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Calibration of Permeability Models from Sandstones to Carbonates Using Capillary Pressure: Applicable to U.S. Shallow Marine Reservoirs

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Abstract. Permeability estimation plays a crucial role in reservoir characterization and is commonly determined through core analysis. Additionally, permeability can be inferred from mercury injection test data. Several models have been developed for this purpose, with their parameters influenced by factors such as pore structure, rock heterogeneity, and pore throat distribution. The widely recognized permeability prediction models of Winland, Pittman, and Dastidar, have been primarily developed based on sandstone formations, with Winland's model also applied to both sandstone and carbonate rocks. However, due to the inherent heterogeneity of carbonate reservoirs particularly in terms of petrophysical properties and diagenetic alterations the accuracy of these models becomes debatable, especially in complex carbonate reservoirs such as those in Texas and Oklahoma, United States. To improve permeability predictions in carbonate reservoirs, these models require further adjustments to account for their unique pore structures. Since these permeability models were originally calibrated based on sandstone formations, they need to be recalibrated for carbonate rocks due to the significant differences in heterogeneity, as well as variations in petrophysical properties and diagenetic processes between carbonate and sandstone reservoirs. This study calibrates sandstone-based permeability models for carbonate rock formations through a comprehensive investigation of carbonate rock properties and formations. In this study, a total of 1,367 thin section reports and 70 porosity-permeability tests were conducted. The average sampling interval was 25 cm. Porosity in the plug samples was measured using Boyle's Law, while permeability was determined based on Darcy's Law. A thin section was prepared from each plug sample and examined under a polarizing microscope. In this study, permeability ranges from 0.01 to 450 mD, and porosity ranges from 1% to 30%. This model calibrates the widely recognized permeability prediction models of Winland, Pittman, and Dastidar for carbonate reservoirs. This model resolves the limitations of permeability models originally adjusted for sandstone reservoirs by recalibrating them for carbonate reservoirs. It incorporates a comprehensive study of the geological and petrophysical characteristics of carbonate formations to enhance accuracy in permeability prediction.

Keywords: Permeability Prediction, Capillary Pressure Model, Carbonate Reservoirs

1 Introduction

The extraction of oil and gas from subsurface reservoirs relies on several key factors, including porosity, permeability, relative permeability (RP), capillary pressure, and wettability, among others (Feng et al. 2021). Rock permeability is strongly influenced by the distribution of pore throat sizes, making mercury injection capillary pressure (MICP) analysis a valuable method for permeability prediction. The RP curve describes the relationship between the permeability of different fluid

https://doi.org/10.31223/X5KB04

phases, such as oil and water, within a porous medium. This relationship governs fluid movement through the reservoir's pore structure and fracture networks, contributing to the accuracy of reservoir simulation models. The RP curve plays a crucial role in reservoir modeling, as it significantly affects history matching, production strategy development, and enhanced recovery techniques. Many carbonate reservoirs, such as those found in Texas and Oklahoma, exhibit complex pore structures, making accurate RP curve determination essential for improved reservoir characterization. Therefore, the development of efficient and precise methods for obtaining RP curves remains a critical aspect of optimizing hydrocarbon extraction and reservoir management. Various methods have been utilized to obtain RP curves, broadly categorized into direct and indirect approaches. The direct method involves conducting laboratory experiments on rock cores using either steady-state or unsteady-state measurement techniques (Swanson 1981; Pittman 1992; Dastidar et al. 2007; Krevor et al. 2012; Feng et al. 2018; Rezaei 2025). One widely applied technique is mercury injection, where mercury is introduced into microscopic pores under controlled pressure conditions, establishing a relationship between pressure and the volume of injected mercury. The RP curves generated from these experiments are influenced by the intricate micro-pore structure of the medium. Due to the convenience of data acquisition and the ability to analyze relatively large sample sizes, many researchers have developed RP models based on capillary pressure experiments (Purcell 1949; Burdine 1953; Corey 1954; Brooks and Corey 1966; Rezaei 2025).

