Prediction of Water Saturation in Tight Gas Sandstone Formation Using Artificial Intelligence

Ahmed Farid Ibrahim, Salaheldin Elkatatny,* and Mustafa Al Ramadan

ABSTRACT: Water saturation ($S_w$) is a vital factor for the original oil and gas in place (OOIP and OGIP). Numerous available equations can be used to calculate $S_w$, but their values have been unreliable and strongly depend on core analyses, which are costly and time-consuming. Hence, this study implements artificial intelligence (AI) modules to predict $S_w$ from the conventional well logs. Artificial neural networks (ANNs) and the adaptive neuro-fuzzy inference system (ANFIS) were applied to estimate $S_w$ using gamma-ray (GR) log, neutron porosity (NPHI) log, and resistivity ($R_t$) log. A data set of 782 points from two wells (Well-1 and Well-2) in tight gas sandstone formation was used to develop and test the different AI modules. Well-1 was used to construct the AI models, then the hidden data set from Well-2 was applied to validate the optimized models. The results showed that the ANN and ANFIS models were able to accurately estimate $S_w$ from the conventional well logging data. The correlation coefficient ($R$) values between the actual and estimated $S_w$ from the ANN model were found to be 0.93 and 0.91 compared to 0.95 and 0.90 for the ANFIS model during the training and testing processes. The average absolute percentage error (AAPE) was less than 5% in both models. A new empirical correlation was established using the biases and weights from the developed ANN model. The correlation was validated with the unseen data set from Well-2, and the correlation coefficient between the actual and the estimated $S_w$ was 0.91 with an AAPE of 6%. This study provides AI application with an empirical correlation to estimate the water saturation from the readily available conventional logging data without the requirement for experimental analysis or well site interventions.

INTRODUCTION

Most of the oil and gas reservoirs contain at least two phases: gas—water or oil—water phases. Water saturation ($S_w$) is a crucial parameter to estimate the hydrocarbon saturation in the formation ($1 - S_w$) and then the calculations of the oil or gas in place volumes.3–8 $S_w$ estimation is one of the most challenging petrophysical calculations.7 Numerous techniques were used to calculate $S_w$.3–8

Special core analysis (SCAL) is one of the common methods to determine water saturation. SCAL includes retrieving a core from the formation of interest and then extensive experimental analysis to measure $S_w$.5–11 The main challenge with this method is the high cost for the coring process, time-consumption during the experimental laboratory analysis, and it provides discrete values for $S_w$ at a certain depth.

Well logging provides a way to estimate a continuous value for the water saturation with depth. There is no tool that directly measures the formation $S_w$; however, $S_w$ was calculated from other logs such as formation resistivity, gamma rays, and porosity logs.12 Archie proposed an equation to estimate $S_w$ for a clean formation with no clay content using the formation resistivity and porosity as shown in eq 1.13

$$S_w = \left( \frac{a R_w}{\Theta m R_t} \right)^{1/n}$$

where $S_w$ is the formation water saturation, $R_w$ is the formation true resistivity, $\Theta$ is the formation porosity that can be estimated from neutron porosity (NPHI), density, or acoustic logs, $R_w$ is the formation water resistivity that can be estimated from the self-potential log (SP), $a$, $m$, and $n$ are constants that are based on the rock type, tortuosity, and rock cementation and consolidation.

The main limitations of Archie’s equation are the estimation of $R_w$ in the absence of SP log, which is common in different oil and gas fields, the low accuracy of porosity estimation when the rock matrix is unknown, $m$ and $n$ uncertainly, and the need of core samples to fit the Archie equation. Moreover, the Archie equation is applicable only for clean formation with no clay content, which is not the case in most of the oil and gas reservoirs.5,14 The presence of clay adds an additional conductivity that leads to an error in the resistivity measurements. As a result, a correction is needed for the water saturation estimation from Archie’s equation.

