S-wave velocity prediction from P-wave velocity for different reservoir rocks based on deep neural network

Introduction

The conventional S-wave velocity prediction methods can be divided into three categories, empirical formula method, rock physics model prediction method and machine learning prediction method. The empirical formula method is to use the existing logging data from the target area to statistically analyze the relationship between these data and the shear wave velocity. The formula is generally obtained by fitting data point pairs based on some kind of mathematical expression. There is no need to have a complete theoretical derivation process, and this method is only applicable to specific geological environments (Castagna, 1985; Han, 1986). The rock physics model prediction method is to establish the relationship between elastic parameters and reservoir parameters based on theoretical models; therefore, the S-wave velocity prediction is often more accurate than the empirical formula. Theoretically, the rock physical model is not specifically limited to a particular region, but there are many assumptions in the establishment of each model, making it difficult to apply them across different regions. For complex reservoirs, the accuracy of S-wave velocity predicted by rock physical model is not sufficiently high (Gassmann, 1951; Xu and White, 1995). Deep learning is a branch of machine learning, which has great advantages in parallel processing, feature extraction and data prediction, etc. Deep learning algorithms such as backpropagation artificial neural network (BPNN) and recurrent neural network (RNN) for S-wave velocity prediction are widely used (Eskandari et al., 2004; Alimoradi et al., 2011). However, these deep learning algorithms are all designed to build different neural networks driven by data for a certain area, without considering physical correlations between features and lack of actual physical meaning.

In this abstract, first, theoretical rock physics models for multi-type reservoirs are established based on different rock physics theories; then, based on the rock physics model output data, the deep neural network approach (DNN) is used to predict the S-wave velocity from P-wave velocity and other input parameters. Last, the accuracy of the DNN model is estimated for each and all the reservoir types, which is used to validate the effectiveness of the DNN model for universal S-wave velocity prediction, irrelevant of the reservoir type.

Theoretical rock physics modeling for multi-type reservoirs

The rock physics responses of different types of reservoirs are quite different. For example, for tight sandstone reservoirs, fractured limestone reservoirs and heavy oil reservoirs, specific theoretical rock physics models have been established. Conventional rock physical modeling firstly uses the equivalent medium theory to obtain the moduli of the composite medium, then adds different types of pores to the rock matrix to obtain the moduli of skeleton, and finally uses fluid substitution theories to obtain the moduli of saturated rock. In the following, we establish appropriate rock physics models for tight sandstone reservoir, fractured limestone reservoir and heavy oil reservoir, respectively.

For tight sandstone reservoirs, the heterogeneity, microscopic pore structure and pore fluid distribution of rocks are quite complex. When saturated with different fluids, the fluid flow caused by wave propagation makes the overall elastic responses of rocks more complex. A simple squirt flow model (Gurevich et al., 2010) and a patch saturation model can be used to characterize wave-induced flow effects occurring both at mesoscopic and microscopic scales in tight sandstone. The idea of a simple squirt flow model is to modify the dry skeleton of the rock in the medium and high frequency ranges so that the soft pores are saturated with fluid and the stiff pores remain dry. The modified dry skeleton modulus is $K_{mf}$ and $\mu_{mf}$, which are expressed as follows.

$$\frac{1}{K_{mf} (P, \omega)} = \frac{1}{K_h} + \frac{1}{K_{dry} (P)} - \frac{1}{K_h} \frac{1}{K_{dry} (P)} \frac{1}{K_g} \frac{\phi_s (P)}{K_s}$$

(1)
For fractured limestone reservoirs, the simultaneous development of matrix pores and fractures and the directional arrangement of fractures will cause anisotropy of the reservoir, which has a significant impact on the elastic properties of the reservoir. We use the linear-slip model to add fractures into the rock matrix. Then, we use the anisotropic Gassmann equation (Eq. 3) for fluid substitution to obtain the modulus of the saturated rock.

\[
C_{mn}^{sat} = C_{mn}^{dry} + \beta_m \beta_n K_p^*, m, n = 1,2,...6
\]  

(3)

where, \(C_{mn}^{sat}\) represents the stiffness coefficient of saturated medium; \(C_{mn}^{dry}\) represents the stiffness coefficient of dry media; and \(K_p^*\) represents the pore space modulus of anisotropic media.

Heavy oil exists in the rock pores in the form of high viscosity fluid or even solid, which has a great influence on the elastic properties of the rock. Therefore, the Cole-Cole model is used to model the variation of the elastic moduli of heavy oil with temperature and frequency. The coherence potential approximation (CPA) method (Eq. 4 and Eq. 5) and the solid squirt flow theory are used to describe the elastic responses of the heavy oil substitution, an appropriate rock physics model for heavy oil reservoir is established.

\[
\phi(K_f - K)P_f + (1 - \phi)(K_s - K)P_s = 0
\]

(4)

\[
\phi(\mu_f - \mu)Q_f + (1 - \phi)(\mu_s - \mu)Q_s = 0
\]

(5)

where, \(\phi\) is porosity, \(K_f\) and \(\mu_f\) are bulk and shear modulus of pore filling, \(K_s\) and \(\mu_s\) are the bulk and shear moduli of the matrix, \(P\) and \(Q\) are invariants of Wu tensor (ref). The composition of the tensor depends on the aspect ratio of the pore and the bulk and shear moduli of the pore filling and the matrix.

