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Brittleness index prediction in shale gas reservoirs based on efficient network models

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A B S T R A C T

Brittleness index is one of the critical geomechanical properties of unconventional reservoir rocks to screen effective hydraulic fracturing candidates. In petroleum engineering, brittleness index can be generally calculated from the mineralogical composition by X-ray diffraction (XRD) test or rock mechanical parameters by tri-axial experiments and well logs. However, mineral composition analysis or tri-axial experiments cannot produce continuous brittleness profile. Well log-based brittleness index prediction conventionally relies on Young's modulus and Poisson's ratio, but sometimes shear compressional velocity is not available to derive elastic inputs for the brittleness index calculation. This study proposes some data-driven practical brittleness prediction approaches based on back-propagation artificial neural network (BP-ANN), extreme learning machine (ELM) and linear regression using commonly available conventional logging data and lab mineralogical-derived brittleness. A dataset of 71 mineralogical-derived brittleness measurements from Silurian Longmaxi marine shale, Jiaoshiba Shale Gas Field, Sichuan Basin, China were established. The model comparisons and error analysis reveal that the application of artificial intelligence models can be more effectively applied to brittleness prediction compared with simple regression correlations. Both BP-ANN and ELM models are competent for brittleness prediction while BP-ANN model can produce slightly better brittleness prediction results with same inputs and ELM model require less running time. Thus, more choices can be made according to accuracy and computational speed demand. Moreover, an overall ranking of sensitivity degree is then provided to show the impacts of different well logs as inputs on the BP-ANN and ELM model, which is helpful to find optimal inputs in given case. Comparing to traditional well-log based brittleness approaches, data-based approaches show its wider applications because the integration of mineralogical composition and well log information can provide continuous brittleness profile in terms of high accuracy while acoustic full waveform velocities are no longer necessary inputs in brittleness evaluation.

1. Introduction

Shale gas is becoming a significant contributor to gas production across the world. Due to the ultra-low permeability of shale reservoirs, the combination of horizontal drilling and multistage hydraulic fracturing technology is commonly used to enhance shale gas production, but field experiences reveal that not all hydraulic fracturing targets can yield commercial production. Consequently, screening prospected fracturing candidates are necessary before multi-stage hydraulic fracturing treatments (Cipolla et al., 2008; King, 2010; Zhou et al., 2015). Typically, brittle shales are easy to be fractured under tensile and shear loads, so brittleness is introduced as a critical indicator to assign perforation locations. Since brittle rocks may be relatively easy to fracture, thus high brittleness is generally equivalent to a high possibility of large

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stimulated reservoir volume (SRV) (Sondergeld et al., 2010). Moreover, in addition to indicate efficient fracture initiation and propagation and increased fracture network complexity, formation brittleness can be used to justify the resistance to proppant embedment (Kias et al., 2015). Therefore, an accurate prediction of brittleness is significant for both shale gas well completion and production.

In recent years, rock brittleness has been extensively studied by many researchers in the geo-mechanics filed. However, the definitions of brittleness are still ambiguous, an agreement of the measurement standards of brittleness has not yet been reached (Kahramana, 2002; Altindag, 2003; Goktan and Yilmaz, 2005; Wang and Gale, 2009; Wang et al., 2015; Zhang et al., 2016). Current approaches include stress-strain curves upon loading and failure, pre-peak and post-peak behaviors or mechanical properties from tri-axial tests can be used to evaluate brittleness. Since stress-strain curved based brittleness indexes are hard to obtain thus UCS (unconfined compressive strength) and tensile stress, and brinell hardness tests are commonly proposed as alternatives for brittleness evaluation (Hucka and Das, 1974; Holt et al., 2011; Li et al., 2012; Zhou et al., 2014). Except for stress and stain based and elastic based parameters, shale brittleness also can be calculated by mineralogical compositions. Compared with clay minerals, the high content of quartz and carbonate would increase shale brittleness. (Jarvie et al., 2007; Sondergeld et al., 2010). In addition, feldspar and dolomite are sometimes regarded as brittle components in some shale gas plays (Jin et al., 2014a). The big advantage for mineral-based brittleness calculation is mineralogical information can be obtained from well logs, cores or drilling cuttings although lab experiments are time-consuming and expensive. However, rock brittleness from laboratory mechanical testing is still preferred at the interval of interest because additional information can be provided for compatible proppant and fracturing fluids preparation.

