



Prediction of free flowing porosity and permeability based on conventional well logging data using artificial neural networks optimized by Imperialist competitive algorithm – A case study in the South Pars gas field



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ABSTRACT

Nuclear Magnetic Resonance (NMR) logging is one of the most effective tools in determining permeability and porosity of a formation layer, so it is a reliable method to characterize a reservoir. Since NMR logging is not applicable in certain circumstances, its parameters are usually correlated with conventional logging parameters. In this research, an Artificial Neural Network (ANN) with Multi Linear Perceptron (MLP) structure and a feed-forward back-propagation algorithm is employed to predict the NMR logging parameters from their conventional counterparts. The ANN is optimized using the Imperialist Competitive Algorithm (ICA). The ANN-ICA model is applied to two data sets measured in two separate gas wells of south Pars gas field. The data obtained from one well are used as the training data set and the other well data are utilized to test the proposed model. Finally, a sensitivity analysis (based on the parameters of the ICA algorithm and the number of neurons in the ANN) is applied to explore their effects on the ANN's performance. According to the results, the accuracy and efficiency of the proposed model are more desirable than the traditional neural network. It is found that the optimization method is not sensitive to the ICA parameters.

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1. Introduction

NMR is a well logging technique which applies magnetic fields to extract certain information from the formation layers. It involves aligning the protons of the water hydrogen atoms and the hydrocarbon fluids in the direction of magnetic fields and measuring their response signal relaxation versus time. The basic output of the NMR logging is the transverse relaxation curve. Experiments show that transverse relaxation curve is related to the pore size. Therefore, certain characteristics of the formation are obtained by studying the relationship between the curve and the pore structure. Generally, three properties of the formation are extracted

from NMR logs: permeability, Free Flowing Porosity (FFP) and bounded fluid porosity. Permeability and porosity are the most functional and complicated properties of reservoirs and play a significant role in both the reservoir characterization and the flow unit identification (Aminian et al., 2013; Jamialahmadi and Javadpour, 2000; Lim, 2005). It is usually expensive and time-consuming to correctly measure these parameters by the NMR logs. In addition, running this log in cased wells is not possible. Therefore, it is not practical to run these logs for already producing cased wells. Hence, efforts have been made to find an inexpensive, rapid and accurate method so that these parameters could be predicted. Moreover, a quantitative formulation for the conventional well logs and their NMR counterparts is a potent method to achieve the aforementioned objective. Several researchers have tried to estimate the petrophysical parameters from the conventional well logs (Kadkhodaie-Ilkhchi et al., 2009a, 2009b; Malki and

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Baldwin, 2002; Rezaee et al., 2008; Shahab Mohaghegh, 2000). Many other researchers have studied applicability of the intelligent systems in geosciences (Jamialahmadi and Javadpour, 2000; Mohaghegh, 2005; Nikravesi et al., 2003; Ogilvie et al., 2002; Saggaf and Nebrija, 2003), but limited studies have focused on the application of the intelligent systems in predicting the NMR logging parameters. Shahab Mohaghegh (2000) used neural networks (NN) to estimate the NMR logging parameters of a field located in East Texas. Malki and Baldwin (2002) proposed the use of neuro-fuzzy techniques for producibility estimation using NMR logging data (Ogilvie et al., 2002) applied the Fuzzy Logic (FL) and Genetic Algorithm (GA) separately to predict the permeability using the NMR data. Rezaee et al. (2008) used intelligent tools to synthesize petrophysical logs including neutron, density, sonic and deep resistivity.

ANNs with their considerable capability in inferring results from complex data can be used to extract difficult and unrecognizable patterns (Aggarwal et al., 2014; Hagan et al., 1996). Due to the fact that all training problems lead to optimization problems, evolutionary optimization methods such as GA (Qu et al., 2008), pruning algorithm (Reed, 1993), and simulated annealing (Yamazaki et al., 2002) are employed as early solutions. The use of evolutionary algorithms in the NNs has the advantage of escaping local minimum points and also independency to the network's structure. To optimize the training of the artificial neural network, ICA is used so as to determine the ANN's weights (Ghaedi et al., 2014). ICA is a new technique in evolutionary computations which seeks to answer various optimization problems. The ICA's procedure is based on the mathematical modeling of socio-political processes (Atashpaz-Gargari and Lucas, 2007).

