Fracture Conductivity Prediction Based on Machine Learning in Shale – Support Vector Regression

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Abstract: Hydraulic fracturing extracts oil and gas from deep underground, with fracture conductivity being crucial for efficient production. Traditional lab techniques for measuring conductivity are costly and time-consuming. This paper explores using machine learning, specifically support vector regression, to predict fracture conductivity based on experimental data like Poisson's ratio and proppant size. Optimizing these models can enhance hydraulic fracturing efficiency in shale formations.

Hydraulic fracturing, often referred to as fracking, is a technique used to extract oil and gas from deep underground formations. This process involves injecting a high-pressure fluid mixture into the rock layer, creating fractures through which hydrocarbons can flow more freely to the production well. A crucial aspect of hydraulic fracturing is fracture conductivity, which refers to the ability of the created fractures to allow the flow of hydrocarbons. High fracture conductivity is essential for maintaining efficient hydrocarbon production. It depends on various factors, including the proppant type and size, the closure stress, and the properties of the fracturing fluid. Optimizing these factors ensures that the fractures remain open and conductive over the lifespan of the well (Montgomery, 2013; Holditch, 2006; Sharma et al., 2014).

Determining fracture conductivity in situ is a very challenging task and conducting lab measurements using Hassler core technique on shale are expensive and time consuming. The Hassler core experiment is a laboratory technique that simulates in-situ conditions to measure the permeability and conductivity of fractures in core samples. This method involves placing a core sample within a Hassler sleeve, applying confining pressure, and injecting fluid to simulate the hydraulic fracturing process. Researchers measure the resultant fracture conductivity, which is a key parameter influencing the efficiency of hydrocarbon extraction from shale formations. (Wu et al., 2017, Wu et al., 2019).

Machine learning is being used to advance scientific computing in a variety of fields, such as fluid mechanics, (Raissi et al., 2019, Zhang et al., 2020, Wang el al., 2017) solid mechanics, (Haghighat et al., 2020, Zheng et al., 2022, Arora et al., 2022) materials science etc (Kim et al., 2021). Machine learning techniques can also be applied to predict the fracture conductivity of new shale formations based on models built using data collected from experiments.

Good experimental data is key to building a well-performing prediction model. In order to build a model to predict fracture conductivity, the following information about various shale samples needs to be recorded while conducting experiments: Poisson's ratio, Young's Modulus, Temperature, Closure pressure, Proppant particle size, and Sand concentration. The wider the range of the above-mentioned parameters, the better the model will be.

There are various machine learning techniques that can be used to build the above model. In this paper we will discuss about support vector regression.

Support Vector Regression

To build a support vector regression (SVR) model for predicting fracture conductivity, we start with the same essential step of collecting comprehensive and high-quality experimental data. This involves conducting a series of controlled experiments on various shale samples and meticulously recording relevant parameters such as Poisson's ratio, Young's Modulus, Temperature, Closure pressure, Proppant particle size, and Sand concentration. Ensuring a wide range of values for these parameters enhances the robustness and generalizability of the model, allowing it to make accurate predictions across different shale formations.

Data Preprocessing

Once the data collection phase is complete, we need to preprocess the data. This includes handling any missing values, normalizing or standardizing the data to ensure that all parameters are on a comparable scale, and possibly performing feature selection to identify the most significant predictors of fracture conductivity. Preprocessing is crucial as it directly impacts the performance of the SVR model, helping to eliminate biases and improving the overall quality of the dataset. For instance, normalization can be performed as follows:

$$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

where xi is an original feature value, min(x) is the minimum value of the feature, and max(x) is the maximum value of the feature.

Model Formulation and Training

Support Vector Regression (SVR) operates by finding a function that deviates from the actual observed values by a value no greater than a predefined margin, while simultaneously being as flat as possible. The SVR model can be expressed mathematically as:

$$f(x) = \langle w, x \rangle + b$$

where ⟨w,x⟩ represents the dot product between the weight vector w and the input vector x, and b is a bias term.