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Numerous studies modified Archie’s equation to calculate $S_w$ in shaly formations such as the Simandoux equation, the dual-water model, the Waxman–Smits equation, and the Indonesia model.\textsuperscript{15–18} These models were all developed on the basic idea presented in ref \textsuperscript{13}, with adding a shale factor into the original equation to offer a simple way to calculate $S_w$ in shaly formations. In addition to clay content, kerogen also can influence the formation resistivity, especially in shale. Kerogen is a non-conductive material that causes a reduction in rock conductivity and underestimates $S_w$.\textsuperscript{19} Moreover, the main drawbacks remain in these equations due to their dependency on experimental core analyses with a high cost and long experimental time. Hence, this study aims to implement different artificial intelligence (AI) tools to estimate $S_w$ from the conventional well-log data.

### ARTIFICIAL INTELLIGENCE APPLICATIONS

AI has been applied in different problems in the petroleum field. Several AI systems including random forest (RF), adaptive neuro-fuzzy inference system (ANFIS), function networks (FN), artificial neural network (ANN), and support vector machine (SVM) can be applied to predict specific factors from available logging data without adding more cost or well intervention.\textsuperscript{20–25}

The ANN as a supervised learning technique has recently become well known for its high capability of modeling several engineering problems with a high degree of complexity. The literature reported many ANN applications to estimate different geomechanical parameters. Usually, the ANN design consists of three different layer types: input, hidden, and output layers. The input layer has the input data that are handled with a different number of neurons in the hidden layer(s) to ultimately calculate the objective function in the output layer.\textsuperscript{26} These different input, hidden, and output layers are connected with different weights and biases.\textsuperscript{26} These weights and biases are adjusted in the optimization operation to finally reach the lowest error in the objective function (difference between the actual and the estimated outputs).\textsuperscript{27,30}

The ANFIS uses the concepts of fuzzy logic combined with neural networks to custom a hybrid intelligent system that boosts its capacity to automatically train and adapt. After recognizing the input and output features, fuzzy if-then rules are implemented for nonlinear regression. The number of fuzzy rules and epoch size can be adjusted to optimize the ANFIS model performance to attain precise calculations without overfitting.\textsuperscript{25,26} The ANFIS technique was applied in different petroleum-related regression problems.\textsuperscript{23,33,34}

Water saturation determination is important for reservoir characterization and hydrocarbon in place calculations. SCAL analysis provides accurate measurements for $S_w$. However, SCAL analysis is expensive, time-consuming, and gives discrete values with depth without a continuous profile along the reservoir section. Estimating $S_w$ from the conventional well logs can give a continuous profile for $S_w$. However, its accuracy is subjected to the selected model and the certainty of these model constants. Therefore, this paper introduces the application of ANN and ANFIS techniques to estimate $S_w$ from the conventional well logs. An empirical correlation will be provided using the weights and the biases extracted for the developed ANN model to predict $S_w$ from the well logs without the need to run the AI models.

## METHODOLOGY

### Data Description

A data set of 727 data points were collected from a tight gas well in a sandstone formation. Table 1 summarizes the statistical analysis for the data set that includes the data range, mean, standard deviation (STD), and skewness. The ranges of the data are as follows: GR 95–220 API unit, NPHI 0.01–0.08 fraction, $R_o$ 15–463 $\Omega\m$, and the corresponding $S_w$ 0.1–0.35 volume fraction. For the data visualization purpose, a scatter matrix plot was constructed for the data set to examine the connections between the features (Figure 1). Moreover, the diagonal displays the data distribution for each parameter. The different parameters are mostly distributed normally around its mean, with the exception of $R_1$ showing lognormal distribution. $R_o$ data were intense toward the lower end of the $R_o$ values that were confirmed by a high skewness of 3.36. Hence, log($R_o$) values were used instead of $R_o$ in the model development process.

Spearman’s correlation coefficient ($R$) was calculated with the following equation to study the influence of the inputs in the $S_w$ prediction.

$$ R = \frac{\sum (x_i - \mu_x)(y_i - \mu_y)}{\sigma_x \sigma_y (n-1)} $$

where $R$ is the correlation coefficient output parameter ($S_w$) and input parameter, $x_i$ is the input parameter that include GR, NPHI, and $R_o$, $y_i$ is the output parameter ($S_w$), $\mu_x$, $\mu_y$, and $\sigma_x$, $\sigma_y$ are the mean and the STD values for the input and output parameters, respectively.