In the current research, NMR output parameters are predicted from conventional logging parameters by an ANN. The weights of the network are optimized by the ICA. The essential NMR and Logging data have been provided from two wells in south Pars gas field.

2. Artificial neural networks

ANNs, inspired by the biological nervous system, are interconnected parallel structures that include successive layers of processing elements known as neurons. Parallel neurons form layers which receive inputs and send outputs to a common destination. There exist three distinctive layers in an ANN: the input layer which receives the independent variables, the hidden layer which is the intermediate layer, and the output layer that in turn transmits the dependent variables. The number of neurons in the input and output layers relies on the dimension of the dependent and independent variables. Each neuron operates by applying a weight, a bias and an output transfer function. The network correlates the dependent and independent variables by the learning process (a process by which the weights and biases are modified so that the network prediction errors are minimized).

The applied ANN is comprised of an MLP network with one input layer, one output layer and one or several hidden layers. Training is accomplished by the feed-forward back-propagation approach in which the input layers feed the output; after that, the prediction errors are calculated and then propagated in the previous layers (Ndiaye et al., 2014; Silvestre and Ling, 2014). Training steps in the feed-forward back-propagation approach are as follows: I) assigning a random weight matrix to the junctions, II) selecting appropriate input/output vectors, III) calculating the neuron outputs and successively the output layer, IV) normalizing the network weights by back-propagating the network errors which are caused by dependent variables and the network output, V) evaluating the performance of the trained network based on the

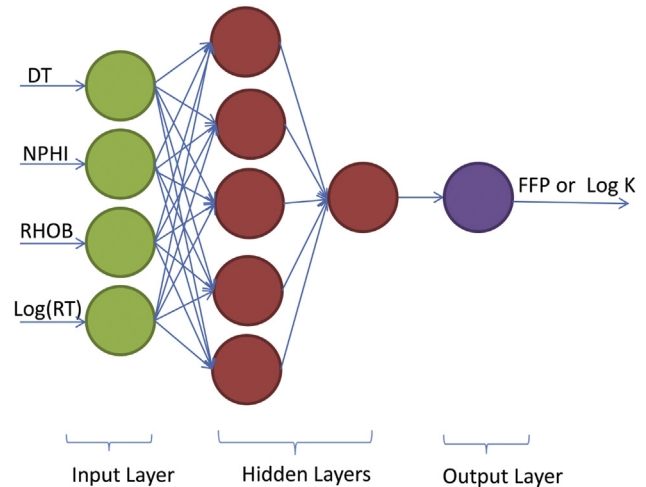


Fig. 1. Multi linear perceptron structure (sonic transit time (DT), neutron porosity (NPFI), bulk density (RHOB) and electrical resistivity (RT)).

Mean Squared Error (MSE) or any other criterion and VI) repeat the step III or stop training if needed. Fig. 1 illustrates the network's structure. The network's training consists of optimizing the biases and the weights for each nodal interconnection until the results of the output layer are close to the actual outputs as possible.

3. Imperialist competitive algorithm

To solve the optimization problems by the ICA, N countries are assumed each of which is represented by a vector indicating a point in n -dimensional space. The points with the minimum objective function costs are known as the imperialists and other points are colonies (Atashpaz-Gargari and Lucas, 2007; Lucas et al., 2010). The normalized cost for each imperialist is obtained as follows:

$$C_n = c_n - \max\{c_i\} \quad (1)$$

where $\max\{c_i\}$ is the maximum cost among the imperialists, C_n designates the cost of the n th imperialist, and c_n represents its corresponding normalized cost. Given the normalized cost, the relative normalized power of each imperialist is calculated as follows. Based upon this power, the colonies are divided among the empires.

$$P_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right| \quad (3)$$

Therefore, the initial number of the colonies of n th empire will be:

$$N \cdot C_n = \text{round}\{P_n \cdot N_{col}\} \quad (3)$$

where $N \cdot C_n$ designates the initial number of the colonies, and N_{col} represents the total number of the colonies in the initial population. As the initial states of all empires are determined, the ICA starts operating. Colony movements towards the empires are depicted in Fig. 2. As it is shown in this figure, x is derived as:

$$x \sim U(\cdot, \beta * d) \quad (4)$$

where β is close to 2 and larger than 1. $\beta = 2$ Can be a proper choice. $\beta > 1$ Makes the colony to move towards the empire in various directions. In order to broaden the search zone around the

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