Purcell (1949) proposed a permeability model based on the capillary pressure curve, assuming that water flows through smaller capillary tubes while gas moves through larger ones, resulting in a simplified RP model. Building upon this foundation, Burdine (1953), Corey (1954), and Brooks and Corey (1966) introduced RP models that incorporated pore size distribution and tortuosity; however, these models did not consider the presence of an irreducible water film. The application of percolation theory in RP calculations, first introduced by Helba et al. (1992), has since been adopted and refined by various researchers, including Salomao (1997), Dixit et al. (1998), Phirani et al. (2009), and Kadet and Galechyan (2014). One of the key challenges in this approach is accurately determining coordination numbers and pore fractions within network models. Many existing permeability models are derived from the MICP curve, which can generally be classified into two main categories (Comisky et al. 2007). The first category consists of permeability models based on percolation theory, which assumes that flow paths in porous media can be represented by a single-scale aperture. Prominent models within this category include the Kozeny-Carman model (Schwartz et al. 1989; Bernabé and Maineult 2015), the Katz-Thompson model (Katz and Thompson 1986). The second category comprises permeability models that utilize Poiseuille's equation and Darcy's law, conceptualizing flow paths in porous media as a network of interconnected capillary tubes. Variations in petrophysical characteristics between carbonate and clastic rocks can lead to inconsistencies in permeability predictions using these models. According to Rezaei et al. (2024), differences in Mg/Ca concentrations were noted across parallel calcite crystal faces. Additionally, crystallographic orientation may play a role in how impurities are incorporated into minerals, ultimately influencing their physical and chemical properties (Rezaei, 2023). Gabitov et al. (2022) highlighted the uneven distribution of trace elements in carbonates, which affects pore structure and adds complexity to permeability

https://doi.org/10.31223/X5KB04

assessments. Understanding the influence of structural properties is essential for predicting material behavior in complex environments (Sanchez-Lecuona et al., 2024), including fluid flow and permeability in porous systems. Structural and compositional variations in materials play a crucial role in determining their physical and chemical properties, influencing factors such as permeability, adsorption capacity, and overall performance in various applications (García Ponce et al., 2021).

Prominent models within this category include the Purcell model (Purcell 1949; Zhang et al. 2017), the Thomeer model (Thomeer 1960, 1983), and the R35 model, initially introduced by Winland and later refined by Kolodzie (1980). Additional noteworthy models include the Swanson model (Swanson 1981; Kamath 1992), the R25 model (Pittman 1992), the Capillary Parachor model (Guo et al. 2004; Liu et al. 2016; Xiao et al. 2017), the Huet model (Huet et al. 2005), the R50 model (Rezaee et al. 2006; Gao and Hu 2013), the R_{WGM} model (Dastidar et al. 2007), which represents the weighted geometric mean radius, and the comprehensive integrated model (Rezaei 2025). Given the complexity of carbonate reservoirs, such as those found in Texas and Oklahoma, further refinement of these models is necessary to enhance permeability prediction and improve reservoir characterization. Zhou et al. (2023) utilized the ensemble Kalman method to predict RP curves based on saturation data, whereas Lanetc et al. (2024) introduced an innovative approach combining hybrid pore network and fluid volume methods for RP curve estimation. Additionally, Rezaei et al. (2020) worked on adapting permeability models originally developed for sandstones to improve their suitability for carbonate reservoirs. While these studies have contributed significantly to RP curve acquisition through different methodologies, each approach comes with inherent limitations.

Therefore, developing a more efficient framework for obtaining RP curves remains a crucial goal. Various permeability models, such as those proposed by Pittman (1992), Swanson (1981), and Dastidar (2007), have been calibrated using clastic rock samples and rely on different parameters for permeability prediction. However, these models face limitations when applied to carbonate reservoirs due to fundamental differences in rock properties. Adjusting these models for carbonate formations requires a comprehensive study of core plugs, integrating their geological characteristics and calibration based on detailed core plug analyses and relevant geological information.

While these models have significantly contributed to permeability prediction, they have occasionally demonstrated inaccuracies when applied to specific carbonate samples (Nooruddin et al. 2014). To overcome these challenges, this study introduces an approach for adapting empirical permeability models to carbonate reservoirs based on capillary pressure. By refining existing models to account for the distinct characteristics of carbonate formations, this study aims to enhance the accuracy of permeability predictions and improve reservoir characterization.

https://doi.org/10.31223/X5KB04

2 Materials and Methods

This study utilized 70 core plug samples obtained from three wells within a carbonate reservoir. Each core plug measured one inch in diameter and two inches in length. The mercury injection capillary pressure (MICP) test was conducted by injecting mercury into the samples under increasing pressure, generating a saturation curve as a function of pressure. This curve was analyzed to determine key petrophysical properties. Three widely recognized permeability prediction models Winland, Pittman, and Dastidar were assessed, and their predictions were compared to permeability values measured in the laboratory. The study also extracted data on pore-throat sizes and porosity to evaluate the models' accuracy.