To find the optimal w and b, we solve the following optimization problem:

$$\text{minimize}_{w,b} \frac{1}{2}\|w\|^2 \quad \text{subject to} \quad |y_i - \langle w, x_i \rangle - b| \leq \epsilon + \xi_i^+, \quad \xi_i^- \geq 0$$

Kernel Trick

In many practical scenarios, the relationship between the input features and the target variable is nonlinear. To address this, SVR uses the kernel trick, which allows it to operate in a high-dimensional feature space without explicitly computing the coordinates of the data in that space. Common kernels include linear,

polynomial, and radial basis function (RBF) kernels. The kernel function $K(x_i,x_j)$ maps the input features into a higher-dimensional space where a linear separation is possible:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)$$

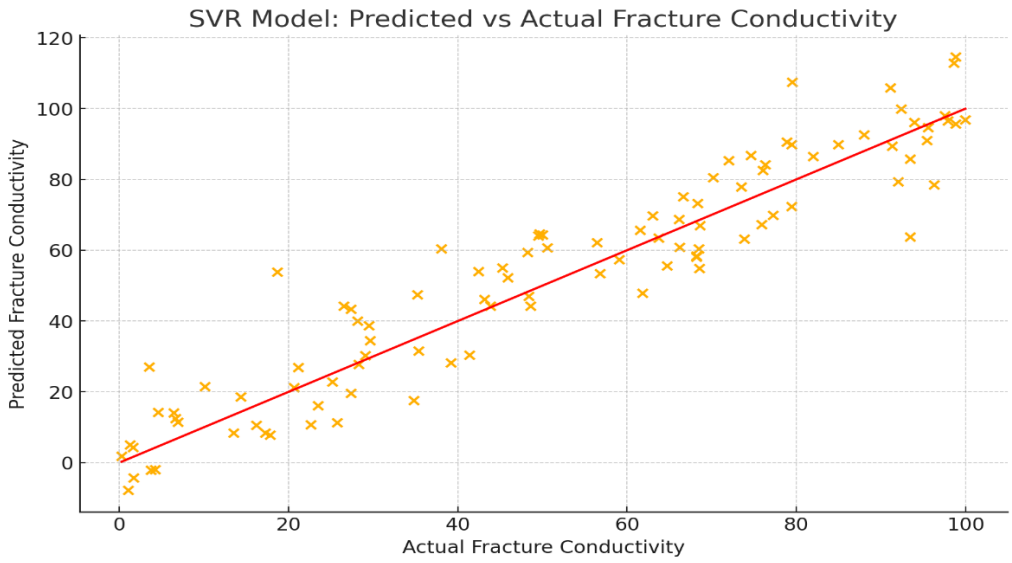
Model Evaluation and Validation

After training the SVR model, we evaluate its performance using metrics such as the coefficient of determination (R^2), mean squared error (MSE), and root mean squared error (RMSE). Additionally, cross-validation techniques, such as k-fold cross-validation, are used to ensure the model's reliability and to avoid overfitting. For example, in k-fold cross-validation, the data is divided into k subsets, and the model is trained k times, each time using a different subset as the validation set and the remaining k-1 subsets as the training set. The performance metrics are then averaged to obtain a more robust estimate of the model's performance.

Interpretation and Visualization

Interpreting the results involves examining the coefficients of the SVR model and the support vectors. The support vectors are the data points that lie within the margin of tolerance and are crucial in defining the decision boundary. Visualizing the SVR model can help in understanding its behavior and the impact of different features. For instance, plotting the predicted versus actual values of fracture conductivity can highlight how well the model generalizes to unseen data.

Below is a sample plot showing the predicted versus actual values of fracture conductivity:



Conclusion

By following these steps, a comprehensive and accurate SVR model can be developed, providing valuable insights for predicting the fracture conductivity of shale formations. The combination of good experimental

data, thorough preprocessing, appropriate model selection, and rigorous validation ensures the model's reliability and applicability in real-world scenarios.

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