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ARTICLE REVIEW :EVALUATION OF POROSITY AND PERMEABILITY USING WELL LOGS

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Abstract
One of the key fundamental problems faced in reservoir engineering is proper determination of porosity and permeability of sub-surface reservoirs. Well logging tools and practices have significantly been developed in the last few decades providing the geoscientists and reservoir engineers ample opportunities to characterise the essential petrophysical parameters of the reservoir rocks. This literature survey attempts to synthesise the present status of research on the application of well logs (such as sonic, density, neutron, nuclear magnetic resonance (NMR) and resistivity logs) for determining reservoir parameters porosity and permeability. A comparative study has been made between empirical, neural networks and fuzzy logic based methods; also application of combined methods and incorporation of core data have been discussed. Role of the factors like effects of lithological heterogeneity and borehole environmental condition as well as issues in permeability-porosity transform are critically

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examined and the research gaps and the future prospects in well logging practices for characterizing reservoirs are finally addressed.

Keywords: Porosity, Permeability, Well Logs, Petrophysics, Reservoir Characterization, NMR, Machine Learning

1. Introduction

Porosity (ϕ) and permeability (k) are the two most significant petrophysical properties that control reservoir storage capacity and the ability of a reservoir to flow fluids. The proper determination ofThese two parameters are crucial for any meaningful reserve calculations, prediction of the well's ability to produce, and prudent management of a hydrocarbon reservoir. (Doveton, 1994; Asquith & Krygowski, 2004).

Ever since Schlumberger brothers performed their first electric log in the 1920s, in-situ continuous measurement of the physical, chemical and structural properties of formations is deemed to be one of the most important methods for reservoir characterization. Well logging technology has evoloved from early resistivity measuring tool to nuclear magnetic resonance (NMR) tool and borehole imaging tool in a significant manner. (Ellis & Singer, 2007).

Still, these advancements have not yet eliminated the inherent challenges associated with calculating the correct porosity and permeability from well logs. As porosity estimates can be confidently calculated from density-, neutron-, and sonic-logs, permeabilities – which can not be directly measured from a log – are often calculated from empirical correlations, theoretical models or-in an age where data is king-data-driven algorithms. (Timur, 1968; Coates et al., 1999).

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These methods are systematically considered below. Each is explored in terms of theory, practical application, and constraints.

2. Porosity Evaluation from Well Logs

2.1 Density Log

The FDL measures the bulk density (b) of the formation by sending a gamma ray and counting the number of backscattered gamma rays. Porosity is computed by utilizing the linear dependence between bulk density, matrix density (ma) and fluid density (fl). This tool is most useful for clean sandstone and carbonate rocks, however its resolution is reduced by gas presence, because of the very low density of gas (Schlumberger, 1989). The density log responds to washouts. (Rider & Kennedy, 2011).

2.2 Neutron Log

Neutron log (CNL) Sensitive to hydrogen index, so useful for estimating fluid filled porosity. Neutrons read low in gas due to the low hydrogen index of gas which is known as the 'gas effect'. When used with the density log, a neutron-density cross-plot will give information on lithology and fluid type, as well as an estimate of porosity. (Bateman, 1985) have shown the effectiveness of combined neutrons and density for a good porosity estimation in complex carbonate rocks.

2.3 Sonic Log

The sonic log, measured the transit time of compressional waves, (t), through the formation. The commonly accepted equation, developed originally for clean, water saturated formations, used for calculating the porosity from seismic data, is the Wyllie time-average equation. (Wyllie et al., 1956). For shallow carbonates, unconsolidated sands, and formations with secondary porosity, major adjustments are needed. The Raymer-Hunt-Gardner (RHG) transform provides better results for a larger portion of the porosity range. (Raymer et al., 1980).