The MICP test was performed on all core plug samples, with porosity determined based on the volume of mercury injected. Permeability was measured using air following Darcy's law, with values ranging from 0.01 mD to 450 mD, while porosity varied between 1% and 30%. To establish an empirical relationship between permeability and MICP data, a multiple linear regression model was applied. Linear regression, combined with actual permeability measurements, was used to adapt permeability models originally developed for sandstone reservoirs to better suit carbonate formations. The newly calibrated carbonate-based model was then tested against actual permeability values to evaluate its improvements in prediction accuracy. This approach ensures a quantifiable relationship between key variables and permeability while maintaining model simplicity and interpretability. Incorporating multiple predictive factors and validating the model with real data enhances its reliability and precision.

The predicted permeability values were compared with laboratory-measured permeability using the linear modeling approach. Additionally, 1,367 thin sections were analyzed to examine the geological characteristics of rock formations. This geological data provided critical insights into the properties of carbonate reservoirs, supporting the calibration and validation of the newly developed carbonate-based permeability models.

3 Results and Discussion

3.1 Geological Features

Reservoir Classification. Analysis of 1,367 thin section reports, along with core sample tests, established that geological factors control reservoir quality, with porosity and permeability thresholds set at 3% and 0.02 millidarcies, respectively. Sections falling below these limits were classified as non-reservoir. The studied gas reservoir required a minimum permeability of 0.02 millidarcies for production viability. The results indicate that 50.6% of the examined sections are non-reservoir, while 49.4% qualify as reservoir rocks. (Figure 1).

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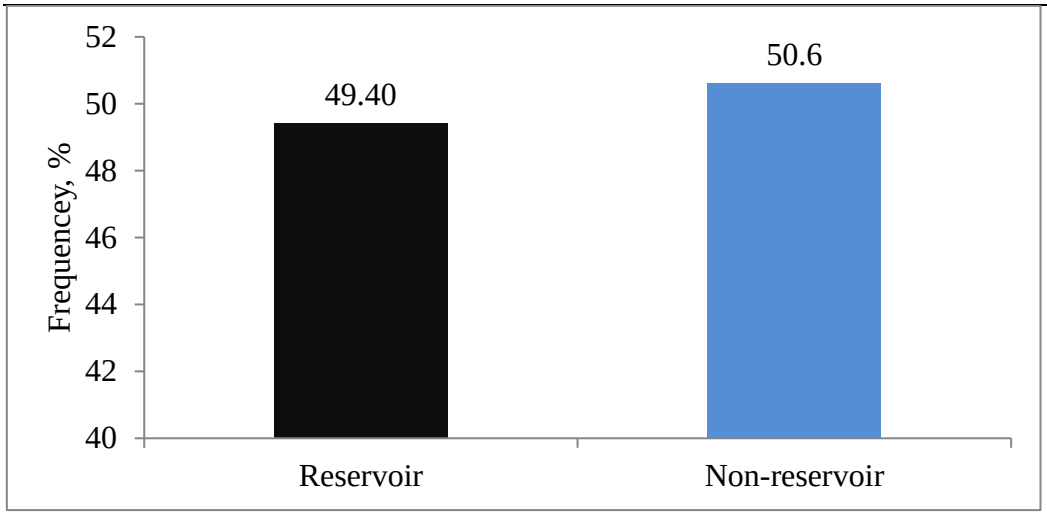

Figure 1—Reservoir vs. Non-Reservoir Distribution

Facies Distribution. The studied section includes packstone, grainstone, wackestone, and mudstone facies, each occurring at varying percentages. Among these, grainstone and wackestone are the most abundant, as shown in Figure 2. The energy levels associated with each facies vary across different sections, as indicated in the corresponding table.

