Application of Artificial Neural Networks for Predicting Relative Permeability in Talang Akar Formation

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Abstract. Relative permeability is a substantial parameter for estimating multi-phase fluid flow in porous rocks. It is a complex physical property that is influenced by the behavior and interactions between the fluid and rock phases. Relative permeability measurement of rock samples in laboratory can be carried out using steady-state or non-steady-state techniques. Permeability measurement is relatively difficult and time consuming. Because of the difficulty in measurement, empirical models are often used to estimate relative permeability or extrapolate to limited laboratory data. Artificial neural network (ANN) is a method that can be applied to obtain complex correlations of parameters that influence each other. In this study, ANN is used to predict the relative permeability of oil and water. The proposed model evaluates the relative permeability of a phase as a function of rock absolute permeability, porosity, depth, permeability of other phases and water saturation. A total of 159 relative permeability data from Talang Akar Formation were used for the training and testing processes. Based on the comparison between measured and calculated data, the correlation coefficients for relative permeability to water and oil using ANN method are 0.77 and 0.94 respectively. While those using regression analysis are 0.88 and 0.73 respectively.

1 Introduction

Relative permeability is a parameter used to describe rock properties in flowing multiphase fluids. It is a significant and essential parameter to characterize the flow ability for each phase. Relative permeability can be obtained from direct measurements in the laboratory. Relative permeability measurements in the laboratory can use the unsteady state or steady state method. For steady state, two or three fluids are injected simultaneously into the rock sample at a constant flow rate and a certain ratio of flow rates until they reach equilibrium. The experiment was repeated by changing the flow rate ratio. Whereas for the non-steady

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method, one fluid phase is injected to saturate the rock sample first. Then the rock sample was injected with another fluid phase [1-6].

Relative permeability parameter is used for almost fluid flow calculations in hydrocarbon reservoirs. The data are required in making engineering approximations of ultimate recovery, injectivity and productivity of the reservoir for the planning and evaluation of production operations and can also be used to diagnose an expected formation damage under various operational conditions [7], [8]. Previous researches have indicated that the phenomena of multi-phase fluid flow are very complex [2], [9], [10]. Various theoretical methods or laboratory experiments have been performed to analyse parameters affecting relative permeability, such as wettability, viscosity, overburden pressure, injection rate, interfacial tension, miscibility, temperature, pore network structure, pore pressure, capillary pressure, displacement pressure [11-21]. Among these factors, wettability, reservoir temperature, pore network structure, overburden pressure, fluid properties, capillarity, and interfacial tension are not easily controllable during hydrocarbon production in water injection stage [20]. While the factors that can be directly controlled are injection rate and injection pressure.

Experimental and modeling methods are used to determine the relative permeability of the reservoir. Relative permeability measurements in the laboratory are technically difficult and require skilled personnel to operate, the equipment is relatively expensive, and takes a long time to perform. Although the measurement of permeability in the laboratory is relatively difficult, this method is preferred. If laboratory data are not available or are lacking, then correlations to estimate relative permeability can be used. Many correlations have been proposed. Among these correlations, the Honarpour and Corey correlations are among the most widely used [6].

The ability of ANN to obtain complex relationships among parameters by learning input and output data makes the ANN method suitable for estimating the relationship of relative permeability with the factors affecting it. In 1999, Guler et al. introduced the application of ANN to estimate the relative permeability characteristics of oil and water. In the study, a large amount of water and oil relative permeability data was obtained from the literature. Part of it is used for the training of the neural network. The positively trained networks were then used to predict oil and water relative permeabilities for the data sets that were not used in the training stage. In compiling ANN architecture, several physical properties of rocks and fluids are combined including permeability, porosity, air viscosity, oil viscosity, interfacial tension, water saturation, irreducible water saturation, and residual oil saturation [22]. In 2002, Silpngarmers and Ertekin applied ANN for two-phase and three-phase relative permeabilities. The physical properties of rocks and fluids used for predicting relative permeability were porosity, permeability, air saturation, oil saturation, gas saturation, critical gas saturation, residual oil saturation, and irreducible water saturation [23]. In 2009, Al-Fattah and Al-Naim applied ANN to real data sets to predict relative permeability for carbonate reservoirs. Wettability, well location, porosity, residual oil saturation, and Initial water saturation were considered as the main input variables that contribute significantly to the estimation of relative permeability data [8]. In 2020, Kalam et al. proposed relative permeability model using ANN. The data were obtained from laboratory experiments, of which 70 percent were used in training and 30 percent were used in testing. The input parameters included in the study were water saturation, initial water saturation, residual oil saturation, wettability, porosity, and absolute permeability [24]. In this study, core samples were obtained from several depths. Relative permeability of the cores was measured in laboratory. After that ANN and Regression Analysis were applied to produce the correlation of water and oil relative permeability. The input parameters used in this study were relative permeability of oil or water, permeability, water saturation, porosity, and true vertical depth (TVD).
2 Method

ANN has been used to obtain complex correlations between a parameter and the parameters that influence it. The structure of ANN is represented by the number of layers, and each layer has a basic component called a neuron. The sigmoid function is used for training data as an activation function for the neuron in the hidden and output layers. The sigmoid function has a minimum value of 0 and a maximum value of 1 and can be distinguished everywhere by a positive slope [25-27]. Therefore, the input-output numeric values need to be normalized in the interval 0 and 1. Backpropagation of errors and data processing is applied from the input layer to the output layer during the training phase. After that, the estimated output parameters are compared with the actual output. For an efficient ANN model, the biases and weights of each layer are updated to estimate the output with minimum error [28-31].

