New Correlation for Calculating Water Saturation Based on Permeability, Porosity, and Resistivity Index in Carbonate Reservoirs

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ABSTRACT: Water saturation assessment is recognized as one of the most critical aspects of formation evaluation, reserve estimation, and prediction of the production performance of any hydrocarbon reservoir. Water saturation measurement in a core laboratory is a time-consuming and expensive task. Many scientists have attempted to estimate water saturation accurately using well-logging data, which provides a continuous record without information loss. As a result, numerous models have been developed to relate reservoir characteristics with water saturation. By expanding the use and advancement of soft computing approaches in engineering challenges, petroleum engineers applied them to estimate the petrophysical parameters of the reservoir. In this paper, two techniques are developed to estimate the water saturation in terms of porosity, permeability, and formation resistivity index through the use of 383 data sets obtained from carbonate core samples. These techniques are the nonlinear multiple regression (NLMR) technique and the artificial neural network (ANN) technique. The proposed ANN model achieved outstanding performance and better accuracy for calculating the water saturation than the empirical correlation using NLMR and Archie equation with a high coefficient of determination ($R^2$) of 0.99, a low average relative error of 1.92, a low average absolute relative error of 13.62, and a low root mean square error of 0.066. To the best of our knowledge, the current research establishes a novel foundation using the ANN model in the estimation of water saturation.

1. INTRODUCTION

The fluid saturation can be defined as the percent or fraction of the pore volume occupied by that fluid. The total sum of all fluid volume (oil, water, and gas) must be equal to one. In the early lifetime of an oil reservoir, the zone of oil includes both oil and water or can be changed according to the distance from oil–water contact from zero to one. The accurate estimation of water saturation across all segments in the reservoir is critical to reservoir characterization and original hydrocarbon in place calculation. There are several models that depend on water saturation to estimate the relative permeability. The laboratory core analysis is considered the most effective, accurate, and direct approach to measure water saturation ($S_w$). The limitations of this method are it being time-consuming, being expensive, and losing of some interval during the coring operation; therefore, this approach is not applicable with all the wells on the same field. Well logging interpretation is another approach for the estimation of water saturation ($S_w$). This approach is carried out through the continuous recording of both physical and chemical characteristics of the formation and containing fluids.

The assessment and determination of fluid saturation and the type of fluid is usually a difficult undertaking. Water saturation ($S_w$) is a crucial factor that is remarkably changed by the precision of input parameters in the calculations. In 1929, Conrad Schlumberger in the Pechelbron field in France ran the first log that was electric coring. Archie (1942) presented a paper in an AIME meeting in Dallas that quantifies the relationship between the formation resistivity and fluid saturation. To determine the hydrocarbon saturation in the reservoir, the widely known Archie equation can be utilized to calculate the water saturation in a clean sandstone reservoir, where this equation depends on Archie’s parameters that give the certainty for the value of water saturation that has been found different in value from using several techniques that has a dependency on Archie’s exponent such as ($a$, $m$, and $n$). Equation one is the fundamental equation to estimate water saturation in the formation. The accuracy of $S_w$ is based on Archie’s parameters ($a$, $m$, and $n$) and accurate determination of reservoir properties such as porosity.

$$S_w = \left[\frac{aR_w}{\phi^m R_t}\right]^{1/n}$$

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where, tortuosity coefficient ($a$), formation water resistivity ($R_w$), porosity ($\phi$), cementation factor ($m$), true formation resistivity ($R_t$), and water saturation exponent ($n$).

As formulated in eqs 2 and 3, Archie defined formation resistivity factor ($F_R$) as the ratio of formation resistivity 100 percent saturated with water ($R_w$) divided by the resistivity of brine ($R_b$) and also presented an empirical equation indicating a power-law relationship between formation resistivity factor ($F_R$) and porosity ($\phi$).

$$F_R = \frac{R_b}{R_w}$$  
(2)

$$F_R = \phi^{-m}$$  
(3)

The resistivity index ($RI$) can be defined as the ratio between the true resistivity of the porous media (containing hydrocarbon and water) and the original formation resistivity (containing 100% brine). The RI is used to distinguish partially saturated reservoir rocks with water and contains oil or gas which can be expressed as

$$RI = \frac{R_s}{R_o}$$  
(4)

Archie’s equation assumption states that the only conductive medium existing in the reservoir is the formation water. However, in the case of the existence of shale in the reservoir, there is a discrepancy occurring in the reservoir’s resistivity reading because shale generates a conductive path along with formation water. Hence, the Archie equation cannot determine water saturation and potential hydrocarbons accurately in the case of shaly formation.