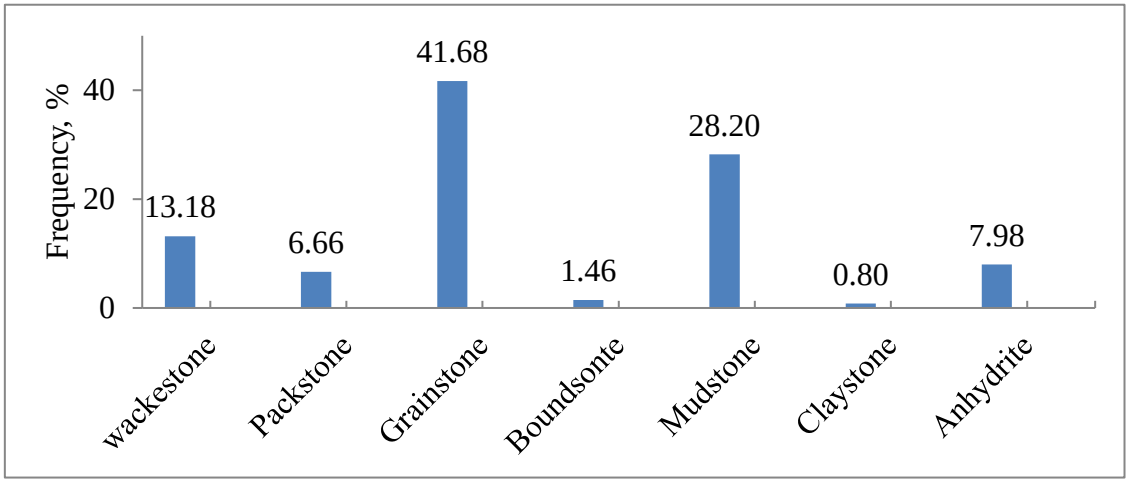

Figure 2—Sedimentary facies in the studied carbonate reservoir.

Depositional Environments. This study identifies the percentage of the reservoir associated with shoal, lagoon, tidal flat, and open marine environments. As expected, carbonate shoals play the most significant role in reservoir formation

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due to their high-energy conditions, making them the most favorable for reservoir development provided diagenesis has not degraded their quality (Figure 3).

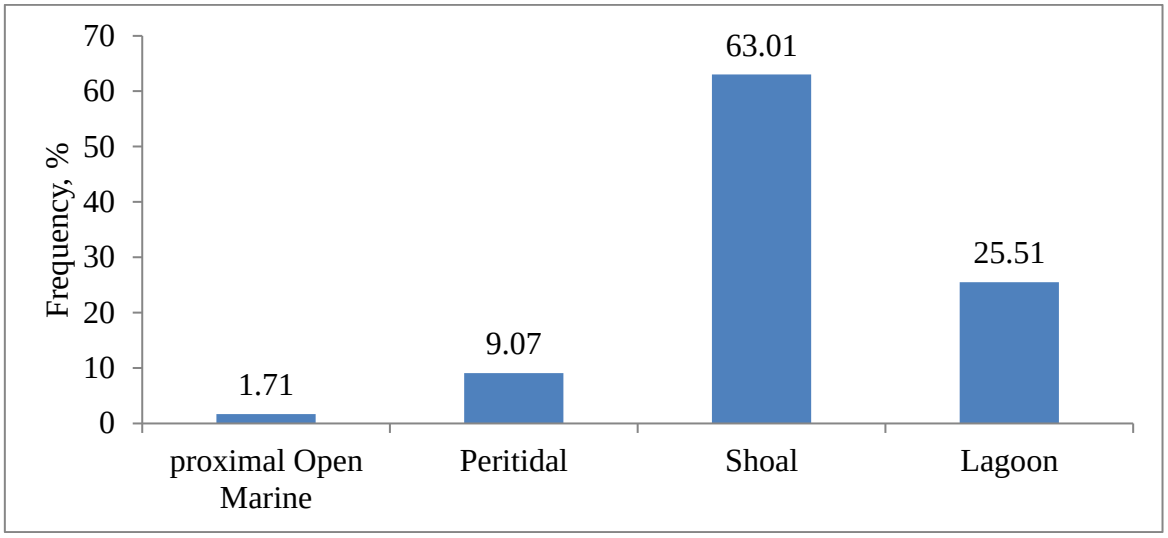

Figure 3. Reservoir Contribution of Depositional Environments.

3.2 Permeability Predictions Using Initial Models and a Modified Model for Carbonate Reservoirs

Winland vs. Modified Winland Permeability Models for Carbonate Reservoirs. Winland developed an empirical correlation linking porosity, permeability, and pore throat diameter, represented by the following equation. Figure 4 illustrates the comparison between the Winland permeability model and the modified Winland permeability model for carbonate reservoirs.

