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Application of extreme learning machine and neural networks in total organic carbon content prediction in organic shale with wire line logs

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ABSTRACT

Total organic carbon (TOC) is a critical parameter for source rock characterization in shale gas reservoirs. In this work, the use of extreme learning machines (ELM) for predicting TOC from well logs data have been investigated. We use log data from two wells located in an unconventional shale gas reservoir in the Sichuan Basin, China. Seven wireline logs from this well and a total of 185 TOC observations from core measurements were incorporated. Prediction accuracy of the model has been evaluated and compared with commonly used artificial neural network which is based on Levenberg-Marquardt logarithm (ANN-LM). An Extreme Learning Machine (ELM) network is a single hidden-layer feed-forward network with many advantages over multi-layer networks, such as fast computing speed and better generalization performance. The results demonstrated that TOC prediction by the ELM model and the ANN model, but the ELM method can achieve high accuracy while maintains high running speed. This study shows that ELM technology is a promising tool for TOC prediction, and this work can be incorporated into a software system that can be used in quick 'sweet spot' determination and well completion guidance.

1. Introduction

Shale gas refers to an unconventional natural gas stored in low permeability shale, thus reservoir characterization is the essential step for shale gas well planning decisions (Pope et al., 2009; King, 2010). Shale gas well productivity depends on reservoir quality and successful hydraulic stimulations (Rickman et al., 2008; Glorioso and Rattia, 2012). Because not all shales are viable targets for economic hydrocarbon production, shale gas companies universally make special shale gas assessment criteria to help them rank appropriate stimulation strategies at wellbore, regional and basin scales (Chong et al., 2010). The definition of productive shale quality is based on many petrophysical properties, such as total organic carbon (TOC) content, thermally mature, permeability, porosity, saturation, rock mineralogy and mechanical properties et al. Most productive shale gas reservoirs can be judged by some critical reservoir properties qualitatively according to previous successful activities in shale plays, a potential commercial shale gas reservoir typically has at least 2% TOC, and Ro (vitrinite reflectance) ranges within maturity windows (more than 1.4 in gas dry window). Furthermore, it needs to have less than 40% saturation and more than 2% porosity and 100 nanodarcy permeability, which means good gas storage and flow capability. Besides, commercial shales also need to have more than 40% quartz or carbonate in mineralogy, low differential stress and a certain degree of natural fractures, which means good fracability (Sondergeld et al., 2010). Among all the factors, TOC is considered to be a fundamental and important indicator for describing the resource potential of gas in kerogen-rich shale plays, thus a continuous and accurate TOC interpretation profile is highly desirable.

Direct geochemical analysis and well logging are used conventionally for TOC determination in current petroleum industry. However, core TOC data are not available because of the cost and time required for testing and the challenges associated with gathering a representative and intact sample. Although laboratory tests of TOC are difficult, they are still the necessary and preferred methods (Zhu et al., 2003; Jarvie et al., 2015). Moreover, the lab results are often applied as references for further prediction by mathematical approaches. Log-based TOC predictions are more

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universally applicable because they can provide continuous TOC profiles that cover the whole interval of interest. Some particular geophysical responses (e.g., gamma ray, neutron, resistivity, density) of the source rock can be detected comparing to surrounding rocks. Empirical mathematical equations are generally used when carrying out log-based TOC prediction. However, the estimation results by logging information rely greatly on equation quality. Meanwhile, the uranium and gamma ray correlation methods are sometimes not suitable for gas marine shale reservoirs that have natural radioactivity in phosphatic fish plates, thus elevated uranium and gamma ray counts cannot reflect TOC. (Passey et al., 1990; Carpentier et al., 1991).

