Journal of Engineering Research and Reports

Volume 26, Issue 3, Page 63-70, 2024; Article no.JERR.111120
ISSN: 2582-2926

An Artificial Neural Network Model for Predicting Initial Water Saturation of Petroleum Reservoirs

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/JERR/2024/v26i31093

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/111120

Original Research Article

Received: 04/11/2023
Accepted: 09/01/2024
Published: 26/02/2024

ABSTRACT

Initial Water saturation is the water saturation of a reservoir before production commences. It enables the reservoir engineer to properly estimate the correct volume of Oil or gas reserves and to produce without water. And over the years over estimation or under estimation had caused major changes in the decision making of oil companies. New techniques are developed as technology advances to measure water saturation. These are the most widely used techniques for determining water saturation, nevertheless. Measurements obtained directly from a sealed core, which are more expensive, or calculations made using the Archie equation on sample well logs, which are less expensive. In this Project, Artificial Neural Network (ANN) model is the sole purpose of the modelling. The datasets are gathered, processed, trained, tested and validated.

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Keywords: Artificial neural network; reservoir modeling; water saturation; petro-physical calculations.

1. INTRODUCTION

The initial Water saturation is that the saturation of associate degree undisturbed reservoir with no previous production from any earlier well. Proper analysis of initial Water saturation is crucial for correct reserves analysis, abreast of choices on that zones to complete to get water-free production and influences a spread of productivity and formation damage problems. Calculating the initial water saturation is one of the most challenging petro-physical calculations (Swi). Because there are various alternative ways to compute water saturation, each of which yields slightly different Swi values, completions develop. Additionally, each method has weaknesses that could cause a sizable difference in the (OOIP) or (OGIP) volumes [1].

Reservoir engineers use Saturation Height Function (SHF) reached from cap-curves for integrating water saturation in dynamic models. SHF is deduce from accessible log data [2]. The saturation height function was developed using pseudo capillary pressure curves and log-derived porosity-permeability relationships to classify rock types and calculate Leverette-J functions for each type. This model demonstrates a strong connection between the water saturation calculated using a resistivity-based technique and the water saturation calculated using pseudo-capillary pressure curves in wells with current log data [3]. By combining the novel capillary pressure model with Swi vs. depth data from logs, it is possible to obtain a consistent initial fluid saturation distribution in integrated dynamic and static reservoir modeling [4].

Distributing Sw inside 3-D reservoir fine geological models is a major objective of an integrated reservoir description. Coupled with determining reference estimates of fluids in situ, the division of Sw will in some manner influence how the Sw distribution is modelled in dynamic simulation models [5]. In a different study, the complexity of rock types (RRTs) with comparable dynamic behavior but a wide range in initial water saturation (Swi) is considered. Using the SATNUM Keyword in Eclipse, a link was created between the reservoir quality index (RQI), effective water saturation, and height above free water level (HAFWL) of core and also log data. In the dynamic model, each grid cell is assigned values for SHF and a curve representing the relative permeability of the rock based on the rock's classification [6].

The Waxman-Smits equation is a semi-empirical model developed in the 1960s to improve the understanding of shaly sands, which are sands containing a significant amount of shale. It was developed based on theoretical considerations, fresh experiments, and Archie's equation, and has become one of the most important equations for shaly sands, along with Schlumberger's Dual-Water model [7]. In order to use standard equations to calculate water saturation, it is necessary to obtain certain exponents, like the saturation and cementation exponents (m) and (n), through electrical measurements on cleaned core plugs. Accurate estimates of water saturation may be difficult to obtain if the values of n and m used in the calculations are not reflective of the actual conditions in the environment [8].

Petro-physical well logs are used as input parameters then the Dean-Stark observed water saturation is used as an output parameter to create a model to forecast water saturation. Particle swarm optimization (PSO), differential evolution, and covariance matrix adaption evolution method were among the optimization techniques used to improve the created Functional Network (FN) model. The FN model optimized with PSO was determined to be the most effective artificial intelligence tool for predicting water saturation in carbonate rocks [9]. The parallel resistivity model is founded on the idea that the conductivity of the sandstone and shale components exist in parallel within a shale-sand reservoir. The conductivity of shale is dependent on bound water saturation and bound water resistivity [10].

An exponential relationship is used to determine how Sw as well as J function are related. Due to the variability in the exponential model, vertical non-stationary random field models that can handle the capillary effect and variable correlation should be used to spatially simulate initial water saturation [11]. The core data defines rock types and evaluated with its log data. A prediction made for rock types on intervals and un-cored wells with a mathematical model. Then populated throughout a reservoir using geo-statistical techniques. With matching rock type, porosity, permeability models and rock type based J-functions a reliable initial water saturation model of a reservoir is estimated [12].