The 86 data used for this study were obtained from Talang Akar Formation in South Sumatera (Indonesia). The data include water saturation, relative permeability of water (krw), relative permeability of oil (kro), absolute permeability (k), porosity, true vertical depth (TVD), and irreducible water saturation (Swir). The descriptive statistical analysis of the data is given in Table 1. From the laboratory data, 80 percent was used in training and 20 percent was used in testing for ANN model. While all data were used for regression analysis correlation.

Table 1. The descriptive statistical analysis of the data

<table>
<thead>
<tr>
<th>Property</th>
<th>Sw</th>
<th>k_{rw}</th>
<th>k_{ro}</th>
<th>k, mD</th>
<th>(\phi)</th>
<th>TVD, ft</th>
<th>Swir</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>0.20</td>
<td>0.00</td>
<td>0.00</td>
<td>0.98</td>
<td>0.17</td>
<td>4317.10</td>
<td>0.20</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.75</td>
<td>0.62</td>
<td>0.86</td>
<td>164.00</td>
<td>0.32</td>
<td>4348.85</td>
<td>0.35</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.43</td>
<td>1.66</td>
<td>2.68</td>
<td>0.11</td>
<td>-0.65</td>
<td>1.08</td>
<td>0.44</td>
</tr>
<tr>
<td>Range</td>
<td>0.54</td>
<td>0.62</td>
<td>0.86</td>
<td>163.02</td>
<td>0.15</td>
<td>31.75</td>
<td>0.14</td>
</tr>
<tr>
<td>Median</td>
<td>0.57</td>
<td>0.06</td>
<td>0.01</td>
<td>47.00</td>
<td>0.28</td>
<td>4323.30</td>
<td>0.27</td>
</tr>
<tr>
<td>Mean</td>
<td>0.54</td>
<td>0.11</td>
<td>0.10</td>
<td>72.61</td>
<td>0.26</td>
<td>4327.39</td>
<td>0.27</td>
</tr>
<tr>
<td>Standard Error</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>4.47</td>
<td>0.00</td>
<td>0.87</td>
<td>0.00</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>-0.84</td>
<td>3.58</td>
<td>7.16</td>
<td>-1.49</td>
<td>-1.12</td>
<td>-0.48</td>
<td>-1.07</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.14</td>
<td>0.11</td>
<td>0.18</td>
<td>56.32</td>
<td>0.05</td>
<td>11.01</td>
<td>0.05</td>
</tr>
<tr>
<td>Sample Variance</td>
<td>0.02</td>
<td>0.01</td>
<td>0.03</td>
<td>317.70</td>
<td>0.00</td>
<td>121.29</td>
<td>0.00</td>
</tr>
</tbody>
</table>

The rock and fluid properties measured in the laboratory were selected as input parameters. Therefore, this study focuses on the obtained data. In addition, the parameters chosen must have a significant effect on the relative permeability. The input parameters selected in this study include water saturation, relative permeability of other phases, permeability, porosity, and true vertical depth. So that the correlation form for the determined relative permeability of water and oil can be stated by the following Eq. (1) and Eq. (2).

\[
k_{rw} = f(S_w, k_{ro}, k, \phi, TVD) \tag{1}
\]

\[
k_{ro} = f(S_w, k_{rw}, k, \phi, TVD) \tag{2}
\]

In the process of making a model with the ANN method, the parameters involved need to be normalized. The normalization equations used are as following Eq. (3) and Eq. (4).

\[
S^* = \frac{(S_w-S_{wirr})}{(1-S_{wirr})} \tag{3}
\]

\[
k_{rw}^* = \frac{k_{rw}}{k_{rw@S_0}} \tag{4}
\]
Several statistical parameters have been used in this research to compare the precision of the ANN (Fig. 1) and Regression models. The parameters are coefficient of correlation (r), average root mean square error (ARMSE), mean absolute error (MAE), and mean square error (MSE).

\[
k_{ro}^* = \frac{k_{ro}}{k_{ro@Swc}} \quad (5)
\]

\[
k^* = \frac{k-k_{min}}{k_{max}-k_{min}} \quad (6)
\]

\[
\phi^* = \frac{\phi_{max}-\phi_{min}}{\phi_{max}-\phi_{min}} \quad (7)
\]

\[
TVD^* = \frac{TVD-TVD_{min}}{TVD_{max}-TVD_{min}} \quad (8)
\]

\[\]