Figure 2 presents a heat map for the $R$ values. $R$ varied from $-1$ with a strong inverse relationship between the input parameter and $S_w$, and 1 for a strong direct relationship. A negative $R$-value was found between $S_w$ with GR and $R_o$. At low $S_w$, low formation conductivity is expected. Hence, higher formation resistivity can be measured. Higher GR represents high clay content and lowers misleading resistivity. As a result, $S_w$ decreases to correct for the additional conductivity. Positive $R$ values were found between NPHI and $S_w$.

### Table 1. Statistical Parameters for the Collected Data Set

|                 | GR  | API | NPHI, fraction | $R_o$, $\Omega\m$ | $S_w$, fraction |
|-----------------|-----|-----|----------------|-------------------|----------------|
| mean            | 161.51 | 0.04 | 70.09          | 0.25              |
| standard deviation | 28.63 | 0.02 | 69.65          | 0.04              |
| minimum         | 95.62 | 0.01 | 15.04          | 0.10              |
| 25% percentile  | 141.83 | 0.03 | 33.42          | 0.22              |
| 50% percentile  | 152.65 | 0.04 | 49.83          | 0.25              |
| 75% percentile  | 181.60 | 0.05 | 76.03          | 0.28              |
| maximum         | 220.78 | 0.08 | 463.75         | 0.34              |
| skewness        | 0.55 | $-0.28$ | 3.36          | $-0.28$            |

### Model Development

Several AI techniques can be applied. However, the ANN is well known for its capability of modeling several engineering problems with a high degree of complexity. In addition, the neuron’s biases and weights can be extracted from the developed model to generate an open box correlation that can be used in the $S_w$ calculation directly without the need of running the AI. The ANFIS is the concept of fuzzy logic combined with neural networks to custom a hybrid intelligent system that boosts the ANFIS capacity to automatically train and adapt. However, other AI techniques will be examined for future work. ANN and ANFIS machine learning techniques
were applied to the well-log data to predict $S_w$. For each technique, the data set from the gas well (727 points) was used to develop the model with a training to testing data ratio of 75/25. An unseen data set (55 points) was used to validate the developed model for each technique. The quality of the model was measured using the absolute average error (AAPE) that represents the error between the actual and the estimated values of $S_w$. The AAPE was calculated as follows:

$$\text{AAPE} = \frac{\sum_{i=1}^{N} \frac{|y_{i\text{ actual}} - y_{i\text{ estimated}}|}{y_{i\text{ actual}}} \times 100}{N}$$

where $y_{i\text{ actual}}$ and $y_{i\text{ estimated}}$ are the actual and the estimated output value ($S_w$), respectively, and $N$ is the number of points in the data set. The correlation coefficient ($R$) was calculated as the goodness of fit indicator, and it was calculated using eq 1, where $x_i$ and $y_i$ are the actual and the estimated $S_w$ values, respectively.

Figure 3 presents a flowchart for the different model development processes. After data collection and transformation, the data sets were used to build the ANN model. Different ratios were tested for the training set ranging from 70 to 90%. Meanwhile, different options of the ANN parameters were tested to optimize the network. These parameters include hidden layer numbers, neuron numbers in each hidden layer, the learning rate, and the training and transferring functions. Table 2
summarizes the different ANN hyperparameters that were used to optimize the ANN model.

| parameter             | tested options/ranges | optimized parameters                     |
|-----------------------|-----------------------|------------------------------------------|
| number of hidden layers | 1−3                   | single hidden layer                      |
| number of neurons in each layer | 5−40       | 30                                        |
| training/testing split ratio | 70−90%   | (training/testing)75/25%                  |
| training algorithms    | trainlm, traincfg, trainlrp, “trainbr” |                                           |
| transfer function      | tanh, logsig, elliot sig, logsig |                                           |
| learning rate          | 0.01−0.9              | 0.05                                      |

ANFIS performance was optimized by adjusting the number of fuzzy rules and epoch size. Therefore, the fuzzy network, cluster radius, and epoch size optimized the model performance.

