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Estimation of geomechanical parameters using log data and MLP neural network algorithm in one of Iran's hydrocarbon fields

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Abstract

Today, geomechanics and accurate estimation of geomechanical parameters have played a significant role in various stages of petroleum studies. The aim of this study is to estimate geomechanical parameters using log data and MLP algorithm in one of the hydrocarbon field wells in southwest Iran. In order to estimate geomechanical parameters, one of the important parameters is shear wave velocity, which is estimated in this article using multilayer perceptron (MLP) neural network algorithm and experimental relationships. Considering the better estimation of MLP algorithm in training, test and blind data, its output has been used to estimate subsequent studies. The value of error (MSE) and coefficient of determination (R^2) of the blind data are 0.0013 and 0.8875 respectively. Next, Young's modulus and Poisson's ratio were calculated and dynamic brittleness index was calculated using these two parameters. In the next step, the uniaxial compressive strength, tensile strength were calculated and then the static brittleness index was calculated and the relationship between the dynamic brittleness index and the static brittleness index was investigated. The brittleness index was then calculated using the volume percentage of minerals and compared with the dynamic and static brittleness index values. The results show a good relation between the dynamic and static brittleness index obtained using the predicted shear wave velocity from MLP algorithm and the brittleness index obtained from the volume percentage of minerals.

Keywords: *Model evaluation, Log data, Shear wave velocity, Brittleness index, MLP algorithm*

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Extended Abstract:

1. Introduction

Geomechanics of hydrocarbon reservoirs plays an important role in the evaluation and development of oil and gas fields. Today, numerous studies have been conducted in the field of geomechanics, geomechanical parameter estimation, and geomechanical modelling. Ore and Gao (2021) predicted the brittleness index using artificial neural networks and support vector regression. Jin et al., (2022) predicted the compressive strength and elastic modulus of rocks using machine learning. They used a hybrid GWO-ELM model was built based on a machine learning network optimized by the gray wolf algorithm. Faraj et al., (2022) estimated the internal friction angle using density and gamma neutron profiles using Plumb correlation. Shahani et al., (2022) estimated the internal friction angle and adhesion using machine learning (LR), (RR), (DT) and (SVM) methods and well log data. Gholami et al., (2022) predicted the slow and fast shear wave velocity using machine learning (artificial neural network algorithm, fuzzy and neuro-fuzzy logic) and petrophysical logs. Nasrnia et al., (2023) predicted the shear wave velocity by combining intelligent methods and rock physical models. Based on the review of previous studies, identifying a method that provides an accurate estimation of geomechanical parameters is of great importance. So, this study aims to estimate geomechanical parameters, including shear wave velocity, Young's modulus, Poisson's ratio, uniaxial compressive strength, tensile strength, and dynamic and static brittleness indices, within a well in one of the hydrocarbon fields in southwest Iran using well log data, the MLP algorithm, and empirical relationships. This research integrates intelligent methods with empirical approaches to estimate geomechanical parameters. Additionally, to examine the brittleness index, which has been less studied, dynamic and static brittleness indices were calculated and compared with the brittleness index derived from the volumetric percentage of minerals.

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2. Materials and methods

In this study, well log data including RHOB, CALIPER, NPHI, LL7, PEF, Vp, Vs, and CGR were utilized to estimate shear wave velocity (Vs) using the MLP algorithm. To identify the most effective features and suitable inputs for the algorithm, the correlation coefficients of the features with shear wave velocity were analyzed by calculating Pearson correlation coefficient matrix. Based on the Pearson correlation coefficient results, Vp, RHOB, NPHI, and CALIPER logs data were selected as input features for the algorithm. Next, out of the total dataset of 11,640 samples, 1,432 were set aside as blind data to validate the algorithm's performance, while the remaining data were split into training and testing sets, with 80% allocated for training and 20% for testing. To enhance accuracy, data normalization was then applied using the Min-Max Normalization technique, which scales the data to a range between zero and one. Subsequently, the Adam optimizer function was employed for optimization purposes. Model performance was evaluated using metrics such as mean square error (MSE), root mean square error (RMSE), and the coefficient of determination (R^2).

