Deterministic Smart Tools to Predict Recovery Factor Performance of Saline Water Injection in Carbonated Reservoirs

Introduction

Throughout decades due to the scarcity of petroleum sources and weak performance of traditional waterflooding on increasing oil recovery factor (RF), enhanced oil recovery (EOR) processes have been applied to improve the ultimate oil recovery (Maghsoudian et al., 2020b). Hence, determining a suitable and cost-effective method to enhanced the ultimate recovery is still notable for developing oil fields, particularly in carbonated fields (Derkani et al., 2018). Among all EOR methods the role of low water salinity gets higher attention in numerous studies on both sandstone and carbonate reservoirs due to their potential advantages such as cost-effectiveness, simple preparation procedure, and appropriate stability (Kondori et al., 2020; Maghsoudian et al., 2020a). Low salinity (Losal) waterflooding prepared by diluting high salinity water containing various divalent and monovalent ions. According to previous studies, Losal has an immense impact on underlying mechanisms in petroleum reservoirs in order to change the wettability condition into water-wet state and dwindle the final residual oil (Liu and Wang, 2020). Besides, a large number of coreflooding tests analysis illustrated Losal has a great effect in both the secondary and the tertiary oil recovery process (Katende and Sagala, 2019). Experimental procedures commonly are time-consuming, high cost, and low accessibility. Therefore, applying artificial intelligence (AI) techniques as an alternative method to overcome the aforementioned barriers will be a suitable and trustworthy approach to predict objective function(s) and improve future practical research, in the absence of deep knowledge and related mathematical formulation to targeted procedures. The most well-known models based on AI are the artificial neural network (ANN), genetic algorithm (GA), neuro-fuzzy inference system (ANFIS), genetic programming (GP), least-squares support vector machine (LSSVM), etc (Li et al., 2020). These models have a great capability to develop precise and reliable output variables and have a low cost and swift computational procedure with high accuracy (Kondori et al., 2020). Despite numerous comprehensive research and data gathering in sandstone reservoirs, lack of sufficient comprehensive studies in carbonated reservoirs is still required due to the presence of harsh reservoir conditions such as heterogeneity, high temperature, and different physio-chemicals phenomenon (Hao et al., 2019). Based on the previous researches, precise studies on the effect of Losal waterflooding on recovery factor performance in carbonate reservoir by applying smart predictive models is still required. Thus, this paper purposed to cover this important gap by using practical deterministic models. The main purpose of this research is to introduce smart predictive tools such as ANN and multigene genetic programming (MGGP) for obtaining RF of LSWI process based on different parameters including porosity, permeability, temperature, injection rate, total dissolved salinity (TDS), viscosity and initial water saturation (Swi). These models are trained using 145 data point related to carbonate reservoirs. In the final step, the accuracy of the models are investigated based on statistical parameters such as root mean square error (RMSE), average relative error (ARE), and coefficient of determination ($R^2$).

Theory and Research Methodology

Deterministic Tools Theory

**Artificial neural network.** ANN is applied for a non-linear multivariate regression and pattern diagnosis among the inputs and output data without using related equations. This predictive tool is including input layer(s), a hidden layer(s), and output layer(s) (Esene et al., 2020).

**Multigene genetic programming.** MGGP is a biologically inspired machine learning method that employs computational software to carry-out a task. The logic beneath MGGP model is to dwindle the technical obstacles to applying, comprehending, observing and extended data point from GP deterministic models (Searson, 2015).

Methods

The main objective of this article is about to hire two distinguish deterministic smart tools including ANN and MGGP to evaluate the secondary and tertiary wide range saline waterflooding process on RF in carbonated reservoir.

**Selection of modeling tool.** To perform the ANN smart modeling, utilizing appropriate code from the MATLAB (R2018a). Also, the optimal number of hidden layers and neurons were selected by trial and
errors. As well as, suitable codes from MATLAB employed to implement MGGP method as the second predictive tool in this scientific paper.

**Data screening.** To introduce proper deterministic models, a diverse factors including different production parameters, crude-brine-rock (CBR) properties, and reservoir conditions are selected based on their effects on recovery performance. These parameters include permeability, porosity, temperature, injection rate, TDS, oil viscosity at experimental condition, and initial water saturation (Derkani et al., 2018; Hao et al., 2019; Liu and Wang, 2020). The number of literature data points which used in this study are 145 (Al-Shalabi et al., 2014; Alameri et al., 2014; Alotaibi et al., 2010; Chandrasekhar, 2013; Chandrasekhar et al., 2016; Hamouda and Gupta, 2017; Hamouda and Maevskiy, 2014; Mohammadkhani et al., 2018; Mohsenzadeh et al., 2016; Nasralla et al., 2018; Nasralla et al., 2014; Sari et al., 2017; Winoto et al., 2012). The minimum and maximum number of choosing factors have been demonstrated in Table 1. It is noteworthy to mention that all gathered data point are distributed randomly in training (80%), testing (15%), and validation (5%) steps.