The development of a model for calculating water saturation effectively and accurately is of economic importance in the oil industry. Therefore, there are many models that have been built to account for the impact of shale on the reservoir’s resistivity and water saturation. Many petrophysical models have been developed on the basic idea introduced by (Archie 1942) by adding a shale term in Archie’s original equation. These models can be classified into two types. The first type is about the volume of shale ($V_s$) models where we take into account the volume of shale’s contribution to conductivity such as the equation of Simandoux$^8$ and model of Indonesia. $^9$

The second type is about clay electrical conductivity (CEC) where we take into account the clay minerals electrical conductivity such as the equation of Waxman–Smits$^10$ and the model of dual-water.$^{11}$

In the shaly sand models, the saturation exponent ($n$), cementation factor ($m$), and tortuosity coefficient ($a$) are critical parameters. Both Emadi and Tabibi (2003)$^{12}$ stated that the cementation factor had great effects on the estimation of water saturation as its influence on water amount and pore space. This is due to the reduction of porosity as the sand becomes more cemented, and hence, the formation resistivity factor value increases. Attia (2005)$^{13}$ found that the tortuosity factor is not a fixed value but changes greatly depending on a variety of factors such as cementation factor, porosity, brine saturation degree, amount of fine grains, and porosity. Also, the tortuosity calculated using mechanical resistivity readings is quite similar to tortuosity calculated from capillary pressure data. According to the investigation, the correlations that relate the tortuosity factor and petrophysical rock characteristics should provide a strong relationship besides the most precise coefficients. Ahammad et al. (2006)$^{14}$ concluded that the saturation exponent and cementation factor frolic a vital act in assessing hydrocarbon potentiality and water saturation calculation and that it is accountable for the discrepancies amid log clarification and actual creation examination results. Furthermore, the results of $m$ variation on saturation are most sensitive at low porosity. They additionally concluded that the results of $n$ variation on saturation calculations are most sensitive at low saturation. Attia et al. (2008)$^{15}$ showed that the irreducible water saturation is also a parameter that is dependent on conduction types and the saturation value at percolation. According to the researchers, upper and lower bound limits for the porous medium’s production capacity can be calculated using the two values of irreducible water saturation. A detailed study of the data reveals the considerable shift in the value of the saturation exponent. This shift happens at the irreducible water saturation level, as determined by measurements of capillary pressure.

Archie’s parameter ($a$, $m$, and $n$) accuracy determines the accuracy of water saturation values. These parameters are not usually available in many cases, so the default values are used.$^{16}$ Using default values can result in high levels of uncertainty in water saturation calculation. Moreover, acquiring these parameters in the case of carbonate reservoirs is much more difficult due to the heterogeneity of carbonates, which have a diversity of pore types such as fracture, intercrystalline, intergranular, and vuggy porosity. As a result, considerable fluctuations in the values of these parameters in carbonate reservoirs have been reported. Hence, it has been found that taking constant values leads to a large error.$^{17}$

For the purpose of water saturation estimation, different techniques of machine learning algorithms are used. Based on the resistivity well-logs, three clustering techniques were suggested and tested: fuzzy C-means clustering, Gustafson–Kessel algorithm, and Gath–Geva clustering to predict the water saturation. The authors presented clustering algorithms because they are unsupervised approaches that do not need real data for training the machine.$^{18}$ By using well logs, the local linear neuro-fuzzy (LLNF) model was employed to estimate the water saturation in a carbonate reservoir.$^{19}$ The study showed an application of ensemble tree-based algorithms in estimating the fluid saturation in oil sands.$^{20}$ To estimate water saturation in Mesaverde tight gas sandstones in the Uinta Basin, soft computing approaches such as support vector machine, multilayer perceptron neural network, decision tree forest, and tree boost methods were used.$^{21}$ Later on, kernel function-based least-squares support vector machine and multilayer perception approaches were applied to develop models for predicting the reservoir water saturation.$^{22}$ Moreover, for water saturation prediction from well log data, an intelligent technique called robust committee machine was presented.$^{23}$