3. Tests results

The results of the MLP algorithm for predicting shear wave velocity were examined to estimate other geomechanical parameters, and RMSE, MSE and R^2 were calculated for training, testing and blind data. The configuration of the MLP algorithm used in this study includes two hidden layers,

with the first layer containing 500 nodes and the second layer comprising 100 nodes. Attempts were made to train the model with a greater number of hidden layers, but these adjustments neither enhanced the prediction results nor justified the increased computational cost, as the training time rose significantly with the additional layers.

To validate the performance of the algorithm, the blind dataset was later used to evaluate the algorithm's ability to estimate shear wave velocity, with the predicted values compared against the measured ones. For the blind data, the MLP algorithm achieved an MSE of 0.0013, an RMSE of 0.0371, and an R^2 of 0.8875. Figure 1 presents a comparison between the measured and predicted shear wave velocity values for the blind dataset using the MLP algorithm.

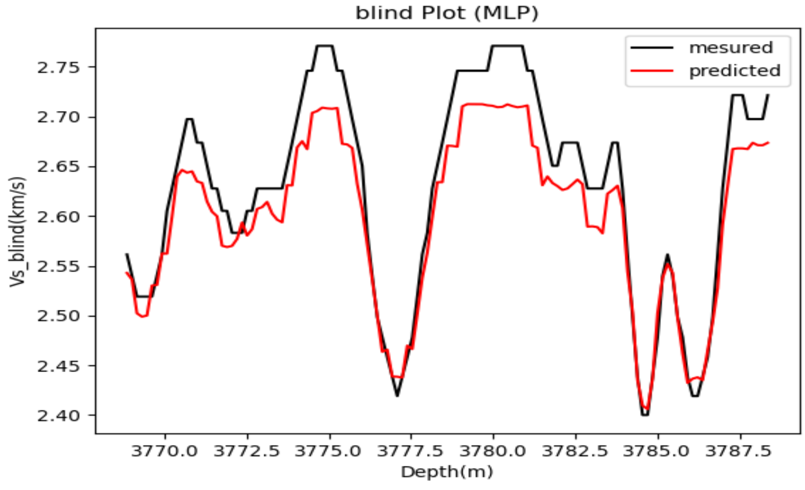

Figure 1. A comparison of the measured and predicted shear wave velocity using the MLP algorithm for bind dataset.

Next, the estimated shear wave velocity using the MLP algorithm was compared with the empirical relations, and according to the obtained results, the output of the MLP algorithm was used to estimate other geomechanical parameters. In the following step, the dynamic Young's modulus (E_{dyn}) and dynamic Poisson's ratio (υ_{dyn}) were calculated using the shear wave velocity predicted by the MLP algorithm. The static Young's modulus (Est) was then derived from the dynamic Young's modulus using Wang's equation (2000).

The dynamic brittleness index was then determined using the dynamic Young's modulus and Poisson's ratio, with these parameters derived from the estimated shear wave velocity using machine learning techniques. For the calculation of the static brittleness index (Bst), the relationship between this index and the uniaxial compressive strength (σ_c) as well as tensile strength (σ_t) was applied. The uniaxial compressive strength was estimated using Christaras's relationship (1997) and Bradford's relationship (1998), while the tensile strength was assumed to be 10% of the uniaxial compressive strength.

Finally, for estimating the brittleness index based on mineral composition, the method proposed by Jarvie et al. (2007) was utilized. This approach defines the brittleness index as a function of the volumetric proportions of quartz, carbonate, and clay. The results demonstrated a strong correlation between the dynamic and static brittleness indices, as well as the brittleness index derived from the volumetric mineral composition.

4. Conclusion

In this research, some geomechanical parameters were estimated using the MLP algorithm and empirical relationships. First, shear wave velocity was calculated using the MLP algorithm and several empirical relationships, and found that the results of the MLP method have higher accuracy compared to empirical relations. Therefore, the output of this algorithm was used to estimate the shear wave velocity and other geomechanical parameters. In the next step, the dynamic and static Poisson's ratio and Young's modulus were calculated to estimate the uniaxial compressive strength and brittleness index. Subsequently, the uniaxial compressive strength, tensile strength, dynamic and static brittleness index, and brittleness index using the mineral volume were calculated and their results were compared. The results indicate that in areas where the quartz volume percentage increases, both the dynamic and static brittleness indices also increase.

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