The availability of cores in a reservoir substantially improves the determination of water saturation as an input to volumetric calculation. To create a saturation height function, the water saturation log was created using core data from an analogue reservoir [13]. One alternative approach for predicting water saturation distribution in reservoirs is to use a machine learning method called Long Short-Term Memory (LSTM) to build a prediction model. This method has been shown to produce more accurate results in terms of computation. Datasets from monitoring and modeling an actual reservoir are used to train and test models, which are validated then used to forecast oil production, pressure distribution, and water saturation distribution [14].

The proposed approach of electrical rock typing states that each electrical rock type is made up of all the rock samples that have the same functionality in terms of dynamic electrical efficiency, or $(\eta ele,D)^{1/n}$. This technique allows for the estimation of water saturation at all depths in the reservoir without the need to determine the saturation exponent at any specific depth [15]. A model using an artificial neural network (ANN) with feedforward-back propagation error optimization by imperialist competitive algorithm (ICA) is proposed for predicting the water saturation in TGS reservoirs. To get the best ANN contribution for a more accurate water saturation prediction, ICA is used. Traditional well log data are employed as input, while the ANN model output variables are water saturation data collected from core samples [16].

1.1 Geology of the Niger Delta

On the continental shore of the Gulf of Guinea is the Niger Delta, a delta dominated by Paleogene waves. With a drainage area of 2.23 million km2, the Niger River is the third largest river in Africa and has the ninth largest drainage area worldwide.

With a maximum thickness of 12 km near the basin's center, the delta has a surface area of 75,000 km^2. With an estimated 34 billion barrels of oil and 93 trillion cubic feet of gas reserves, the Niger Delta is one of the largest hydrocarbon provinces in the world, ranking 12th in terms of known hydrocarbon accumulation. Agbada Formation structural traps are the primary targets for oil and gas recovery.

2. METHODS

2.1 Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) is made up of a number of intricately interconnected processing units, each of which has a weighted connection to another processing unit or to itself; both delay leads and lag-free connections are acceptable.

ANNs were developed as an attempt to replicate the architecture of the human brain in order to perform tasks that traditional algorithms struggled to accomplish. They stopped trying to stay faithful to their ancestors and instead focused on improving their findings based on empirical evidence. In order to allow the input of certain neurons to be transmitted as the output of other neurons, the neurons are connected to each other in different ways. This system creates a graph with weighted, directed connections.

2.2 Procedures for Designing ANN Models

The procedure for developing ANN models is as follows: data gathering, data pre-processing, build the network, train the network, validate the model, and output the visible ANN model.

2.2.1 Data pre-processing

In Pre Processing Data, the data which at the time of gathering did not have all needed parameters. In most cases, Correlations are sought after to solve those Problems.

$$NTG = \frac{NT}{GT} \times 100 \quad (1)$$

Where

NTG is net to gross, NT is net thickness, GT is gross thickness
Permeability Estimation (K)

$$K = 307 + 26552 * \phi_e{}^2 - 34540 * (\phi e \times Sw)^2 \quad (2)$$

Where

$Ø_e$ = Effective Porosity and S_w = Water Saturation

2.2.2 Build the network

To Build the network, the following factors are specified: the number of hidden layers, the number of neurons in each layer, the transfer function for each layer, the training function, the weight/bias learning function, and the performance function. This project uses a multilayer perceptron network (MLP).

2.2.3 Train the network

Training is essential when using Artificial Neural networks. In training, the determined input is iterated till a desired output is derived. The inputs are known as Neurons. Layers of aggregated neurons are formed. Different layers may change the input data in different ways. The input data passes through the layers, potentially more than once, from the initial layer (the input layer) to the final layer (the output layer).

3. RESULTS AND DISCUSSION

3.1 Results of Analysis of the Ann Model in MATLAB

The analysis of the ANN model run in MATLAB yielded the following results as presented in Fig 4 and 5 the properties analyzed and estimated for use in ANN Model include; Formation Thickness (ft), Porosity (Ø), Shale Volume (%), Net to Gross, and Water Saturation (%). The interpreted well Log data was gotten from significant wells around the Niger Delta. As stated earlier, not all parameters were available or provided at the time of data gathering. Correlations were used in filling the noted gaps.

The data is properly trained to prevent and limit inaccuracies as much as feasible. This is accomplished by calculating or obtaining the appropriate number of hidden layers and neurons through a process of trial and error.

For training, Levenberg-Marquardt equation is used this is because of its rate of speed and a little accuracy compared with the likes of Bayesian-Regularization and Scale Conjugate Gradient.