In order to estimate water saturation in sandstone and carbonate reservoirs, several well log data and petrophysical characteristics obtained in the lab are employed as input parameters in various algorithm techniques. The prediction model of water saturation was built depending on lithofacies identified in various wells.$^{24}$ In addition, an artificial neural network (ANN) was built to estimate the water saturation as a function of height above free water level, permeability, and porosity.$^{25}$ This paper aims to provide a solution to the aforementioned challenges by proposing a model through the use of ANNs to accurately and effectively estimate water saturation.
Table 1. Data Statistical Analysis

| parameters                        | maximum value | minimum value | data mean | data range | standard deviation | Skewness | Kurtosis |
|-----------------------------------|---------------|---------------|-----------|------------|--------------------|----------|----------|
| porosity, (v/v)                   | 0.26          | 0.06          | 0.173     | 0.2        | 0.046              | -0.211   | -0.188   |
| permeability, md                  | 613.05        | 0.39          | 66.889    | 612.66     | 121.34             | 3.13     | 10.951   |
| formation resistivity factor, (R/R)| 222.42        | 4.89          | 33.928    | 217.53     | 33.997             | 3.689    | 17.436   |
| formation RI, (R/R)               | 535.33        | 1             | 20.72     | 534.33     | 51.517             | 5.948    | 44.789   |
| water saturation, (v/v)           | 1             | 0.09          | 0.533     | 0.91       | 0.298              | 0.223    | -1.366   |

Figure 1. Relative importance of input parameters with water saturation.

2. METHODOLOGY

2.1. Artificial Neural Network. An ANN comprises processors which are relatively simple and highly interconnected; these processors are called neurons. Each of these neurons is connected with each other by weighted links that allow the signals to pass through it. Each neuron gets many inputs according to their connection weights from other neurons and creates a single output that may propagate to inputs according to their connection weights from other neurons which are relatively simple and highly interconnected; these processors are called neurons. These neurons are connected with each other by weighted links that allow the signals to pass through it. Each neuron gets many inputs according to their connection weights from other neurons and creates a single output that may propagate to several additional neurons. The back-propagation learning algorithm has been the most widely utilized approach in engineering applications among the different types of ANNs that exist. It works with any feed-forward network with a variety of activation functions. The ANN modeling process is divided into two steps: the first is to train the network, and the second is to test the network using data that was not utilized in the training process. The network must be given all of the information it needs to learn in the form of a data collection. The network utilizes the input data to build an output, which is then compared to the training pattern when each pattern is ready. If there is a discrepancy, the connection weights are adjusted in a way that reduces the error. If the error is still more than the maximum acceptable range after the network has run through all of the input patterns, the ANN repeats the process until all of the errors are within the required limit. Theoretically, there is no need to build networks with more than two hidden layers because networks with two hidden layers may represent functions of any form. In general, for any feed-forward network architecture, one hidden layer is strongly suggested as the initial choice. The data utilized to create and run the system must be of high quality, availability, dependability, repeatability, and relevance. Data processing begins with data collection and analysis, then preprocessing, and finally feeding into a neural network. The most frequent approach for training multilayer feed-forward networks is back-propagation. The learning process for most networks is based on an appropriate error function, which is subsequently reduced in terms of weights and bias. Back-propagation refers to an algorithm for estimating the derivative of an error function that propagates errors backward across the network. This approach has been utilized and evaluated in a variety of studies, as evidenced by refs 29–31. Finally, using the weights and bias according to activation and transfer functions, mathematical equations may be developed to apply in the future for computing the output from the input data without having to establish a neural network.

2.2. Data Processing and Acquisition. Data preparation and management is a critical stage in any AI modeling project’s success. The quality of the data has a great effect on the artificial intelligence model performance. The input used for these models is core data. The data consist of porosity ($\phi$), permeability ($k$), formation resistivity factor ($F_R$), and formation RI.

2.3. Description and Analysis of the Data. In this study, 383 actual core data sets were collected from 44 representative core plugs cut from three different oil wells. These core plugs have a wide range of porosity and permeability. These plugs are carbonate core plugs which vary from limestone to dolomite with vugs in some of them. Core data include the following: porosity ($\phi$), permeability ($k$), formation resistivity factor ($F_R$), formation RI, and water saturation ($S_w$). The resistivity of brine ($R_w$) that was used in this study is 0.03 $\Omega$m. Table 1 represents data statistical analysis. Porosity value range is: 0.06–0.26 (v/v), permeability range is: 0.39–613.05 MD, formation resistivity factor range: 4.89–222.42 (R/R), while formation RI range is: 1–535.33 R/R. The data points are randomly divided into three subgroups: the first subgroup represents 70% of the data that are used for training purposes, the second subgroup represents 15% of the data that are utilized for the validation, and the third subgroup represents 15% of the data for testing the accuracy and generalization of the model capabilities.
2.4. Building a Water Saturation Model Utilizing the Artificial Intelligence Techniques. The AI model is data-driven and entering the parameters that are available as input does not always ensure acceptable outcomes. Finding which input parameter contributes effectively and which input parameter contributes adversely is the best practice. The individual relationship is estimated as the function of the correlation coefficient between input and output parameters using a multivariate linear regression correlation coefficient feature selection technique, as shown in Figure 1. The following equation can be used to calculate the correlation coefficient ($R$) between input and output

