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Why Classical Compressibility Models Underperform: A Machine Learning Approach Using GridSearch-Optimized Random Forest

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Introduction

Reservoir compaction represents a critical geomechanical challenge in hydrocarbon production, where pore pressure decline induces effective stress increases on rock matrices, leading to measurable pore volume reduction. Accurate pore volume compressibility (PVC) prediction is vital for multiple aspects of reservoir management, including original oil-in-place estimation, production forecasting, and well integrity preservation. However, conventional PVC models frequently fail to capture the complex behavior of heterogeneous carbonate formations, particularly in Brazil's pre-salt Barra Velha and Morro do Chaves reservoirs, where pore structure variability and stress sensitivity create substantial predictive uncertainties. This limitation underscores the need for advanced modeling approaches tailored to carbonate-specific compressibility behavior.

Method and/or Theory

The experimental methodology combined laboratory core analysis with machine learning techniques to develop an improved PVC prediction model. Core samples from the Barra Velha and Morro do Chaves formations underwent a characterization process beginning with ambient-pressure measurements using an Ultrapore 300 porosimeter to establish baseline porosity and permeability values. Subsequent hydrostatic compression testing was performed in a Coreval 700 system across a confining pressure range of 5.5 - 22.1 MPa, with nitrogen permeability measurements recorded at incremental pressure stages to capture stress-dependent behavior.
The sample's mineral content was estimated from the X-ray diffractometry (XRD), a technique used to determine the crystalline phases in a determined material and the mineral bulk modulus (K_m) was obtained by applying the Voigt-Reuss-Hill average of the estimated mineral fractions. The mineral compressibility ($C_{mineral}$)could then be calculated since it is the inverse of K_m.

PVC values were calculated following the Unalmiser-Swalwell method to ensure consistency with industry standards. These experimental results enabled a systematic comparison between classical models (Hall's correlation and Oliveira's equation) and our machine learning approach. For the Random Forest (RF) machine learning implementation, we employed GridSearchCV to optimize key hyperparameters, such as porosity, permeability, confining pressure and ($C_{mineral}$). The search evaluated parameter combinations to maximize prediction accuracy as measured by R^2 and mean relative percentage error.

Results and Conclusions

Comparative analysis revealed fundamental limitations in classical approaches, with Hall's and Oliveira's models showing consistent deviations exceeding the mean relative error of 54.58% and 66.78%, respectively. In contrast, the optimized Random Forest model achieved superior predictive accuracy of R^2: 0.93 versus 0.14 and 0.34 for these conventional methods, successfully capturing nonlinear pressure-dependent behaviors in heterogeneous carbonates. Feature importance analysis confirmed the physical consistency of the machine learning approach, identifying porosity and permeability as dominant controls, followed by confining pressure and ($C_{mineral}$). These results demonstrate that data-driven methods outperform theoretical correlations for carbonate PVC prediction, particularly in geologically complex reservoirs where traditional assumptions break down. The methodology's success suggests broad applicability for other challenging lithologies requiring enhanced geomechanical characterization.