<table>
<thead>
<tr>
<th>Model</th>
<th>Variables</th>
<th>Porosity (%)</th>
<th>Permeability (mD)</th>
<th>Temperature (°C)</th>
<th>Injection Rate (cc/min)</th>
<th>TDS (ppm)</th>
<th>Oil Viscosity (mPa.s)</th>
<th>( S_{wi} ) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>11.4</td>
<td>0.79</td>
<td>25</td>
<td>0.045</td>
<td>437.3</td>
<td>0.41</td>
<td>7.3</td>
<td></td>
</tr>
<tr>
<td>Maximum</td>
<td>52.04</td>
<td>384.87</td>
<td>120</td>
<td>7</td>
<td>239400</td>
<td>37.26</td>
<td>66.4</td>
<td></td>
</tr>
</tbody>
</table>

**Results and Discussion**

In this work, two strong and practical smart deterministic models including ANN and MGGP have been utilized to predict the recovery factor during saline waterflooding process in carbonated reservoir. As well as, to examine the quality of applying models, statistical analysis has been implemented. Besides, to investigate about the magnitude of all input parameter a precise sensitivity analysis is performed. Finally, results of ANN and MGGP models are compared together on predicting the recovery factor.

**Artificial neural network.** To forecast the RF during saline waterflooding, Levenberg-Marquart for training process and mean squard error (MSE) for performance have been applied for ANN predictive tool. Additionally, two hidden layers with 11 and 5 neurons have been deployed for seven input parameters by trial and errors, respectively. Figure 1a and b illustrate the ANN predictive result for recovery factor. Based on Figure 1, \( R^2 \) value for both training and test steps are 0.9804 and 0.9305, respectively. Final results revealed that this model has a great capability to resemble actual saline waterflooding process.

**Figure 1:** Performance of ANN model: (a) Training and (b) Testing

**Multigene genetic programming performance.** The MGGP performance has been evaluated by applying training, testing, and validation data point separation similar to ANN section. According to outcomes the \( R^2 \) values for training and testing are 0.8287 and 0.7669, respectively. Based on Figure 2a and b, results illustrate that this model has intermediate ability to simulate the real behavior of saline waterflooding process in carbonated reservoirs.

**Parametric sensitivity analysis.** In spite of ANN demonstrating better RF prediction compared to MGGP, MGGP is a suitable method to investigate about the effect of input variables individually on forecasting recovery factor. Table 2 illustrates the significance of each input parameters on RF during saline waterflooding in carbonated reservoirs. Conforming to \( R^2 \) value the important parameters are permeability, porosity, TDS, injection rate, oil viscosity, temperature, and initial water saturation.
respectively. Figure 3a and b demonstrate the most important input parameters (permeability and porosity, respectively) on RF of saline waterflooding process in carbonated reservoirs.

![Figure 2](image-url) Performance of MGGP model: (a) Training and (b) Testing

**Table 2.** Magnitude of input variable parameters on RF by high saline waterflooding

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Permeability</th>
<th>Porosity</th>
<th>Temperature</th>
<th>Injection Rate</th>
<th>TDS</th>
<th>Oil Viscosity</th>
<th>Swi</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$ Value</td>
<td>0.2005</td>
<td>0.1039</td>
<td>0.0567</td>
<td>0.0954</td>
<td>0.1012</td>
<td>0.0623</td>
<td>0.01</td>
</tr>
</tbody>
</table>

![Figure 3](image-url) Significance of input variables for predicting RF of saline waterflooding process (a) Permeability, and (b) Porosity

**Statistical assessment.** The significance of RMSE, ARE (%), and $R^2$ for the training, testing, and total phases for the statistical investigation of ANN and MGGP smart models illustrated in table 3. Based on the results, the ANN deterministic model demonstrates better performance due to higher $R^2$ and lower error compared to MGGP model for RF forecasting during saline waterflooding process in carbonated reservoirs.

**Table 3.** Statistical evaluation of the ANN and MGGP models

<table>
<thead>
<tr>
<th>Statistical Indicators</th>
<th>ANN</th>
<th>MGGP</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Training</td>
<td>Testing</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.4612</td>
<td>11.152</td>
</tr>
<tr>
<td>ARE(%)</td>
<td>0.0283</td>
<td>3.8551</td>
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<tr>
<td>$R^2$</td>
<td>0.996</td>
<td>0.9305</td>
</tr>
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</table>

**Conclusion**

In this study, ANN and MGGP were developed to forecast the recovery factor of saline waterflooding. 145 data point were used in the process of model development. The input parameters cover wide ranges of permeability, porosity, temperature, injection rate, TDS, oil viscosity at experimental condition, and $S_{wi}$. Results show that ANN has a better performance for predicting recovery factor in comparison to MGGP. The $R^2$ for the testing process in ANN and MGGP are 0.9305 and 0.7669, respectively. The results of MGGP were used to clarify the importance of each input parameters on RF. Based on the results of sensitivity analysis, permeability, porosity and TDS are the most important factors on RF.

**References**


Mohsenzadeh, A., Pourafshary, P. and Al-Wahaibi, Y., 2016. Oil recovery enhancement in carbonate reservoirs via low saline water flooding in presence of low concentration active ions; A case study, SPE EOR Conference at Oil and Gas West Asia. Society of Petroleum Engineers.