This all takes place in a Multi-Layer Feed-Forward Network which consist of one or more than one layer. There are layers called hidden layers between the input and output layers. The more the hidden Layers the better the Output.

The Mean Squared Error against Epochs shows the mean squared error gotten after the training data set to an iterative Machine Learning algorithm is completed. The maximum Epoch set for the training was 1000 iterations. However, for this training data it iterated for 16 iterations and gave a MSE of 0.018042. The Validation checks Stops after the iteration fails six (6) times.

Regression R values measure the degree of correlation between the output data and the target data. If the R value is 1, it indicates a strong relationship between the two sets of data. If the R value is 0, it indicates a random or no relationship between the two sets of data.

3.2 Regression Statistics

Multiple R = 0.8816
R^2 (Coefficient of Determination) = 0.7772
Adjusted R^2 = 0.7755
Standard Error = 0.0932
Observations = 129

3.3 Validate the Model

Model validation is a way to assess the quality of a model by evaluating its performance on a separate dataset. The validation set should be similar to the data that the model will be used to predict, and should not be used to train the model. By evaluating the model on the validation set, we can determine if it is accurate, reliable, and able to generalize to new data, rather than just memorizing the training set. This helps to prevent overfitting and improve the model's ability to make accurate predictions on unseen data.

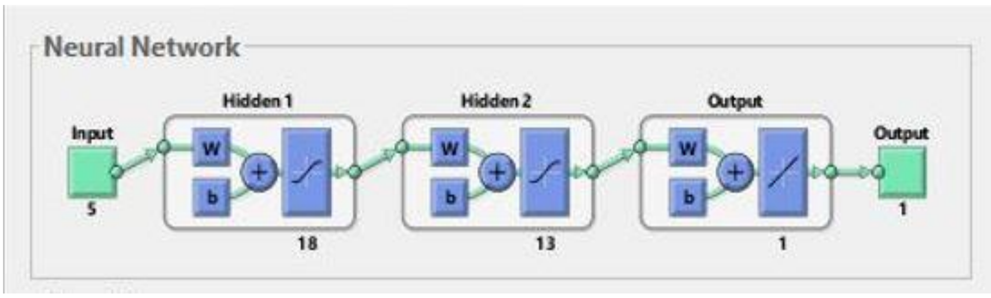

Fig. 1. The neural network training (nntraintool)

