105–128.
17. Abusurra, M.S.M. Using Artificial Neural Networks to Predict Formation Stresses for Marcellus Shale with Data from Drilling Operations. Master’s Thesis, West Virginia University, Morgantown, WV, USA, 2017; p. 5023.
18. Al Khalifah, H.; Glover, P.W.J.; Lorinczi, P. Permeability prediction and diagenesis in tight carbonates using machine learning techniques. Mar. Pet. Geol. 2020, 112, 104096.
19. Ahrimankosh, M.; Kasiri, N.; Mousavi, S. Improved Permeability Prediction of a Heterogeneous Carbonate Reservoir Using Artificial Neural Networks Based on the Flow Zone Index Approach. Pet. Sci. Technol. 2011, 29, 2494–2506.
20. Iturraran-Viveros, U.; Parra, J. Artificial Neural Networks applied to estimate permeability, porosity and intrinsic attenuation using seismic attributes and well-log data. J. Appl. Geophys. 2014, 107, 45–54.
21. Mohebbi, A.; Kamalpour, R.; Keyvanloo, K.; Sarrafi, A. The Prediction of Permeability from Well Logging Data Based on Reservoir Zoning, Using Artificial Neural Networks in One of an Iranian Heterogeneous Oil Reservoir. Pet. Sci. Technol. 2012, 30, 1998–2007.
22. Gholami, R.; Shahraki, A.R.; Jamali Paghaleh, M. Prediction of Hydrocarbon Reservoirs Permeability Using Support Vector Machine. Math. Probl. Eng. 2012, 2012, 670723.
23. Al-Anazi, A.F.; Gates, I. Support vector regression for porosity prediction in a heterogeneous reservoir: A comparative study. Comput. Geosci. 2010, 36, 1494–1503.
24. Gu, Y.; Bao, Z.; Song, X.; Wei, M.; Zang, D.; Niu, B.; Lu, K. Permeability prediction for carbonate reservoir using a data-driven model comprising deep learning network, particle swarm optimization, and support vector regression: A case study of the LULA oilfield. Arab. J. Geosci. 2019, 12, 622.