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2.4 Nuclear Magnetic Resonance (NMR) Log

NMR logging is arguably one of the most important advancements in the field of petrophysical evaluation during the last 30 years. This is due to its ability to detect the pore fluid hydrogen nucleus independently from formation type, and as such, is a true indicator of total porosity. NMR may also measure the distribution of pore size from its T2 distribution which can be used to calculate formation permeability using relationships such as the Timur-Coates and SDR (Schlumberger-Doll Research) equations.(Coates et al., 1999; Kenyon et al., 1988). Further applications of NMR for direct oil, gas and water characterisation in formations was then facilitated by Freedman et al. (2003), applying NMR principles to fluid typing based on diffusion.

3. Permeability Estimation from Well Logs

3.1 Empirical Porosity-Permeability Transforms

Since there is no direct tool for measuring permeability, engineers in the past had to estimate permeability by correlations to log derived porosity. The Kozeny-Carman equation is an equation that relates the capillary tube concept to permeability but is strongly dependent on geometry and distribution of grain sizes (Kozeny, 1927; Carman, 1937). In practice, one has no alternative to a field-specific transform.

3.2 NMR-Based Permeability Models

NMR-based permeability models have become State-of-the-Art methods of estimating permeability from log data. Examples include the Timur-Coates model using free fluid index (FFI) and bound fluid volume (BFV) calculated from the NMR T2 spectrum, and the SDR model using T2LM to indicate pore size. (Timur, 1968; Kenyon et al., 1988).

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Models can be further calibrated to core measured permeabilities to enhance their performance. Hrlimann et al (2002) concluded that both models provided reasonable performance in sandstones, however in the case of carbonates the complexity of pore structures would demand significant modification of the models.

3.3 Machine Learning and Artificial Intelligence Approaches

Permeability prediction from well logs using machine learning (ML) and artificial intelligence (AI) approaches has witnessed a remarkable development in recent times. ANNs trained with core-log datasets has shown to be superior in their predictive power than empirical relationships used in many studies. (Mohaghegh et al., 1997; Wendt et al., 1986).

Additional prediction accuracy has been gained from the use of support vector regression (SVR), random forests and gradient boosting algorithms which account for nonlinear relationship between the logarithm of the response and permeability. (Karimpouli & Tahmasebi, 2016).

More recently deep learning models such as CNN's, LSTM networks have also been utilized for well log sequences to achieve a high resolution permeability prediction in wellbore. (Zhang et al., 2018; Al-Anazi & Gates, 2010). The biggest limitation to those data-driven approaches is that they all rely on huge, high-quality training datasets-something not so easily acquired in a setting of frontier exploration.

4. Challenges and Sources of Uncertainty

4.1 Lithological Heterogeneity and Complex Mineralogy

Lithological heterogeneities seriously complicate the determination of the true porosity from logs. Changes in clay content, mineralogy and diagenetic modifications will affect log responses to such an extent that they can't be properly corrected for without detailed core data or complex multi-mineralic

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petrophysical models. The presence of swelling clays results in the creation of additional bound water and causes an increase of neutron logs. (Clavier et al., 1977).

4.2 Borehole and Environmental Effects

These environmental conditions within the borehole (diameter, mud types, temperature and pressure) will strongly influence the logs that are recorded, hence we must take these conditions into account in corrections, e.g., rugosity on a density log, the salinity correction on a neutron log or cycle skipping in a gas zone on a sonic log. (Asquith & Krygowski, 2004).

4.3 Scale and Resolution Issues

One of the inherent problems with estimating permeability from well logs is the scale discrepancy of well log data and core plug permeability. Well logs penetrate rock volumes of cubic decimeters to cubic meters whereas core plug permeability represents samples of rock of a few centimeters. (Corbett & Jensen, 1992). This This scale difference, combined with reservoir heterogeneity, suggests that permeability derived from well logs is naturally an average value, lacking the sensitivity for fine-scale flow barriers and high permeability streaks.

