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.
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 nodes, 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

$$
MSE_{\text{Approach}} = \frac{1}{2} \sum_{k=1}^{G} \sum_{j=1}^{m} \left( Y_j(k) - T_j(k) \right)^2
$$

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
step is encoding the components of populations into bit-string so-called chromosome. After that, the nobility of the strings, normally named fitness, is assessed with the association of some functions indicating the constraints of the issue. According to the fitness of the chromosomes, they are collected for the following genetic process. It must be highlighted that surviving of the best-fit individuals is a strong function of type of processes. Taking remaining steps, operating the crossover and the mutation rates, becomes possible when the high fitted individuals are selected. Then, manipulating the crossover operation in which the bits (genes) of each two selected strings (chromosomes) are recombined must be executed. Studying the previous projects in this field reveals the fact that randomly collecting the crossover points of any two chromosomes leads to conclude the best results. With a defined rate bits at one or more randomly selected positions of some chromosomes are swapped, the process is termed as mutation. The mutation process inhibits trapping in any local maxima. Returning the generated off-springs as the next population to first step in order to be evaluated again is the final step (see Fig. 1) [65,67].

3.2. Particle swarm optimization

Particle Swarm Optimization (PSO) is an optimization which has mathematically been inspired from studying and modeling the behavior of social organisms like a flock of birds. Similarly to the genetic algorithm (GA), particle swarm optimization (PSO) is initiated with a population of random routs, called particles. These particles are supposed to stir within the defined search space with an adjustable velocity to save the best position. Also, in order to keep an eye on the target, each particle has the ability to update its velocity vector as well. This is possible thanks to their own flying experience and the flying experience of the other particles in the search space as illustrated in Fig. 2 [69].
3.3. Hybrid genetic algorithm and particle swarm optimization

Although applications of genetic algorithm has attained substantial successes within a wide range of engineering, medical, and science issues, it is still a very time-consuming process if it is applied to large-scale optimizations that require several function evaluations for convergence. Hence, to break the addressed limitations, it would be a technical marvel if GA and PSO get combined to provide this opportunity to take the advantages of the suitable characteristics and searching abilities of both algorithms in estimating desired factors. In this study, the great efforts have been made to employ the hybrid of genetic algorithm (GA) and particle swarm optimization (PSO), which has originally proposed by Juang (2004) [72], to estimate the water/oil relative permeability. The referenced frustrations relevant to binary coding and single-point crossover can be compensated by the floating-point representation of parameters in the GA and a search operator that respects contiguous regions in the search space. Thus, a floating point coding map is tuned here for the whole of genetic algorithm (GA), particle swarm optimization (PSO) and hybrid genetic algorithm and particle swarm optimization (HGAPSO). Because of the framework of discrete values design parameters, the solutions are accomplished by rounding the design variables to the closest adequate integer number (See Fig. 3).

4. Results and discussion

4.1. ANN output results

The connectionist models developed in this research involve seven independent variables that have significant impact on amount of relative permeability of water and oil. Independent variables which were chosen in this modeling work are type of wettability, type of formation, porosity, permeability, connate water saturation, residual oil saturation and water saturation. These variables were proposed as inputs of considered neural network approach to estimate the amount of water and oil relative permeability. To design an optimal topology for network system, two routine performance criteria such as mean square error (MSE) and correlation coefficient ($R^2$) were considered. Based on referred criteria, a three layer network which has 7 neurons in hidden layer can predict relative permeability of water and oil with high precision and robustness (see Fig. 4). The developed model was trained with back propagation procedure by implementing Levenberg–Marquardt algorithm to estimate the targeted functions while the transfer functions in hidden and output layer are sigmoid and linear, respectively.

To monitor robustness of the developed neural network approach and further hybrid approach, 1666 data samples were selected in random manner for network training and the remaining 713 samples were put aside to be employed for testing and validating the network's robustness. Moreover, to accentuate effectiveness of various intelligent methods, different performance indexes were utilized. To beat addressed obstacle, common statistical performance criteria such as correlation coefficient ($R^2$) and mean square error (MSE) were calculated to assess performance of each intelligent model. It should be mentioned here that the magnitudes 0.71 and 0.001 were assigned to the learning coefficient and momentum correction factor, respectively to train neural network model with the back-propagation training algorithm. As depicted in Fig. 5, neural network outputs in contrast with relevant experimental data do not show good agreement while some experimental samples were satisfactorily modeled. As earlier discussed in the text, to quantify effectiveness of each model correlation coefficient was obtained. As Fig. 6 demonstrates, the conventional smart approach has unsatisfactory robustness and integrity due to intermediate correlation coefficient which is lower than 0.8.