Initial Winland Permeability Model:

$$\log K = \frac{-(0.732 - 0.864\,(\log \varphi) - (\log R35))}{0.588} \quad \text{.....(1)}$$

where R_{35} is the radius of the pore-throat in 35 % of mercury saturation, K is permeability (mD), and $\boldsymbol{\varphi}$ is porosity (%).

Calibrated Winland Permeability Model for carbonate reservoirs:

$$\log K = \frac{-(0.836 - 0.674\,(\log \varphi) - (\log R35))}{0.588} \quad \text{.....(2)}$$

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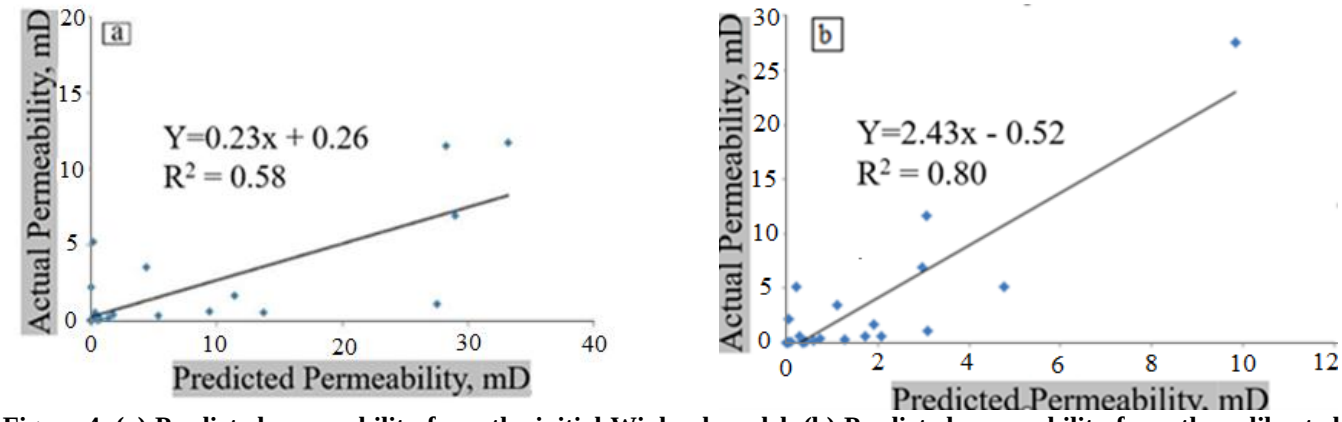

Figure 4. (a) Predicted permeability from the initial Winland model. (b) Predicted permeability from the calibrated Winland model.

The initial permeability model (Figure 4a) was developed using a dataset that included both carbonate and sandstone formations. While this broader calibration aimed to create a general permeability prediction model, its accuracy for carbonate reservoirs was limited. The regression equation in Figure 4a (y=0.23x+0.26) exhibits a relatively weak correlation, with an R^2 value of 0.58, indicating a moderate fit between the predicted and actual permeability values. This suggests that the model, when applied to carbonate reservoirs, does not fully capture the specific pore structure and permeability characteristics unique to these formations. To improve prediction accuracy, the model was recalibrated exclusively using carbonate rock data and validated with a carbonate dataset. The results (Figure 4b) show a significant improvement in prediction accuracy. The regression equation (y=2.43x−0.52) demonstrates a much stronger correlation, with an R^2 value of 0.80, indicating a considerable enhancement in the model's ability to predict permeability in carbonate reservoirs.

This improvement can be attributed to the fundamental differences in pore structure between carbonates and sandstones. Carbonate rocks exhibit more complex and heterogeneous pore networks, often including vuggy and moldic porosity, which influence permeability differently than sandstones. By calibrating the model solely based on carbonate rock data, the influence of sandstone-related permeability trends was eliminated, allowing for a more accurate and representative model for carbonate formations. The results confirm that the new calibrated model, developed and tested exclusively for carbonate reservoirs, provides a more reliable permeability prediction than the initial model. The significant increase in the regression coefficient supports the conclusion that permeability estimation in carbonate formations benefits from a model specifically tailored to their unique geological and petrophysical properties. Therefore, for future permeability predictions in carbonate reservoirs, the new calibrated model should be preferred over the initial mixed-rock model, as it better accounts for the complexities inherent in carbonate pore systems.