Fig. 1. Modeling process of the ANN

### 3 Result and discussion

From the 86 measured data obtained for each well, around 80% is used for the training process. The remaining 20% of the data is applied for testing the accuracy of the model. Before training process, the parameters involved were normalized using Eq. (3) to Eq. (8). Once the ANN model had been trained, it was used to predict the relative permeability for testing process. The predicted relative permeability data were then denormalized. Then the estimated relative permeability data were validated with the measured data for testing. The comparison results are plot in Fig. 2 and Fig. 3.
Besides that, regression analysis (RA) was applied to derive water and oil relative permeability equations. A statistical software was used to find the best appropriate constants of the equations. The constants are given in Table 2. Eq. (9) and Eq. (10) can be used to calculate the predicted relative permeabilities of oil and water, respectively. The calculation results are compared to the measured data of relative permeability for testing. The comparison results are plot in Fig. 4 and Fig. 5.

\[
k_{rw} = aS_w^b + c k_{ro}^d + e k^f + g \phi^h \phi, iTVD^j \]  
\[
k_{ro} = aS_w^b + c k_{rw}^d + e k^f + g \phi^h \phi, iTVD^j \]  

The water relative permeability ANN model has lower MAE, MSE, ARMSE values compared to RA model as shown in Table 3. In addition, the correlation coefficient (R) value of the ANN model is higher than that of RA model. Based on the comparisons of the statistical parameters between ANN model and RA model, the water relative permeability ANN model is more accurate than that of the RA model in representing the data.

Table 2. Constants of Equations (9) and (10)

<table>
<thead>
<tr>
<th>Constant</th>
<th>Eq. (9)</th>
<th>Eq. (10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>-7.442467</td>
<td>-3.658459</td>
</tr>
<tr>
<td>b</td>
<td>-0.062072</td>
<td>0.096795</td>
</tr>
<tr>
<td>c</td>
<td>0.375558</td>
<td>-0.347979</td>
</tr>
<tr>
<td>d</td>
<td>0.737415</td>
<td>0.028302</td>
</tr>
<tr>
<td>e</td>
<td>-0.00043</td>
<td>-0.000118</td>
</tr>
<tr>
<td>f</td>
<td>-0.595336</td>
<td>1.112869</td>
</tr>
<tr>
<td>g</td>
<td>0.000006871</td>
<td>-0.00004971</td>
</tr>
<tr>
<td>h</td>
<td>-5.350991</td>
<td>-4.569235</td>
</tr>
<tr>
<td>i</td>
<td>2.726411</td>
<td>0.000921</td>
</tr>
<tr>
<td>j</td>
<td>0.125974</td>
<td>0.997066</td>
</tr>
</tbody>
</table>

Table 3. The performance of ANN and RA models

<table>
<thead>
<tr>
<th>Model</th>
<th>MAE</th>
<th>MSE</th>
<th>ARMSE</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>(k_{rw}) (ANN)</td>
<td>0.0235</td>
<td>0.0020</td>
<td>0.0445</td>
<td>0.8736</td>
</tr>
<tr>
<td>(k_{rw}) (RA)</td>
<td>0.0351</td>
<td>0.0022</td>
<td>0.0478</td>
<td>0.8631</td>
</tr>
<tr>
<td>(k_{ro}) (ANN)</td>
<td>0.0293</td>
<td>0.0024</td>
<td>0.0488</td>
<td>0.8103</td>
</tr>
<tr>
<td>(k_{ro}) (RA)</td>
<td>0.0250</td>
<td>0.0009</td>
<td>0.0298</td>
<td>0.9178</td>
</tr>
</tbody>
</table>

Fig. 2. Measured and estimated water relative permeabilities for training data using ANN
On the other hand, the table shows that the comparisons of the statistical parameters between the oil relative permeability ANN and RA models indicate reverse results. This means the relative permeability ANN model of oil is less accurate than the RA model. However, in general the ANN models both for relative permeabilities of water and oil provide...
better estimates. This is because all the results of relative permeability prediction of the ANN models are positive. While the use of the RA models gives negative prediction results at low relative permeability data. this means that the RA correlations have limitations in their use. In this case the RA models cannot be used for water relative permeability values equal to or less than 0.0048 or for oil relative permeability values equal to or less than 0.0059. Other RA correlations should be determined for the intervals.

4 Conclusion

Based on the calculation results and analyses shown above, artificial neural network approach was successfully applied for predicting relative permeabilities of oil and water as functions of water saturation, other phase relative permeability, absolute permeability, porosity, and true vertical depth. Furthermore, artificial neural network model provides more accurate approximate values of water relative permeability than the regression analysis model. In general, ANN models provide better relative permeability estimates than analysis regression models because RA models provide negative estimates for low water and oil permeabilities.

References