The brittle and ductile behavior of rocks is considered to be the comprehensive responses of the mineral compositions, stress, strain rate and fluids within a rock matrix under certain pressure and temperature conditions. Moreover, as shale gas formations have extremely wide horizontal span and large thickness, the continuous brittle information obtained directly by well logs is more practical and universally applicable. (Rickman et al., 2008). Well log based rock brittleness prediction needs elastic parameters like Young's modulus and Poisson's ratio, whereas shear wave logging is not conventionally performed due to the cost of logging service, therefore sometimes elastic parameters should be roughly calculated from local empirical fitting equations, which potentially results in tremendous errors for final elastic-based brittleness results. To solve these problems, some authors made some attempts to predict brittleness based on data-based approaches because data-based approaches are free from the constraints of function models and use less core data. Lai et al. (2015) performed a statistical regression analysis to find relationships between brittleness and conventional well logs, and the ratio of gamma rays to the photoelectric absorption cross section index showed a good correlation with mineralogical brittleness. Jin et al. (2014b) attempted to build correlations between mineralogical brittleness and compressional slowness for four U.S. shale plays. The results were more promising for predicted brittleness than only using neutron porosity. Previous study indicates some good relationships between mineralogical brittleness and the ratio of gamma rays to the photoelectric absorption cross section index, porosity, compressional slowness et al. (Heidari et al., 2014; Lai et al., 2015). But these relationships are derived from local data whereas these empirical relationships are random and virtually non-existent in the other shales. In addition, porosity and compressional slowness logs are easily influenced by organic matter content, complicated lithofacies and the other potential geochemical factors at specific locations. Considering high uncertainty in brittleness evaluation with simple regression, artificial intelligence technology is a powerful tool to model complex systems that seek to simulate human brain behavior by processing data on a trial-and-error basis. Because its advantages in recognize, cluster and organize complicated nonlinear relationships between parameters, the application of artificial intelligence approaches have been successfully applied in many well logging fields, including formation permeability, porosity and total carbon content (TOC) prediction (Baneshi et al., 2013; Tan et al., 2015). However, little research has been done on shale brittleness index prediction using any artificial intelligence approaches.

This study seeks to show the application of two artificial intelligent methods (back propagation-artificial neural network(BP-ANN) and extreme leaning machine(ELM)) for rock brittleness prediction with conventional well logs and discrete lab mineralogical brittleness. Moreover, linear regression method was also applied to make a comparison in this study. A mineralogy-based brittleness dataset collected in the Silurian Longmaxi marine shales was used to develop these models. With the help of cross plotting and correlation matrix analysis, sensitivity ranks of each well logs on brittleness was investigated. With these variables, the performances between linear regression model, BP-ANN and ELM model were compared. Numerical results obtained from developed neural network models reveal the high accuracy and efficiency of two artificial intelligent techniques on the prediction process, which can very helpfully be used for better brittleness predictions using available experimental data.

2. Artificial neural networks and extreme learning machine

Artificial neural networks (ANNs) are models of information processing that seek to simulate human brain behavior. It has been well-known as a tool of pattern recognition, function approximation, dynamic modelling, data mining, time-series forecasting et al. (Lu et al., 2003; Dehghani et al., 2008; Mozaffari and Azad, 2014). There are many types of neural networks, but the basic principles are quite analogous. The most popular training algorithm of ANNs is the back-propagation (BP) and some of its different variants. Standard BP is a gradient descent algorithm. There are some inherent problems which are frequently encountered in the use of this algorithm, e.g. slow convergence, easiness in get stuck in a local minimum and poor generalization (Chau, 2007). To overcome these obstacles, many improvements for BP networks have been invented, such as adaptive adjustment of learning rate, adding regularization and introducing momentum terms et al. However, the optimization of BP algorithm is beyond the scope of this paper. Therefore, a simple three-layered back-propagation network is introduced in this study.

The Extreme Learning Machine (ELM) algorithm is considered to be a Generalized Single-Layer Feedforward Neural Network (GSLFN). The essential idea of ELM is the random initialization of weights between the input and hidden layers (Huang et al., 2004; Chorowski et al., 2014; Huang, 2014). Thus, the use of ELMs as neural network algorithms has shown good speed performance. Considering an ELM architecture with M hidden neurons, we assume that the actual outputs are identical to the desired output, which represents the difference between the estimated and the desired output is zero. Then, the weights between hidden and