5. Integration of Well Log Data with Other Sources

As the standard in many reservoir characterisation workflows today, log data is usually coupled to the core analysis, well test information, and seismic attributes. When core-calibrated, log-derived log porosity and permeability are very reliable and geostatistical modelling techniques (krining, co-simulation) permit spreading out these characteristics spatially away from the wells.
(Deutsch & Journel, 1997).
We demonstrate that the seismic inversion products (acoustic impedance, elastic parameters) can be used as a secondary variable in geostatistical co-simulation

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leading to more accurate spatial estimation of the reservoir quality in interwell areas. (Doyen, 1988; Sengupta & Mavko, 2003). Again, a combination of well test-permeability with log values offer crucial validation and upscaling constraints for the dynamic reservoir models.

6. Recent Advances and Emerging Technologies

Some more modern logging advancements include a suite of multi-frequency NMR tools that go further in borehole investigations; image log tools that directly see sedimentary features, fractures; a tool to provide mini-DST permeability in multi-depth formation tester. (Georgi & Menger, 1994; Flavio & Loucks, 2021). A especially exciting developing approach is combining physics-informed neural networks (PINNs) with welllog data, thus drawing upon deep learning's ability to predict while utilizing physical laws established in petrophysics to potentially curb over-fitting and promote the networks to generalize well to unfamiliar formation rocks. (Raissi et al., 2019). Moreover, the adoption of digital rock physics - micro-CT scanning of core samples, for the purpose of simulating petrophysical properties at pore scale - also offer a great tool to bridge the gap between pore scale data and log scale data. (Blunt et al., 2013).

7. 2. Previous Studies

During the last 30 years the estimation of porosity and permeability from well logs has been a popular research topic for scientists working in various fields of geology and engineering. These researchers have developed and utilized an assortment of techniques – ranging from traditional empirically derived correlations to novel machine-learning methodologies – for predicting formation characteristics from wireline log measurements. This review provides a chronological discussion of the literature for this topic and covers fifteen representative landmark articles along with their significant results and findings.

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Timur (1968) laid one of the most successful foundations for the quantitative estimation of permeability from well logs. Based on empirically derived correlation between the effective porosity, the irreducible water saturation and the permeability in sandstones, he concluded that permeability can be expressed as a power-law of the normalized porosity and the square of irreducible water saturation. That equation for estimation of effective permeability (called the Timur eq. In reference book), widely used and is mentioned in even today's applications, highlights the basic controls of the permeability as determined by the pore structure, flow paths and distribution of fluids inside the rock mass

Coates and Dumanoir (1973) Developed Timur's work by improving on the permeability-porosity-saturation model and also developing the Coates equation, which is currently one of the most common formulae in use during NMR log analysis. Their research evaluated how the bound fluid and free fluid saturations in the rock could be used to better predict the permeability of reservoir rocks. Their final statement was that splitting total porosity into capillary bound fluid and free fluid portions increased the success in the prediction of permeability, especially for rock in a mixed or complex wetting state.

Lucia (1995) Researched the petrophysical pore space classification of carbonate pore space and its application to understanding the pore-permeability relationship. He showed that carbonate reservoirs are not homogenous and must be separated into different classes, which he referred to as rock-fabric classes, based on the presence of different pore types (interparticle, vuggy, and fractures). Lucia established that each of these rock-fabric classes has its own porosity-permeability trend. If differences between the rock-fabric classes are not taken into account in porosity-permeability relationships, there will be significant errors when estimating permeability from well log data.

Asquith and Krygowski (2004) ' compiled an in-depth reference text that methodically explains how to obtain porosity from the sonic, density, and neutron logs. These references provided generalized procedures for calculation of both

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total and effective porosity and evaluated limitations such as sources of errors associated with each tool; (e.g., formation and borehole effects, and changes in hole fluid density). They also recommended that at least two porosity tools be used together. ' indicate that a combination of at least two tools are superior for most determinations, and that for gas, use of combined neutron and density values produces better porosity information. ' noted the typical gas log crossover signature.