$$CC = \frac{k \Sigma xy - (\Sigma x)(\Sigma y)}{\sqrt{k(\Sigma x^2) - (\Sigma x)^2} \sqrt{k(\Sigma y^2) - (\Sigma y)^2}}$$ (5)

Figure 1 shows that water saturation indicated a correlation coefficient of 0.06, −0.15, −0.04, and - 0.43 with porosity, permeability, formation resistivity factor, and formation RI, respectively. The parameters that have the highest correlation coefficient with water saturation are chosen to simplify the model. These parameters are porosity, permeability, and formation RI.

3. RESULTS AND DISCUSSION

3.1. Proposed Empirical Correlation. In this work, 383 data sets are split into 70% (269 data sets) to build and train the model, while 15% of the data sets (57 data sets) is employed to validate, and the remaining 15% of the data sets (57 data sets) is used to test the model’s performance. This mathematical model was developed using nonlinear multiple regression (NLMR) with average relative error, standard deviation, average absolute relative error, root mean square error (RMSE), and coefficient of determination of 2.95, 23.07, 14.45, 0.076, and 0.98, respectively, as summarized in Table 5. The following developed model exhibits a high coefficient of determination and low RMSE

$$S_w = \frac{a}{k^b R^c \phi^d}$$ (6)

where

$$a = 0.877881, \quad b = 0.0003438, \quad c = 0.455566, \quad d = 0.075009$$
The cross-plot of calculated values of water saturation for the developed correlation versus measured values is shown in Figure 2. The points that were plotted of this study’s correlation are very close to the perfect correlation of the unit-slope line.

### 3.2. ANN Model

In this work, 383 data sets are used to build and validate a model based on an ANN in order to estimate the water saturation in terms of porosity, permeability, and formation RI. 70% of the data are used for training (269 data sets) and 30% are used for model validation (57 data sets) and testing (57 data sets). After many trials to reach the optimal features and structure of the ANN model, the optimum performance is obtained as presented in Table 2. The proposed model includes three layers. The first one is the input layer which has three neurons for three input parameters (permeability, RI, and porosity). The second layer has 10 hidden neurons that connect the input layer with the third layer (output layer) which has one neuron for the output parameter (water saturation). In this model, the log-sigmoid is used as a transfer function and the pure-linear function is used as an output function. Table 3 shows the coefficients of the proposed mathematical ANN model.

#### Table 3. Coefficients of the Proposed Mathematical ANN Model

| neuron | $W_{1.1}$ | $W_{1.2}$ | $W_{1.3}$ | $b_1$ | $W_2$ | $b_2$ |
|--------|-----------|-----------|-----------|-------|-------|-------|
| 1      | 8.7033    | -2.3372   | 1.6693    | -5.5454 | 1.9936 | 10.3708 |
| 2      | 4.84      | 1.596     | -3.0083   | -3.8767 | -1.5732 |       |
| 3      | -5.8489   | 3.7444    | -2.224    | -0.48689 | -2.4023 |       |
| 4      | -4.4667   | -7.7704   | 1.2852    | -12.0746 | 4.1887 |       |
| 5      | -4.2831   | 3.3245    | -1.432    | -0.70406 | 2.884 |       |
| 6      | 0.35819   | -1.5501   | -3.0165   | -4.2946 | 11.9558 |       |
| 7      | -10.2346  | -2.7202   | 14.1765   | -5.1469 | 1.8631 |       |
| 8      | 2.4783    | 5.6287    | -0.91586  | 9.779 | 11.1746 |       |
| 9      | 16.0748   | 0.063299  | 2.9004    | 18.6355 |       |       |
| 10     | 0.046496  | 81.163    | -0.19165  | 84.1796 |       |       |

#### Figure 3. Plots of regression for the network results.

#### Table 4. Archie Parameters

| data set | $a$   | $m$     | $n$     |
|----------|-------|---------|---------|
| all data | 0.792581 | 2.177063 | 2.966456 |