Pittman vs. Modified Pittman Permeability Models for Carbonate Reservoirs. The Pitman permeability model has been developed and calibrated using the following approach:

https://doi.org/10.31223/X5KB04

$$\log K = -0.848 + 0.612\,(\log \varphi) + 0.645\,(\log R25) \quad (3)$$

where, R_{25} is the radius of the pore-throat in 25 % of mercury saturation, K is permeability (mD), and φ is porosity (%). The correlation and coefficient of determination (R^2) between the measured and predicted permeabilities are presented in Figure 5.

Calibrated Pittman Permeability Model for carbonate reservoirs:

$$\log K = -1.221 + 1.415\,(\log \varphi) + 1.512\,(\log R25) \quad (4)$$

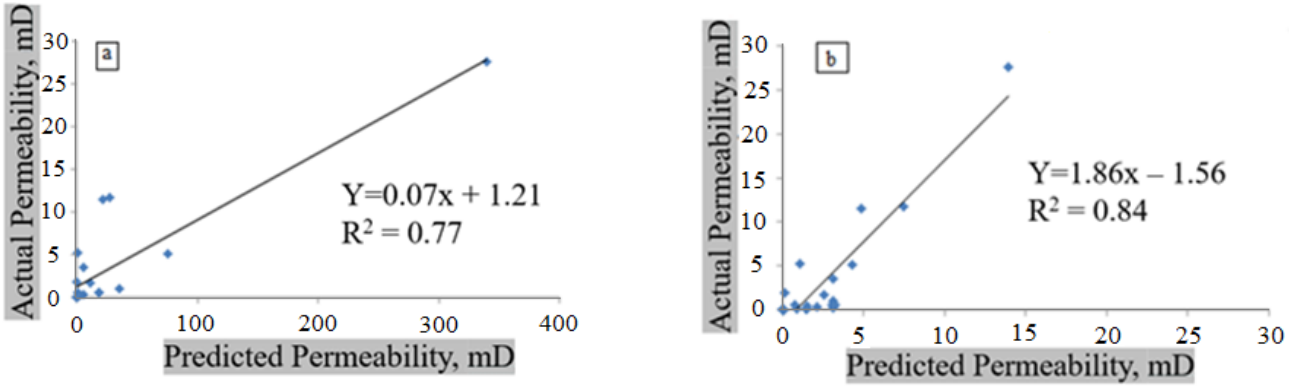

Figure 5. (a) Predicted permeability from the initial Pittman model. (b) Predicted permeability from the calibrated Pittman model.

The initial Pittman permeability model (Figure 5a), calibrated using a dataset primarily based on sandstone formations, shows limitations when applied to carbonate reservoirs. The regression equation (Y=0.07x+1.21) and an R^2 value of 0.77 indicate that while the model provides a reasonable correlation, it significantly underestimates permeability in carbonate rocks. This discrepancy arises due to the distinct pore structures in carbonates, which differ from the intergranular porosity typical of sandstones. To enhance prediction accuracy, the model was recalibrated using only carbonate rock data (Figure 5b). The recalibrated model exhibits a significantly stronger correlation, with an improved regression slope and a higher R^2 value of 0.84. This demonstrates that the new model better captures the permeability trends specific to carbonate reservoirs, eliminating the inaccuracies introduced by including sandstone data. The improvement is attributed to the unique heterogeneity of carbonate formations, which often feature vuggy and moldic porosity, creating complex permeability pathways. The recalibrated model, developed solely from carbonate data, more accurately reflects these petrophysical characteristics, leading to superior predictive performance. The results confirm that the carbonate-specific calibration of the Pittman model is more suitable for permeability prediction in carbonate reservoirs. Therefore, the recalibrated model should be preferred over the initial model, as it provides a more reliable representation of permeability trends in carbonate formations.

https://doi.org/10.31223/X5KB04

Dastidar vs. Modified Dastidar Permeability Models for Carbonate Reservoirs. The permeability model proposed by Dastidar et al. (2007) integrates the weighted geometric mean of the pore-throat radius (R_{WGM}) along with porosity. This relationship is expressed through the following model:

$$\log k = -2.51 + 3.06\,(\log \varphi) + 1.641\,(\log R\,(WGM)) \quad (5)$$

where K is permeability (mD), φ is porosity (%), and R_{WGM} is weighted geometric mean of the pore-throat radius (µm). The predicted and the measured permeabilities and their linear modeling are shown in Figure 6.