Jennings and Lucia (2003) Study on the prediction of permeabil-ity in carbonate formations from well-log data with a comprehensive survey of the relevant cor-relations and a detailed case study on a het-erogeneous carbonate field from Oman. They determined that single porosity-per-meability correlations are not valid for carbonate rocks because of the complex pore sys-tems and other pore-geometry related log parameters such asthose generated by NMR andboreholeimage logs need to be included in the prediction. They found that NMR logs combined with a rock-fabric analysis approach to characterisation of carbonate rocks yield the most successful and accurate results for prediction of reservoir permeabil-ity.

Mohaghegh et al. (2000) 3,4,5. Were among the first to utilize ANNs for modelling NMR responses from conventional welllog data . In those cases where the logs contain neither NMR logs nor other high resolution logs, they proved how a trained network could synthesize the NMR log response from such data as a well'sgamma-ray, density, and neutron porosityand spontaineous potentiallogs with adequate fidelity . The research proved that if well logging can not be employed to collect high-resolution data to generate NMR logs it might be economical to make use of intelligent computer methods to simulate those tools, with an adequate accuracy of free- fluid volume and permeability estimations being guaranteed .

Ellis and Singer (2007) Covered well logging physics and its petrophysical interpretation in their highly cited book. They traced the evolution of logging

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technology, from primitive electric resistivity tools to today's multi-sensor tool strings and described the physical basis of sonic and nuclear and NMR measurements. The paper concluded that improved tool physics and data processing algorithms has dramatically enhanced depth of investigation and vertical resolution of logs to characterize thin bed reservoir and complex geology which was impossible before..

Al-Anazi and Gates (2012) However, these results were achieved with a standard method of well log analysis using a simplified, analytical relationship. Applied SVR to the prediction of porosity and permeability from standard well logs in a heterogeneous reservoir and compared results with simpler regression methods. It showed that the kernel-based machine learning approach SVR gave improved performance in describing relationships between log responses and reservoir parameters with non-linear responses, as compared with standard multivariate linear regression and simpler neural networks. They recommended its use for routine work in petrophysics especially for those areas where the relationship between porosity and permeability can not be clearly explained using conventional analytical approaches.

Sadeq and Wan Yusoff (2015) In addition, an investigation into porosity and permeability of the fractured, vuggy, and intercrystalline carbonates of the KF2 oil field in Iraq has been done based on well log data and core data. The study adopted Archie's cementation exponent for discrimination of the predominant pore type of each reservoir zone and to obtain graphically the porosity-permeability cross plots including texturing and grain sizes. They found that carbonates of the study area could be grouped into rock types with their signature of physical property and that combined use of the cementation exponent and porosity-permeability plots is far superior for predicting permeability than any of empirical correlations.

Baouche et al. (2017) Did a comparative study on back-propagation neural networks, fuzzy logic, support vector machines for the permeability prediction on

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sandstone reservoir on conventional well log data and found out that fuzzy logic and back-propagation neural network model perform better than support vector machines at validation level at interval with rapid lithologic changes. Also it mentioned the quality of training data is important and that the representative sampling over all the well lithofacies is needed, ensemble modeling using combination of multiple ML models improve prediction reliability over individual one..

Nooruddin and Hossain (2019) Tested the applicability of NMR predicted permeability on a carbonate reservoir in south of Iran and tested some standard NMR permeability models with core values for twenty-six carbonate samples, covering a variety of pore systems (vuggy, moldic, intraparticle, and fine pores). They noted a perfect correlation of NMR porosity with the core measured porosity but that the standard NMR permeability coefficients are calibrated for clastic rocks systematically predict high values for carbonate rocks with complicated pore structure. They suggest site-specific recalibration of NMR permeability transform coefficients in carbonates and produced an adapted form of the free-fluid and mean T2 models resulting in less prediction error..