**RESULTS AND DISCUSSION**

**ANN Model Results.** ANN was implemented on 727 data points to train and test the model. The optimum training testing ratio was found to be 75/25. The optimized hyperparameters were selected based on the best model quality indicators. The optimum ANN model was developed with a single hidden layer and 30 neurons. The training function was selected to be “trainbr” with the “logsig” data transfer function. Figure 4 presents the cross plot for the actual vs the estimated $S_w$ from the ANN model in both training and testing data sets. Figure 4 shows the capability of the ANN model to predict $S_w$ from the logging data with a good alignment with the 45° line. The training and testing data set have an AAPE of 4.1 and 5.2% with $R$ values of 0.93 and 0.9.

![Flowchart for developing the different AI models.](image)

![Plots of the actual vs estimated $S_w$ using the ANN model for (a) training and (b) testing data sets.](image)

![Residual analysis for the estimated $S_w$ from the ANN-based model. (a) Residuals vs model values and (b) distribution of the residuals.](image)
After fitting a regression model, the residual plot was constructed to examine the regression model’s assumptions to make sure an accurate regression output is obtained.35 Figure 5 shows the residuals of the predicted minus the actual $S_w$ (e) vs $S_w$.

Table 3. $R$ and AAPE Summary for the Different Data Sets from the ANN and ANFIS Models to Predict $S_w$ from Well Logging Data

|               | $R$     | AAPE, % |            |            |            |
|---------------|---------|---------|------------|------------|------------|
|               | training| testing | validation| training   | testing    | validation |
| ANN           | 0.93    | 0.90    | 0.91       | 4.1        | 5.2        | 6          |
| ANFIS         | 0.95    | 0.91    | 0.95       | 3.1        | 5.2        | 6          |

After fitting a regression model, the residual plot was constructed to examine the regression model’s assumptions to make sure an accurate regression output is obtained.35 Figure 5 shows the residuals of the predicted minus the actual $S_w$ (e) vs $S_w$.
values. The residual values are reliable and distributed randomly around a mean of 0. This proves the accurate model prediction on average, with constant variance in ɛ-values. In addition, ɛ-values were distributed normally in the histogram displayed around a mean value of 0, Figure 7b, which illustrates that the data scattering degree is the same for all fitted values.

ANFIS Model Results. ANFIS parameters were optimized to achieve the highest prediction accuracy. The input and output membership function were found to be "gaussmf", and "linear", respectively. The optimum cluster radius was found to be 0.50, and the epoch size was selected to be 200. Figure 6 presents the ANFIS cross plot in both training and testing data sets with good alignment with the 45° line. The ANFIS model was capable of accurately predicting $S_w$ from the well logging with the training and testing data set having an AAPE of 3.1 and 5.2% with $R$ values of 0.95 and 0.90.

Similar to the ANN model, the model regression quality was investigated using the residual plot as shown in Figure 7. The residual values are reliable and distributed randomly around a mean of 0. This proves the accurate model prediction on average. In addition, ɛ-values were distributed normally in the histogram display around a mean value of 0, Figure 7b, which illustrates that the data scattering degree is the same for all fitted values.

Model Validation. The data set from Well-2 was used to validate the AI models. Figure 8 shows the estimated $S_w$ from the ANN and ANFIS models in red and green lines, respectively, vs the actual $S_w$ from core analysis in blue dots. The actual and estimated results are almost identical, which confirm the ability of these models to accurately predict $S_w$ from the logging parameter. Table 3 summarizes the quality indicator for ANN and ANFIS models for the training, testing, and validation data sets. It shows that the ANN and ANFIS models were able to predict $S_w$ from the logging data with $R$ higher than 0.9 and AAPE less than 6%.

During the model development process, as shown in Figure 3, the model behavior was optimized by adjusting the hyper-parameters and the splitting ratios, where the performance indicators ($R$ and AAPE) were the objective function in the optimization process. Hence, the presented results are for the optimized model with the lowest error between the actual and the estimated $S_w$. In the model validation process, ANN and ANFIS models accurately predicted $S_w$ with an error of less than 6%. As shown in Figure 8, the ANN and ANFIS perfectly match the general trend of the $S_w$ profile, and the main sources of this error are the points with values far from the general trend of the $S_w$ profile.