$$\log k = -1.857 + 1.68\,(\log \varphi) + 0.009\,(\log R\,(WGM)) \quad (6)$$

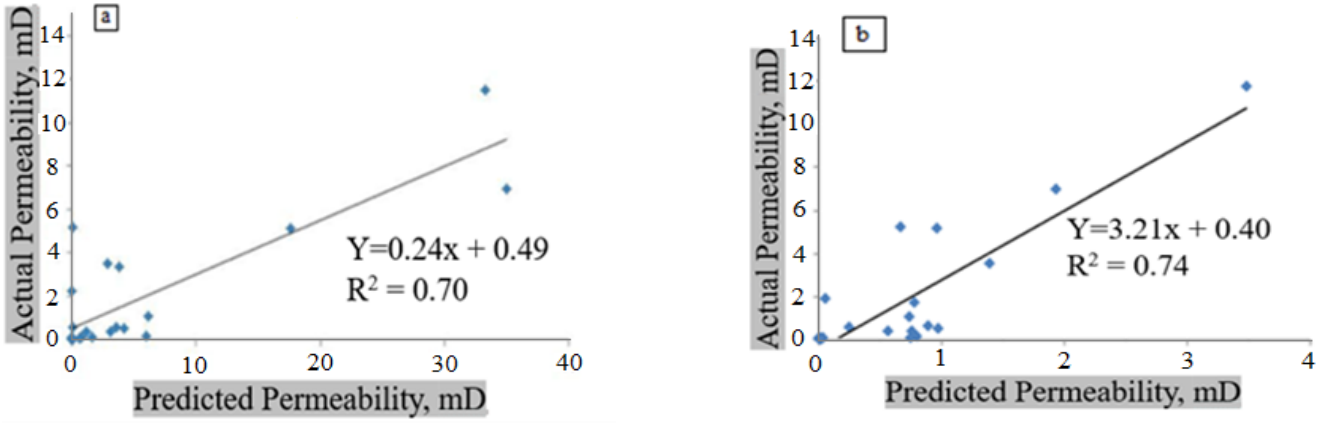

Figure 6. (a) Predicted permeability from the initial Dastidar model. (b) Predicted permeability from the calibrated Dastidar model.

The comparison between the two permeability models highlights the significant improvement achieved through calibration for carbonate rocks. (Figure 6a) represents the permeability model based on the original Dastidar formula, with a relatively weak correlation between predicted and actual permeability values, as indicated by the regression equation y=0.24x+0.49 and an R^2 value of 0.70. The substantial deviation of data points from the 1:1 line suggests that the model struggles to capture the permeability variations in carbonate rocks accurately.

In contrast, (Figure 6b) presents the permeability model that has been specifically calibrated for carbonate rock formations. The revised model demonstrates a significant enhancement in predictive capability, as reflected in the improved regression equation y=3.21x−0.40 and a higher R^2 value of 0.74. The closer alignment of data points along the trend line in this model indicates a more accurate representation of actual permeability values. This improvement suggests that incorporating a calibration factor tailored to carbonate reservoirs effectively refines the permeability estimation by accounting for their complex pore structures and heterogeneity. Overall, the results confirm that modifying the Dastidar permeability model for carbonate rocks leads to a more reliable prediction of permeability, enhancing its applicability for

https://doi.org/10.31223/X5KB04

reservoir characterization and fluid flow modeling in these formations. The improvement in correlation underscores the importance of calibration when applying permeability models to different lithologies, particularly for carbonate rocks, where standard models often fail to account for their intricate pore networks and variable pore-throat distributions.

4. Conclusions

This study demonstrates the necessity of calibrating permeability models specifically for carbonate reservoirs to achieve accurate predictions. The initial models, originally developed using mixed lithologies, exhibited limited reliability when applied to carbonate formations due to their unique pore structures and heterogeneity. By recalibrating the Winland, Pittman, and Dastidar models using carbonate-specific datasets, the predictive accuracy significantly improved, as evidenced by higher regression coefficients and better alignment with actual permeability measurements. These findings highlight the importance of recalibrated permeability models for carbonate reservoirs, ensuring more precise reservoir characterization and improved flow modeling.

5. Conflicting Interests

The author(s) declare that they have no conflicting interests.

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