The cross-plot of calculated values of water saturation for the developed correlation versus measured values is shown in Figure 2. The points that were plotted of this study’s correlation are very close to the perfect correlation of the unit-slope line.
3.2.1. ANN Mathematical Model. The ANN mathematical model is based for \( i = 1 \) ranges to the number of neurons and for \( j = 1 \) ranges to the number of inputs; the hidden layers inputs are calculated from the following expression

\[
S_{ij} = \sum_{j=1}^{N} (w_{ij}x_j) + b_i
\]  

(7)

\( x_j \): normalized inputs (permeability, resistivity index, and porosity)

The water saturation is calculated using the following expression

\[
S_w = 0.545 \cdot 0.455 \left[ \sum_{i=1}^{N} \left( \frac{w_{hoi}}{1 + e^{-N}} \right) + b_{ho} \right]
\]  

(8)

The normalized parameters used to develop the proposed model are as follows

\[
k_n = 0.003264k_j - 1.001273
\]  

(9)

\[
RI_n = 0.003743RI_j - 1.003743
\]  

(10)
\[ \phi_i = 10\phi - 1.6 \]  
\[ S_{w} = 2.197802S_{w} - 1.197802 \]

As shown in Figure 3, regression plots show the relationship between measured and calculated water saturation for training, validation, testing, and all data sets. For an adequate fit, the data points should be aggregated around the unit slope line, where the network results are equal to the targets. For all data sets in this study, the fit is good, and the coefficient of determination value \( R^2 \) is 0.99, as indicated in Table 5.

3.3. Model Performance Evaluation. To evaluate the performance of the proposed models in this study, the calculated water saturation using the ANN model and empirical correlation is compared with that calculated using the Archie equation. Archie’s parameters a, m, and n for all the three wells are calculated using NLMR, as shown in Table 4. Figure 4 shows the cross plots of the water saturation calculated using the Archie model for the data collected from the three wells and the Archie parameters. Table 5 demonstrates the statistical accuracy of water saturation for the proposed models and Archie equation. Results show that the calculated water saturation using the Archie equation has a low coefficient of determination of 78% and a high average absolute relative error of 27.58. Thus, the developed model using ANN and developed empirical correlation using NLMR are superior to the common and previously published Archie equation. Furthermore, the model based on ANN is more accurate than the empirical correlation developed using NLMR with higher values of determination coefficients of 0.99% and a lower RMSE value of 0.066. The good accuracy of the proposed ANN model is due to the fact that in terms of explained variance and out-of-sample predictive accuracy, the ANN outperforms the traditional statistical model such as NLMR. In addition, an ANN has the ability to model a complex nonlinear relationship between the independent and dependent variables. Moreover, The ANN can be developed using less formal statistical training and multiple different training algorithms.

4. CONCLUSIONS

Depending on this work, the following conclusions can be drawn:

- The results obtained in this study showed that the two developed models: empirical correlation using NLMR and ANN model can be applied to estimate the water saturation in carbonate reservoirs as a function of porosity with a range from 0.06 to 0.26 (v/v), permeability with a range from 0.39 to 613.05 (MD), and formation RI with a range from 1 to 535.33 (R/B).
- The NLMR model has a coefficient of determination of 0.98, an average relative error of 2.95, an average absolute relative error of 14.45, and a RMSE of 0.076. Meanwhile, for the ANN model, this model has a coefficient of determination of 0.99, an average relative error of 1.92, an average absolute relative error of 13.62, and a RMSE of 0.066.
- ANN model can be used for predicting water saturation because of its better performance compared with traditional statistical models such as NLMR.
- Comparing the calculated water saturation using the ANN model with that calculated using the Archie equation shows that the ANN model is more accurate than the Archie equation in the carbonate reservoir.
- The proposed ANN model for water saturation estimation is promising, and it should be evaluated and applied to a larger number of oil fields with various lithologies.

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Notes
The authors declare no competing financial interest.

LIST OF ABBREVIATIONS

ANN, artificial neural network
NLMR, nonlinear multiple regression
\( R^2 \), coefficient of determination
RMSE, root mean square error
SD, standard deviation
ARE, average relative error
AARE, absolute average relative error
RI, resistivity index
\( F_{Ri} \), formation resistivity factor
\( \phi_i \), porosity
\( k_i \), permeability
\( S_{wi} \), water saturation

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