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Original article

Evolving simple-to-use method to determine water–oil relative permeability in petroleum reservoirs

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ABSTRACT

In the current research, a new approach constructed based on artificial intelligence concept is introduced to determine water/oil relative permeability at various conditions. To attain an effective tool, various artificial intelligence approaches such as artificial neural network (ANN), hybrid of genetic algorithm and particle swarm optimization (HGAPSO) are examined. Intrinsic potential of feed-forward artificial neural network (ANN) optimized by different optimization algorithms are composed to estimate water/oil relative permeability. The optimization methods such as genetic algorithm, particle swarm optimization and hybrid approach of them are implemented to obtain optimal connection weights involved in the developed smart technique. The constructed intelligent models are evaluated by utilizing extensive experimental data reported in open literature. Results obtained from the proposed intelligent tools were compared with the corresponding experimental relative permeability data. The average absolute deviation between the model predictions and the relevant experimental data was found to be less than 0.1% for hybrid genetic algorithm and particle swarm optimization technique. It is expected that implication of HGAPSO-ANN in relative permeability of water/oil estimation leads to more reliable water/oil relative permeability predictions, resulting in design of more comprehensive simulation and further plans for reservoir production and management.

1. Introduction

Relative permeability, a dimensionless quantity, is the ratio of effective permeability to a base permeability. Effective permeability is the ability of a fluid to flow through a rock when the pore spaces of the rock is not only saturated with that fluid. This property is affected by pore geometry, wettability, fluid distribution and saturation history [1]. The base permeability can be absolute air permeability, absolute liquid permeability or effective oil permeability at irreducible water saturation [2]. The importance of relative permeability measurement concept is due to this fact that nearly all hydrocarbon reservoirs are saturated with more than one phase of homogeneous fluid [2]. Also, it is a fundamental factor in dynamics simulation studies, i.e., history matching and performance forecasting, which make its accurate determination necessary [3].

The common approach to determine the relative permeability is laboratory methods, which started from 1944 [4,5]. There are various methods to experimentally obtain relative permeability.

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Some of these methods are Penn-State [6–8], Single-Sample Dynamic [9–11], Stationary Fluid [12], Hassler [4,13,14], Hafford [9], Dispersed Feed [9], and JBN [15] that can be categorized into two major groups of steady-state and unsteady-state methods. Other methods include Capillary Pressure [16,17] and Centrifuge [18–20].

To attain suitable representative data, restored state analysis is the only way. In many cases, the cores are not preserved properly, and their wettabilities are altered due to mud filtration during drilling. Thus, we should measure relative permeabilities in restored state core rather than native state one [1,3].

Experimental determination of relative permeability is costly and time consuming. Hence, searching for quick and accurate calculation of relative permeability is inevitable. Empirical correlations are one of the methods to obtain this important rock/fluid characteristic.

In the past decades, several correlations have been developed to predict relative permeability of oil reservoirs. In 1954, Corey [21] introduced a correlation to estimate relative permeability of water–oil and gas–oil systems, based on relative permeability measurements on a large number of cores from several formations. This model assumes the wetting and non-wetting phase-relative permeabilities to be independent of the saturations of the other phases. It also ignores the effect of wettability. Sigmund and McCaffery [22] attempted to improve the reliability of Corey's correlation. They added a linear term with an empirical coefficient to the standard power term in the Corey correlation. Honarpour et al. [23] utilized the relative permeability data obtained from oil and gas fields in various parts of the world, to develop a new correlation for prediction of relative permeabilities. They also took into account the impacts of wettability and rock type in their model. One of the main disadvantages of their correlation is that, they proposed a large number of equations to employ the effect of wettability and rock type. In 1984, Chierici [24] suggested a two-parameter exponential relationship to predict relative permeabilities of water–oil and gas–oil systems. Although this correlation is more general than Corey [21] and Sigmund and McCaffery [22] correlations, it may not be appropriate as each of the employed parameters affects the relative permeabilities in the entire saturation range. Ibrahim and Koederitz [6] implemented linear regression approach to develop predictive equations for water–oil, gas–oil, gas–water, and gas-condensate relative permeability. They utilized 416 sets of relative permeability data which were extracted from published literature and various industry sources. The effect of wettability and formation type was also introduced in the correlation to improve its performance for water–oil and gas–oil systems.

Through this current research, potential application of various connectionist models such as Artificial Neural Network (ANN) optimized by different evolutionary algorithms like genetic algorithm is examined to forecast the relative permeability of water, oil and gas in petroleum reservoirs. Evolutionary algorithms are carried out to decide on initial weights of the parameters incorporated in artificial neural network. The suggested intelligent approaches are evaluated through utilization extensive experimental results [25–57]. Results obtained from the developed smart models were compared with the corresponding experimental relative permeability data and discussed in further details throughout this research.

2. Artificial neural network

Artificial neural network, a bio-inspired approach whose initial pattern has been recognized from studying the everyday procedures of human brain, is succinctly capable of correlating numerically and inversely the relationships between inputs and outputs of each objective system through their distinctive mathematical structures. The gathered laboratorial data are technically utilized to train the network then; the prepared network is gained to estimate the imprecise and blurred data [58,59]. The depicted scheme is conductible through relying on synchronous processing units, known as neurons and nods, located in layers. The input layer, a certain number of hidden layers and an output layer are the basic components of each artificial neural network (ANN) which the number of their neurons are specified by the available data, designers and target of the discussed problem. The back-propagation feed forward network and multilayer perceptron (MLP) networks, in terms of development time and data processing potential are the most favorable and common types of ANN in chemical engineering [60–64].

Before providing further details on the optimization methodology, the main ANN parameters including weights and biases should be determined using the trial and error procedure. The referred theme has been followed by dividing the database into two main parts apparently named training and testing sets. The key objective is to decide on the most appropriate network structure by applying the larger group, training ones, while the testing set which has not earlier been faced to the network in the training step is piloted to examine the reliability of the proposed network in the case of correlating the water/oil relative permeability. Running the optimization of interconnected weights and node biases is continued till the performance of the proposed ANN is acceptable based on some statistical criteria like mean squared error (MSE) such that the values of outputs at the neurons of output layer are very close to the corresponding experimental data. The MSE is expressed as follows

$$MSE^{Approach} = \frac{1}{2}\sum_{k=1}^{G}\sum_{j=1}^{m}\left[Y_j(k) - T_j(k)\right]^2 \tag{1}$$

where m is the number of output nodes, G is the number of training samples, $Y_j(k)$ is the expected output, and $T_j(k)$ is the actual output. When the MSE becomes gradually close to the zero, the error of our developed network model starts declining.

3. Evolutionary algorithms

3.1. Genetic algorithm

Capability of fast searching and effective optimization is the inherent feature of Genetic Algorithm (GA) which takes the “survival of the fittest” principle of natural evolution with the genetic propagation of properties. Discovering a variety of zones in the desired area and identifying simultaneously and randomly many probable routs are the most prominent dimensions of GA [65–67]. The GA whose theoretical derivation is from Darwinian natural selection and genetics in biological systems is a viable substitution for the routine and day-to-day optimization approaches. Based on the Darwinian principle of ‘survival of the fittest’, the GA could find the best coordinates in the given space after a series of repetitive computations. Artificial mutation, crossover and selection operators are the most ingredients of the pointed out searching process. To operate the mentioned algorithm, firstly, an initial population, containing an already defined number of solutions under title of individuals or chromosome in the GA approach, is generated to switch the process on. The next