**Deep neural network modeling and training**

These rock physic models are employed to generate training data for the neural network. We generate examples through sampling random distributions for model parameters and then computing elastic moduli, where compressional wave velocity, density and porosity are common parameters of the three models, soft porosity, aspect ratio and frequency are unique parameters of tight sandstone, and fracture density, aspect ratio of fracture, and fluid saturation are unique parameters of limestone reservoir. The characteristic parameters of heavy oil reservoirs are soft porosity, viscosity and temperature. The sampling ranges for these model parameters are chosen to cover all possible values of different types of reservoirs to ensure the generality and abundance of the synthetic data.

Feature normalization is an important step in deep learning. Since different features always have different amplitudes, units, and ranges, the features with high magnitudes will impose higher impact on networks. If the data is not processed to the same range, the network may not converge when it is trained, and the training time is long, giving more weight to features with larger values, which will limit the prediction accuracy of the regression equation. In order to eliminate this effect, it is necessary to normalize the features to the same scale. This study uses the min-max method to normalize the features, and the normalized data are all between 0-1.

DNN is a kind of multi-layer feedforward neural network, in which the upper and lower layers are fully connected, while the neurons in each layer are not connected. First, establish a deep neural network for each type of reservoir, and test the influence of different numbers of features on the prediction results. Then combine the data simulated by the rock physic model of multiple types of reservoirs to obtain a multi-source data set, and build a deep neural network suitable for multiple types of reservoirs. After
parameter debugging, we built a four-layer fully connected deep neural network with 2 hidden layers, 3 inputs, and 1 output. The three parameters of compressional wave velocity, density and porosity were used as the input features, and the shear wave velocity (vertical shear wave velocity) was used as the label for network training. The loss function was the mean square error function, and the activation function was the Rule function to increase the nonlinear characterization ability of the neural network.

Analysis of prediction results

Table 1 and Figure 1 show the prediction results of the deep neural network for different reservoirs. It can be seen from Table 1 that for a single reservoir, the changes in $R^2$ values for different numbers of features are very small, and the average relative errors are also very low, which indicates that S-wave velocity can be well predicted by using P-wave velocity, porosity and density information. With the increase of the number of features, the prediction accuracy of a single reservoir becomes higher. When the features only include P-wave velocity, porosity and density, it can be seen from Figure 1 that the final loss function (MSE) of multi-type reservoir S-wave prediction network is higher than that of a single reservoir, and the prediction error is worse than that of a single reservoir. However, the $R^2$ value of prediction accuracy is above 0.85, and the average relative error is below 10%, which is in line with the error tolerance of real applications. In the heavy oil modeling process, the fluid is fully saturated, while the other two reservoirs are saturated with multiple fluids. Therefore, the prediction accuracy of heavy oil reservoir is higher than that of the other two types of reservoirs in the case of three feature DNN.

Table 1 Comparison of shear wave velocity prediction results of different feature numbers in multi-type reservoirs

<table>
<thead>
<tr>
<th>Number of feature</th>
<th>R² Tight sandstone</th>
<th>R² Lime stone</th>
<th>R² Heavy oil</th>
<th>R² Multi type</th>
<th>Average relative error (%) Tight sandstone</th>
<th>Average relative error (%) Lime stone</th>
<th>Average relative error (%) Heavy oil</th>
<th>Average relative error (%) Multi type</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>0.9667</td>
<td>0.9785</td>
<td>0.9811</td>
<td>0.8547</td>
<td>5.49</td>
<td>4.21</td>
<td>2.01</td>
<td>8.94</td>
</tr>
<tr>
<td>4</td>
<td>0.9823</td>
<td>0.9835</td>
<td>0.9826</td>
<td></td>
<td>3.25</td>
<td>2.67</td>
<td>1.94</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.9901</td>
<td>0.9879</td>
<td>0.9859</td>
<td></td>
<td>1.15</td>
<td>2.26</td>
<td>1.75</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>0.9916</td>
<td>0.9969</td>
<td>0.9902</td>
<td></td>
<td>1.03</td>
<td>1.27</td>
<td>1.62</td>
<td></td>
</tr>
</tbody>
</table>

Figure 1 the value of the final loss function (blue column) and the deterministic coefficient $R^2$ of the neural network on the test set (red column) in the process of deep neural network training

Figure 2 is the result of cross-plot analysis using the velocity value predicted by the deep S-wave velocity prediction network and the given velocity value. It can be seen that the DNN has satisfactory prediction accuracy for the S-wave velocity for different reservoirs, among which the prediction for heavy oil reservoir is the best, and the prediction for tight sandstone reservoir is the worst. This is because the modeling process of tight sandstone is the most complex, while the modeling process of heavy oil is relatively simple. However, for all these reservoirs, the P-wave velocity, porosity and density information can be used to plausibly predict the shear wave velocity using the deep neural network.
Conclusions

In this abstract, rock physic theoretical models for multiple types of reservoirs are established, including the tight sandstone, fractured limestone and heavy oil-bearing reservoirs. Using rock physic models to generate simulation data, the prediction of S-wave velocity from P-wave velocity, porosity and density using deep neural network is analyzed and verified, and the S-wave velocity prediction model for multiple types of reservoirs is established. The accuracy of S-wave prediction for a single reservoir is above 0.96, and the average relative error is less than 6%. The accuracy of S-wave prediction for all three reservoirs is above 0.85, and the average relative error is about 10%. This shows that it is feasible to use P-wave velocity as well as porosity and density to predict S-wave velocity using deep neural network.

Acknowledgements

This work is sponsored by the National Natural Science Foundation of China (41774143, 41930425).

References


