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Committee neural network model for rock permeability prediction

Parisa Bagheripour

Department of Petroleum Engineering, Gachsaran Branch, Islamic Azad University, Gachsaran, Iran

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ABSTRACT

Quantitative formulation between conventional well log data and rock permeability, undoubtedly the most critical parameter of hydrocarbon reservoir, could be a potent tool for solving problems associated with almost all tasks involved in petroleum engineering. The present study proposes a novel approach in charge of the quest for high-accuracy method of permeability prediction. At the first stage, overlapping of conventional well log data (inputs) was eliminated by means of principal component analysis (PCA). Subsequently, rock permeability was predicted from extracted PCs using multi-layer perceptron (MLP), radial basis function (RBF), and generalized regression neural network (GRNN). Eventually, a committee neural network (CNN) was constructed by virtue of genetic algorithm (GA) to enhance the precision of ultimate permeability prediction. The values of rock permeability, derived from the MPL, RBF, and GRNN models, were used as inputs of CNN. The proposed CNN combines results of different ANNs to reap beneficial advantages of all models and consequently producing more accurate estimations. The GA, embedded in the structure of the CNN assigns a weight factor to each ANN which shows relative involvement of each ANN in overall prediction of rock permeability from PCs of conventional well logs. The proposed methodology was applied in Kangan and Dalan Formations, which are the major carbonate reservoir rocks of South Pars Gas Field-Iran. A group of 350 data points was used to establish the CNN model, and a group of 245 data points was employed to assess the reliability of constructed CNN model. Results showed that the CNN method performed better than individual intelligent systems performing alone.

1. Introduction

Permeability refers to the ability of porous rock in transmitting fluids (Ahmed, 2006). It is the most functional and complicated in determining the property of hydrocarbon reservoirs, which plays a significant role in almost all tasks involved in petroleum engineering, including reservoir characterization (Jamialahmadi and Javadpour, 2000; Lim, 2005), flow unit identification (Aminian et al., 2003), well perforation planning, and etc. Therefore, accurate knowledge of reservoir permeability is clearly inevitable. Core laboratory measurements, well testing, and well logging are the main methods of permeability determination. Unfortunately, these strategies are not applicable in all wells and even in the whole depth of a reservoir interval owing to high cost and time-consumption that accompany these strategies. On account of significance and importance, numerous attempts have been done by several researchers to determine permeability. Some great efforts have been done to establish a relationship between rock structural properties (facies, cementation, and sorting) and permeability (Atkinson et al., 1990; Bloch, 1991; Mc Gowen and Bloch, 1985). The influence of composition on permeability is also reported by several researchers (Marion et al., 1989; Pittman and Larese, 1987; Scherer, 1987; Seeman and Scherer, 1984; Smosna, 1989). The consequence of textural parameters and sedimentary structures on permeability was studied by Chilinger (1964), Berg (1970), Beard and Weyl (1973), and Hurst and Rosvoll (1991). Further parameters, used to estimate permeability include the surface area of the pore space (Carman, 1937; Johnson et al., 1987; Schwartz and Banavar, 1989), formation resistivity factor (Archie, 1942), capillary pressure (Rezaee and Lemon, 1997; Serra, 1984), nuclear magnetic resonance relaxation time (Ahmed et al., 1991), and pore throat characteristics derived from image analysis of thin sections (Doyen, 1988; Ehrlich et al., 1991; Rezaee and Griffiths, 1996). These approaches had limitations and are not universally applicable, in spite of their simple implementation. Therefore, the significance of a method for estimating permeability, which has both swiftness and exactness, is undeniable.

A new tendency has been aroused in study and application of intelligent systems in petroleum related sciences which witnesses substantial effectiveness of these approaches (e.g. Asoodeh and Bagheripour, 2012; Cuddy, 1998; Kadkhodaei-Illkchi et al., 2009; Mohaghegh et al., 2000; Saggaf and Nebrija, 2003; Zargar et al., 2014). A recent development has targeted to predict permeability from well log data using neural network techniques (Huang et al., 1996; Kadkhodaei-Illkchi et al., 2005; Mohaghegh et al., 1995; Zhang et al., 2006). However, most previous studies were focused on permeability prediction from a

E-mail address: P.bagheripour@gmail.com.