4.2. Hybrid evolutionary algorithms and ANN output results

To achieve the main goal of this research, various optimization algorithms were carried out to optimize connection weights of neural network approach based on introduced objective function; namely, mean square error (MSE) in this work.
Fig. 5. Measured vs. predicted relative permeability (BP-ANN): a1) water relative permeability Training phase, a2) water relative permeability Testing phase, b1) oil relative permeability Training phase, b2) oil relative permeability Testing phase.
Optimization algorithms used in this study such as genetic algorithm, Particle swarm optimization and hybrid of them are population based algorithm. To attain the targeted goal, MSE should be minimized while implementing optimization process. It is worth noting that every weight in neural network approach must be between $-C_0$ and $+1$.

To evaluate the performance and integrity of the carried out evolutionary algorithms, a back-propagation (Levenberg–Marquardt) neural network was applied using collected real data. For each case, 30 runs with various randomly generated populations were implemented. The hybrid genetic algorithm and particle swarm optimization-artificial neural network approach (HGAPSO-ANN) was run by selecting a population size of 100.

Essential parameters in genetic algorithm approach are called crossover probability and mutation probability. Crossover process is defined as Recombination of the genetic material from two good “parent” chromosomes in order to generate two better offspring.

Due to implementation of mutation probability new strings were created while the mutation operator regenerated the binary digit 1 to 0 and vice versa for each chromosome. Various ways can be performed to operate mutation process in genetic algorithm approach while single-point mutation was tried in this study.

Various crossover probabilities were examined to determine best crossover probability. To do so, 0.5 to 0.9 were assigned to crossover probabilities for the case under study. The same effectiveness criteria such as mean square error (MSE) and correlation coefficient ($R^2$) were determined to find the optimal crossover rate. The sensitivity analysis reveals as the crossover probability increases as the convergence rate declines. As a result, the best precision and integrity was obtained for the crossover rate of 0.9.

Moreover, the same analogy was followed to illustrate sensitivity of genetic approach robustness as a function of mutation rates. To achieve this goal, various mutation probabilities in the range of 0.0001 to 0.05 were evaluated. This crucial point should be noted that, poorer outputs and earlier convergence are achievable due to low mutation probabilities. On the other hand, as the mutation rate increases, it results in superior performance; however, it prevents attaining a high level of convergence. On the basis of statistical investigation, the uniform crossover probability and uniform mutation probability were assigned to 0.9 and 0.0225, correspondingly.

The input parameters of an artificial neural network (ANN) approach are of different types with different orders of magnitudes, such as water saturation ($S_{w}$), Permeability ($K$) and Porosity ($\phi$) in this particular case study. Hence, it is necessary to normalize the input and target variables due to the ranges of gathered data samples as they fall within a peculiar range. As
Fig. 7. Measured vs. predicted relative permeability (HGAPSO-ANN): a1) water relative permeability Training phase, a2) water relative permeability Testing phase, b1) oil relative permeability Training phase, b2) oil relative permeability Testing phase.
clear from Figs. 5 and 7, the normalized water/oil relative permeability is computed by the following expression:

$$\text{Normalized } Kr = \frac{2(Kr - Kr_{\min})}{(Kr_{\max} - Kr_{\min})} - 1$$  \hspace{1cm} (2)

where $Kr_{\min}$ and $Kr_{\max}$ are the minimum and maximum relative permeability of the data utilized in this work, respectively.

Obviously, predicted values of the hybrid genetic algorithm and particle swarm optimization (HGAPSO) approach in contrast to the output results of genetic algorithm and particle swarm optimization algorithm are presented in Fig. 7 demonstrating a satisfactory agreement with the experimental water/oil relative permeability data. The results gained by other intelligent approaches are reported in the Supplementary Information, as well. This implies that training of the neural network approach by hybrid genetic algorithm and particle swarm optimization (HGAPSO) (Fig. 7) leads to superior outcome compared to the genetic algorithm, particle swarm optimization and the back propagation (BP) algorithm (Figs. 5 and 7).