Practically, because the nonlinear and complex relationships between TOC and logs, it is very hard to obtain a universal solution for all wells in one basin. In recent years, the application of artificial intelligence techniques for TOC prediction was found to be more reliable to solve this complicated regression task. In fact, the use of robust artificial intelligence methods approaches has been introduced and successfully employed in many petroleum engineering fields, such as lithology classification, permeability estimation and hydraulic fracturing candidate selection et al. (Shadizadeh et al., 2010; Zoveidavianpoor et al. 2013a,b; Yuan et al. 2014). These methods combine the accuracy of numerical models with the simplicity of analytical approaches, while it is free from constraints of a certain function form. Huang and Williamson (1996) proposed an improved ANN (Artificial neural network) method to map source rock intervals at the Jeanne d'Arc Basin (offshore eastern Canada) by a combination of the 'quickprop' algorithm and 'dynamic node creation' scheme. The Neural-Fuzzy approach proposed by Kamali and Mirshady (2004) is regarded as a good example of TOC prediction through multi-parameter correlation analysis and fuzzy neural networks. Guo et al. (2009) suggested a method integrating cross-plotting, fuzzy ranking and an ANN to predict the TOC content of a mature carbonate resource. Amiri Bakhitiar et al. (2011) adopted a combination of sonic and resistivity logs (ΔlogR method) and a neural network method to calculate TOC values in the Pabdeh formation in the Ahwaz and Marun oilfields, Iran, but only resistivity and sonic logs were applied for TOC prediction in his paper. Except for neural network approaches, the SVM (support vector machine) approach for regression of TOC in gas-bearing shale was presented, and results show that the SVR technology is more effective and applicable than conventional neural network approaches. (Tan et al. 2015). All of these attempts show a certain degree of success but have some shortcomings. More specifically, some inherent problems are encountered with the algorithms employed in neural network methods. Initially, most feed-forward artificial neural networks use gradient descent algorithms, which need to iteratively update the model weights and biases. Thus, the training process is quite slow. In addition, the solutions may become trapped in local minima in the objective functions, resulting in failure to achieve the global minimum (i.e., the global best fit model). Furthermore, the performance is sensitive to the learning rate, which is difficult to optimally choose ahead of time. Therefore, many new algorithms need to be proposed to overcome these shortcomings with respect to low training speed and generalization ability. (Zoveidavianpoor et al., 2012, 2013a,b) Table 1 summarizes current TOC prediction methods using well logs.

Extreme learning machine (ELM) (Huang et al, 2006a,b) is an algorithm for the single-layer feed-forward network, which is considered to be a distinct artificial intelligence technique from the conventional ANNs. This algorithm is capable of solving problems using gradient descent-based algorithms such as back propagation, which is often applied in ANNs. The ELM is also able to be trained in much less time than an ANN. In fact, it has been shown that by utilizing the ELM, the learning process becomes very fast and leads to robust performance, which is preferable for small samples and high-dimensional non-linear learning problems. Accordingly, a number of investigations have been successfully carried out with the application of ELM for solving problems in petroleum engineering, particularly in drilling optimization and permeability estimation (Mortaza et al, 2016). Cao et al. (2015) performed reservoir parameter estimation using an extreme learning machine in a heterogeneous sandstone reservoir. Compared to back-propagation (BP) network and SVM approaches, the robust ELM algorithm provides faster and more accurate prediction results. Sunday et al. (2013) investigated the feasibility of ELMs in forecasting permeability from well logs in a Middle Eastern industrial reservoir; the ELM was shown to have better generalization and to be faster in permeability estimation than other methods. Chandra (2013) also applied an ELM algorithm to predict permeability, reaching similar results showing that the ELM was a better predictor than the SVM. However, ELM has not yet been used for prediction of TOC in any hydrocarbon reservoirs. This paper investigates the application of ELM in predicting TOC in a shale gas reservoir. Moreover, in the process of ELM network construction, the influence of well logs on TOC prediction is studied. The results and performance characteristics of the ELM technique are compared to those obtained by the ANN method to evaluate the efficiency of these two networks during the prediction process.

2. Artificial neural networks and extreme learning machines

2.1. Methodology of artificial neural networks

The mathematical models of ANNs are inspired by the functions of the biological nervous system. They are composed of a large number of neurons which are distributed in different layers based on the distinct functions.

Specifically, there are three types of layers: input layer, one or more hidden layers and output layer, each of them consists of a preset number of neurons. It has been rigorously proved that ANN is an universal approximator as it can approximate any continuous function with an arbitrary precision. For feed-forward neural networks, the information moves in the direction: input neurons, activations through the hidden neurons and to the outputs. In supervised learning, the training process is to adjust the weights of the neurons which minimizes the error function between the networks' actual outputs and the desired value over all the example pairs. There are numerous strategies available for training ANNs (Zoveidavianpoor et al. 2013a,b). The most popular of them is the backpropagation (BP) algorithm. It is a type of supervised learning using for feed-forward neural networks. Error function is computed by the difference between the actual and target outputs.

The standard BP algorithm employs the classical optimal method: gradient descent method. Due to its poor performance on real applications, different variants have emerged in the past decades. On the basis of the different optimizing strategies, the common used variants are: Levenberg-Marquardt (LM), Conjugate gradient method with Powell-Beale, Fletcher-Reeves and Polak-Ribiere updates, gradient descent method with momentum term, penalty term and adaptive learning rate, Bayesian regulation and scaled conjugate gradient.

2.2. Methodology of extreme learning machines

ELM was originally proposed as a single hidden-layer feed-forward neural network and later was extended to more generalized single hidden-layer feed-forward neural networks where the hidden layer may not be made of homogeneous neurons (Huang, 2014). ELM can avoid many obstacles faced by back-propagation