Urang et al. (2020) And developed a hybrid strategy employing Artificial Neural Networks and curve-fitting for predicting porosity and permeability directly from well log data of the Niger Delta, Nigeria. Their technique uses several logs inputs (gamma ray, resistivity, density, neutron porosity) to build and train an ANN model then calibrate it with plug measurement data from the same wells. The results showed a considerable improvement of the ANN approach compared to empirical correlations and an adequate estimation of the lateral variations of reservoir properties in a deltaic depositional environment, thus providing a useful method for reservoir-wide petrophysical characterisation..

Al Khalifah et al. (2020) Provided an in-depth exploration into the challenges of predicting the permeability of tight carbonate reservoirs with the use of machine learning approaches and comparisons between the accuracies provided by

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artificial neural networks (ANNs), genetic algorithms (GAs) and a range of standard empirical models. The study highlights how low porosity, complicated micro-pore network structure associated with tight carbonates mean that the common porosity-permeability models no longer become valid at lower values of porosity, thereby resulting in unique prediction challenges. The authors noted that all of the developed machine learning models provided better performance than traditional, more empirically-derived methods and that genetically-optimised neural networks were considered to be superior to all other developed prediction models. The authors state that the role of overprint diagenesis must also be addressed in order to create an accurate permeability prediction model..

Gamal and Elkatatny (2022) Constructed an artificial neural network (ANN) based model to predict porosity from normal wireline log suites in Arabian carbonate reservoirs. They had developed a well-defined procedure of model training and validation against core porosity as output value, and proved their model has a high prediction accuracy at different lithological ranges. Their model revealed that field-specific ANNs provide a lower uncertainty for reservoir porosity estimates when contrasted to general empirical transforms and that ANN predictability is steadily increased as the number and variety of training data increase..

Bashir et al. (2024) Presented an ensemble machine learning algorithm for the prediction of permeability and porosity simultaneously from well log, called Adaptive Boosting (AdaBoost) and was applied in conjunction with SVR, GP regression and BP neural networks in their research work in comparing their performance. According to their results, AdaBoost surpassed the individual algorithms on training and testing dataset with values for determination coefficients, R2 for permeability as high as 0.98, and 0.96 for porosity. The study pointed that ensemble technique, which leverages multiple base learners to provide stronger and more generalization predictor compared to individual

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learners, are highly applicable in wells where single model fails due to the geologic condition complexity and lithology diversity of the formation..

Together, these studies illustrate a consistent upward path of innovation for porosity and permeability evaluation methods. Initially, classical, empirical relationships were developed and are still in use today. In subsequent work, these evolved through the introduction of NMR log data, multi-log interpretation methods and finally machine learning algorithms. Time and time again, authors in these papers come to the same conclusion: no individual method or logging tool is "king." The most reliable and accurate methods for evaluating porosity and permeability invariably come from combining various sources of information using a suite of interpretation techniques. Throughout this collection of literature there is also emphasis on the necessity for matching logs to core data and using rock and fluid samples as calibration points. This because site specific controlling factors that determine pore size and the flow pathways are typically too complex for simple empirical relationships to fully account for..

8. Conclusions and Future Directions

It has been shown that well log evaluation of porosity and permeability has evolved dramatically, aided by improvements in technology and the application of more refined interpretive techniques. The suite of density, neutron, sonic, and NMR logs supply diverse yet complementary constraints on reservoir pore space, thus limiting the level of interpretive risk. The estimation of permeability is more difficult although NMR models and data analytics provide valid alternatives if calibrated using core data.

While significant advances have been made, several important research gaps still persist. First, the need for a robust, lithology-independent model for permeability calculation which could be applied to various types of reservoir. Second, for a consistent upscaling of pore scale NMR measurements to log scale in heterogeneous carbonates, enhanced workflows must be established. Third, the methodology needs to be systematized for proper logging tool data utilization for

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dual porosity characterization. Fourth, the ongoing research into explainable AI (XAI) on petrophysical prediction tools is a major area for building trust and facilitating machine learning in practice.

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