

Prediction of Total Skin Factor in Perforated Wells Using Models Powered by Deep Learning and Machine Learning

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Summary

An accurate total skin factor prediction for an oil well is critical for the evaluation of the inflow performance relationship (IPR) and the optimization of stimulation treatments such as hydraulic fracturing and matrix acidizing. Performing a well test regularly is not quite economic and the total skin equations may not be accurate, so the goal of this work is to build machine learning-driven models that, using easily accessible field data, can predict the total skin factor in perforated wells.

Machine learning models are developed using available parameters typically gathered during well test by conventional well test analysis, which include liquid Rate, flowing bottomhole pressure, water cut, gas oil ratio, reservoir pressure, reservoir temperature, reservoir permeability, reservoir thickness, perforation diameter, shot density, perforation length, deviation angle of well, partial penetration of net pay thickness as inputs. This model is trained utilizing total skin factor acquired from conventional well test analysis, serving as the model's outputs. Nine distinct machine learning algorithms (Gradient Boosting, AdaBoost, Random Forest, Support Vector Machines (SVMs), Decision Trees, K-Nearest Neighbor (KNN), Linear Regression, Stochastic Gradient Descent (SGD) and Neural Network) are meticulously developed and fine-tuned using a substantial dataset derived from 1,088 wells. This dataset encompasses 19,040 data points, thoughtfully split into two subsets: 70% (13,328 data points) for training the algorithms and 30% (5,712 data points) for rigorously testing their predictive capabilities. Two methods (K-fold cross-validation and repeated random sampling) are used to assess the performance of machine learning models.

The k-fold cross validation outcomes of the top-performing machine learning models, specifically Random Forest, Gradient Boosting, AdaBoost, K-Nearest Neighbor (KNN) and Decision Trees, reveal remarkably low mean absolute percent error (MAPE) values when comparing their predictions of total skin factor to actual measurements. These MAPE values stand at 2.9%, 3.2%, 3.2%, 3.3%, and 3.8%, respectively. Additionally, the correlation coefficients (R^2) for these models are notably high, with values of 0.975, 0.972, 0.968, 0.964, and 0.956, respectively. Furthermore, machine learning models demonstrated their ability to predict total skin factor across various reservoir fluid properties, well geometry and completion configurations using data that the models had never encountered during training. These predictions were then compared against actual total skin factors measurements from conventional well test analysis, revealing a noteworthy alignment between the model's predictions and the real-world measurements.

This paper introduces novel insights by demonstrating how using machine learning models for predicting total skin factor in perforated wells can optimize stimulation treatments and diagnostic analysis. Utilizing machine learning models offers a more efficient, rapid, and cost-effective alternative to a well test (pressure transient analysis) and the total skin equations. Furthermore, these models excel in accommodating a wide spectrum of reservoir fluid properties, well geometry and completion configurations which was a challenge for single total skin equation.