The performance plots based on mean square error for the proposed hybrid of evolutionary approaches and artificial neural network (ANN) model are presented in Figs. 11 and 12, correspondingly. It can be seen that the rate of convergence for the hybrid genetic algorithm and particle swarm optimization approach (HGAPSO-ANN) is noticeably higher than other approaches such as genetic algorithm (GA), Particle swarm optimization (PSO) and the conventional algorithm such as back-propagation (BP-ANN) (Fig. 12).
The mean square error (MSE) and correlation coefficient ($R^2$) values for the six different approaches conducted to validate the proposed smart predictive techniques are listed in Table 1. According to Table 1, the robustness and integrity of the HGAPSO-ANN is better than other intelligent and conventional methods such as the BP-ANN, GA-ANN, PSO-ANN, Honarpour et al., and Corey correlations while hybrid methods have high precision and effectiveness in comparison with back propagation algorithm. It can be concluded that the evolutionary optimization strategy (HGAPSO-ANN) offers excellent effectiveness in both convergence rate and global optima achievement.

Analysis of variance (ANOVA) technique was applied to carried out a sensitivity analysis for the newly developed intelligent approach [80,81]. The dependency of the output variables such as water/oil relative permeability on each of the independent variables such as permeability, porosity, Swc, Sw, Sor, Wettability and Formation Type was appropriately explored using ANOVA. The results of the sensitivity analysis are illustrated in Fig. 13. The higher correlation between any input variable and the output parameter exhibits greater significance of the variable on the magnitude of the dependent variable. Evidently, the formation type and wettability type are the most important parameters affecting the water relative permeability. It is also concluded that effects of formation type and water saturation on the oil relative permeability are the most significant among all parameters.

5. Conclusions

New deterministic tools based on artificial intelligence knowledge were developed to compute water/oil relative permeability at various conditions so that the smart models were and evolved by different optimization methodologies including hybrid genetic algorithm and particles swarm optimization which effectively combine the local and global searching ability of conventional connectionist techniques for estimation of water/oil relative permeability. Experimental
data from the literature [25–57] were utilized to figure out performance and integrity of developed predictive intelligent approaches.

On the basis of the achieved outputs, the following important conclusions can be drawn:

1. The estimation robustness and integrity of the introduced technique is superior to that of conventional back propagation neural network, Corey and Honarpour et al. models.

2. Due to local ability of particle swarm optimization and back-propagation algorithm and global search ability of genetic algorithm, the new technique applied in this study which is known as Hybrid genetic algorithm and particle swarm optimization approach has both global and local searching abilities. Due to these intrinsic abilities, HGAPSO has the potential of avoiding being trapped in local optimums to determine water/oil relative permeability.

3. The BP-ANN, Corey, Honarpour et al., models do not exhibit satisfactory precision and integrity in estimation of water/oil relative permeability; however, there is good agreement between relevant experimental values and the outputs attained from implementation of HGAPSO-ANN.

4. The constructed water/oil relative permeability deterministic tools especially hybrid genetic algorithm and particle swarm optimization (HGAPSO) method can be integrated with existing reservoir simulation softwares such as PETREL, ECLIPSE and CMG to lower the existing uncertainties, leading to enhancement of their estimation and modeling capabilities.

5. A sensitivity analysis using the ANOVA approach dictates that the significance of reservoir parameters on the water/oil relative permeability is in the following order:

   - Water relative permeability: Formation Type > Wettability Type > \( K > Swc \)
   - Oil relative permeability: Formation Type > \( Sw > Swc > Sor \)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>GA-ANN</th>
<th>BP-ANN</th>
<th>Honarpour</th>
<th>Corey</th>
<th>PSO-ANN</th>
<th>HGAPSO-ANN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water relative permeability</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( MSE )</td>
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<td>0.031717</td>
<td>0.0104</td>
<td>0.02156</td>
<td>0.00038</td>
<td>0.00007</td>
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<td>( R^2 )</td>
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<td>0.5069</td>
<td>0.567</td>
<td>0.2644</td>
<td>0.9884</td>
<td>0.9919</td>
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<tr>
<td>Oil relative permeability</td>
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<td></td>
<td></td>
<td></td>
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<tr>
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<td>0.00948</td>
<td>0.06939</td>
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<td>0.9888</td>
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</tbody>
</table>

Fig. 11. Performance plot for the proposed HGAPSO-ANN model; a) water relative permeability, b) oil relative permeability.

Fig. 12. Performance plot for the proposed BP-ANN model; a) water relative permeability, b) oil relative permeability.
$K_r$ relative permeability

$\Phi$ porosity

**Subscripts**

Min minimum

Max maximum

**Appendix A. Supplementary data**

Supplementary data related to this article can be found at
http://dx.doi.org/10.1016/j.petlm.2015.07.008.

**References**


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