Empirical Equation Development. One of the primary outcomes of this study was the development of new empirical equations that can be applied to calculate $S_w$ without the need to run the ANN code. The equation was developed using the weights and the biases extracted from the developed ANN model. The ANN was developed based on a hidden layer. eq 4 defines the empirical equation with the “logsig” transformation function

$$S_w = \sum_{i=1}^{N} W_2 \left( \frac{1}{1 + e^{-\left(W_1 GR + W_3 NPHI + W_4 \log(R_i) + b_1\right)}} \right) + b_2 \tag{4}$$

where $W_2$ is the weight for the neurons $(N)$ between the hidden and the output layers with bias $b_2$. $W_{1,4}$ is the weight between the input and the hidden layer for the well logging data, gamma ray (GR), NPHI, and resistivity ($R_i$), with biases $b_1$. This model was developed to mimic the developed ANN-based model applying the tuned weights and biases of the optimized networks. The optimized weights and biases of the developed $S_w$ model are listed in Table 4 to substitute the weights and biases in eq 4.

The performance of the developed equation was compared with Archie’s equation, the Simandoux equation, and the Indonesia model. Figure 9 presents a comparison between the performance of the ANN-based empirical equation vs the published empirical correlations. The ANN-based equation was able to detect the different changes in $S_w$ with depth with an AAPE of 4%. Archie’s equation revealed an error of 24% with a smoothed curve for all the data points with depth and overestimated $S_w$ in most of the data points. The Simandoux equation and the Indonesia model were developed for shaly formation; as a result, they showed a slightly better behavior with an AAPE of 20 and 19%.

### CONCLUSIONS

This study introduces the application of two AI techniques to estimate $S_w$ using the conventional logging data, including GR, NPHI, and $R_b$. The following are the main findings:

- The R values between the actual and estimated $S_w$ based on the ANN model were 0.93 and 0.91 from training and testing processes.
The ANFIS model was capable of predicting $S_w$ from the conventional logging data with $R$ values of 0.95 and 0.90 for training and testing, respectively.

The AAPE was less than 5% in ANN and ANFIS models.

An empirical correlation was validated with unseen data, and the correlation coefficient between the actual and the estimated $S_w$ was 0.91 with an AAPE of 6%.

This study showed the capabilities of machine learning techniques to estimate the water saturation from the conventional well logs with a goodness of fit ($R$) of 0.90–0.95 and ±6% accuracy error.

**AUTHOR INFORMATION**

**Corresponding Author**
Salaheldin Elkatatny — Department of Petroleum Engineering and Geosciences, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia; Center for Integrative Petroleum Research, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia; orcid.org/0000-0002-7209-3715; Email: elkatatny@kfupm.edu.sa

**Authors**

Ahmed Farid Ibrahim — Department of Petroleum Engineering and Geosciences, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia; Center for Integrative Petroleum Research, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia; orcid.org/0000-0001-7258-8542

Mustafa Al Ramadan — Department of Petroleum Engineering and Geosciences, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia; Center for Integrative Petroleum Research, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia

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Notes
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NOMENCLATURES

\begin{itemize}
\item AAPE average absolute percentage error
\item ANFIS adaptive neuro-fuzzy inference system
\item ANN artificial neural network
\item FN functional network
\item \(N\) number of data points
\item ML machine learning
\item GR gamma-ray log
\item NPHI neutron porosity log
\item \(R_e\) resistivity log
\item \(R\) correlation coefficient
\item RF random forest
\item \(S_w\) water saturation
\item \(x_i\) independent parameter
\item \(y_i\) dependent parameter
\item \(\sigma_x\) and \(\sigma_y\) standard deviation for the independent and dependent parameters
\item \(\mu_x\) and \(\mu_y\) mean for the independent and dependent parameters
\end{itemize}

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