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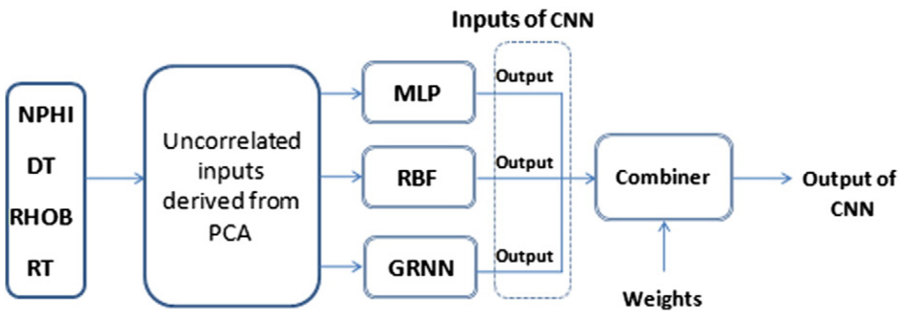

Fig. 1. A schematic diagram of committee neural network (CNN) with multi-layer perceptron (MLP), radial basis function (RBF), and generalized regression neural network (GRNN). Principal component analysis (PCA) is used to remove the overlapping of input data space.

unique type of neural network models. The motivation of this study includes the quest for higher accuracy in working with neural network models. To get this goal, we have presented an integrated method to improve the accuracy of target prediction using the concept of committee machine. In the first stage of this article, different architectures of neural network models were employed to make a quantitative formulation between well log data and rock permeability. Subsequently, a committee neural network was constructed to combine the results of aforementioned neural networks. Due to the different natures of these models, they might either be overestimated and/or underestimated in some regions relative to each other. Therefore, the genetic algorithm, embedded in the structure of committee neural network tunes the final output through integration of neural networks. The proposed committee neural network is capable of significantly enhancing the particularity of final predictions. This strategy was successfully applied to 595 data points from Kangan and Dalan Formations which are the major carbonate reservoir rocks of South Pars Gas Field-Iran.

2. Methodology: committee machine

A committee machine, or committee neural network (CNN), has a parallel framework that produces a final output by combining the results of individual experts (Haykin, 1991; Sharkey, 1996). At this study, two major steps are followed. Firstly, core permeability was predicted from the principal components of petrophysical well log data using generalized regression neural network (GRNN), radial basis function (RBF), and multi-layer perceptron (MLP). Subsequently, a committee neural network (CNN) was constructed by means of genetic algorithm (GA) to enhance the accuracy of final prediction. This methodology combines the results of neural networks and so reaps the benefit of all work. Therefore the performance of the CNN model could be better than any individual neural networks. Each of the individual neural networks has a weight coefficient in constructing CNN, which indicates its contribution in the overall estimation of core permeability. Optimal values of these weights are extracted through the use of GA. A schematic diagram of CNN is illustrated in Fig. 1. CNN provides an improved strategy for prediction of core permeability and is capable of significantly improving the accuracy of target prediction. A brief introduction about the elements, constituting the CM structure is presented in the following sections.

2.1. Neural network

Neural network emulates storage and analytical system of human brain through non-linear processing elements, called neurons. These neurons are arranged in parallel structure named layers, including input layer for gathering input, output layer for producing output, and hidden layer for extracting implicit dependency between input/output data. Neurons of each layer are connected to all the neurons of the next layer by connection weights. Extraction of these weights during

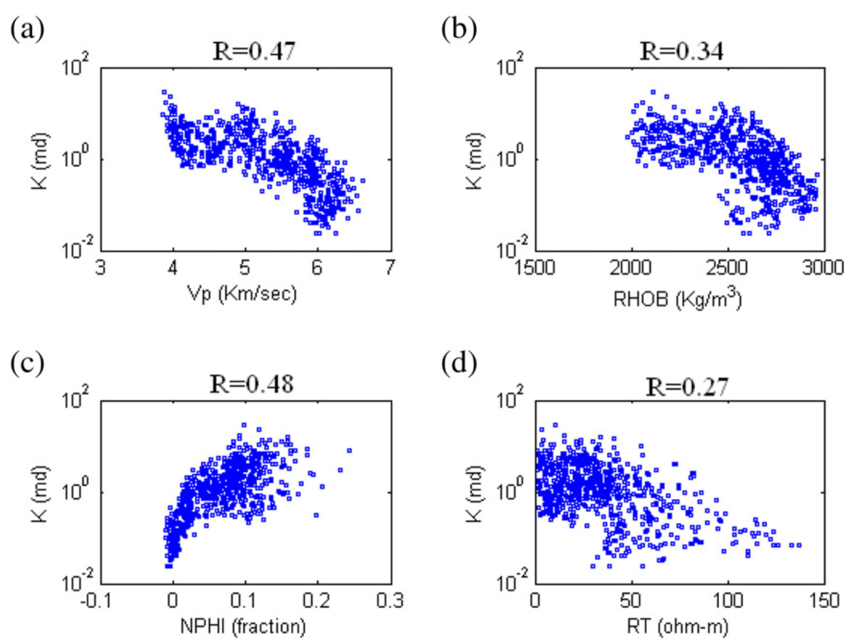

Fig. 2. Cross-plots showing relationships between rock permeability and (a) compressional wave velocity, (b) bulk density, (c) neutron porosity, and (d) formation true resistivity.