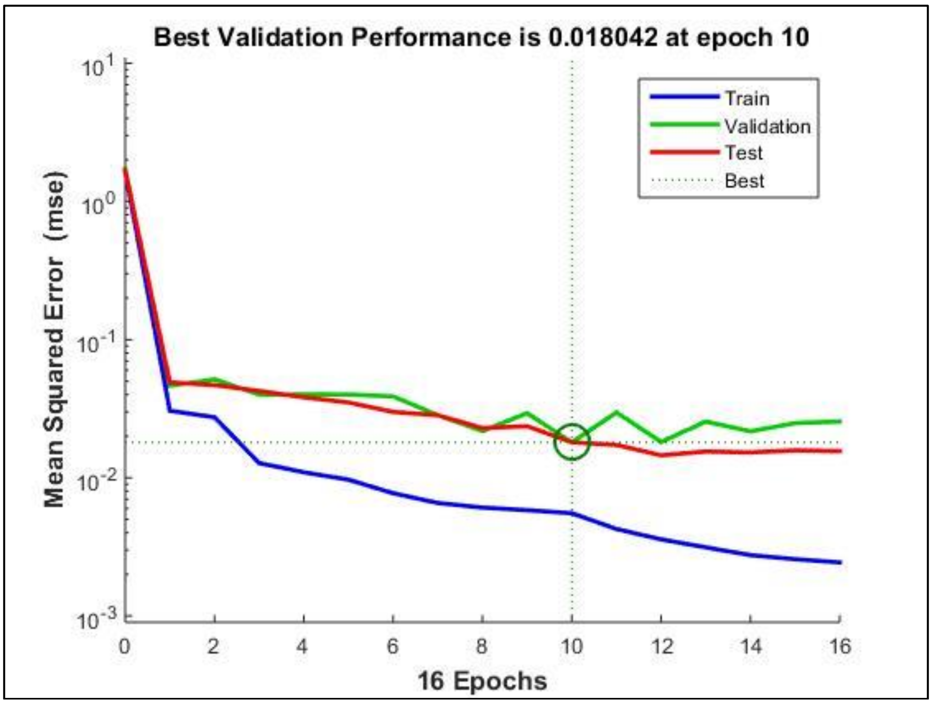

Fig. 2. Mean Squared Error (MSE) against Epochs

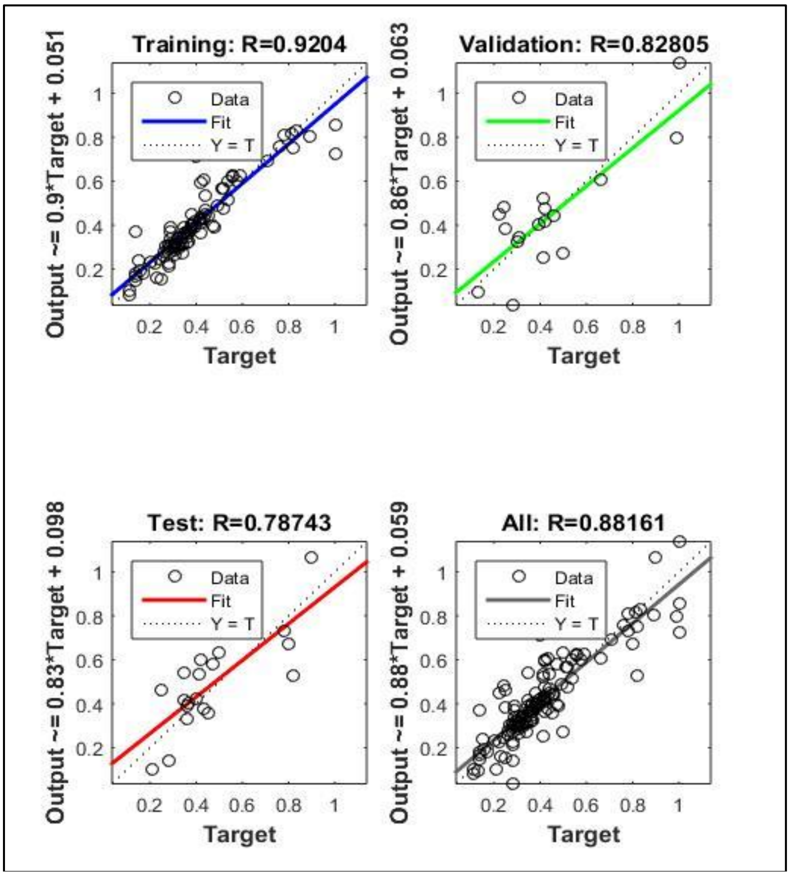

Fig. 3. Regression results

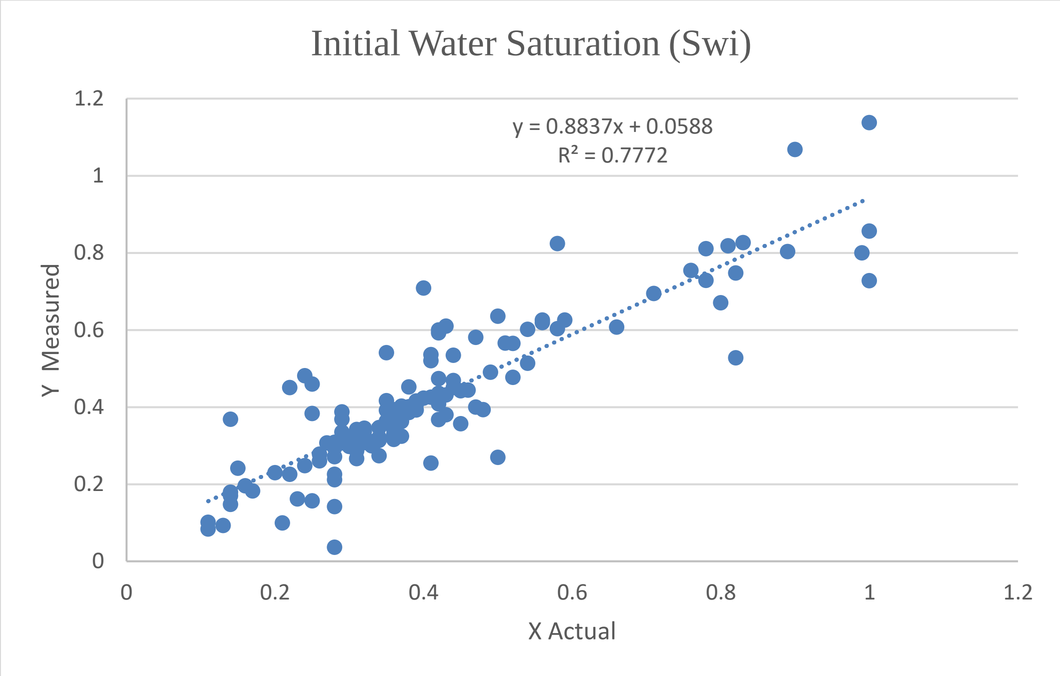

Fig. 4. Cross plot of actual versus predicted water saturation

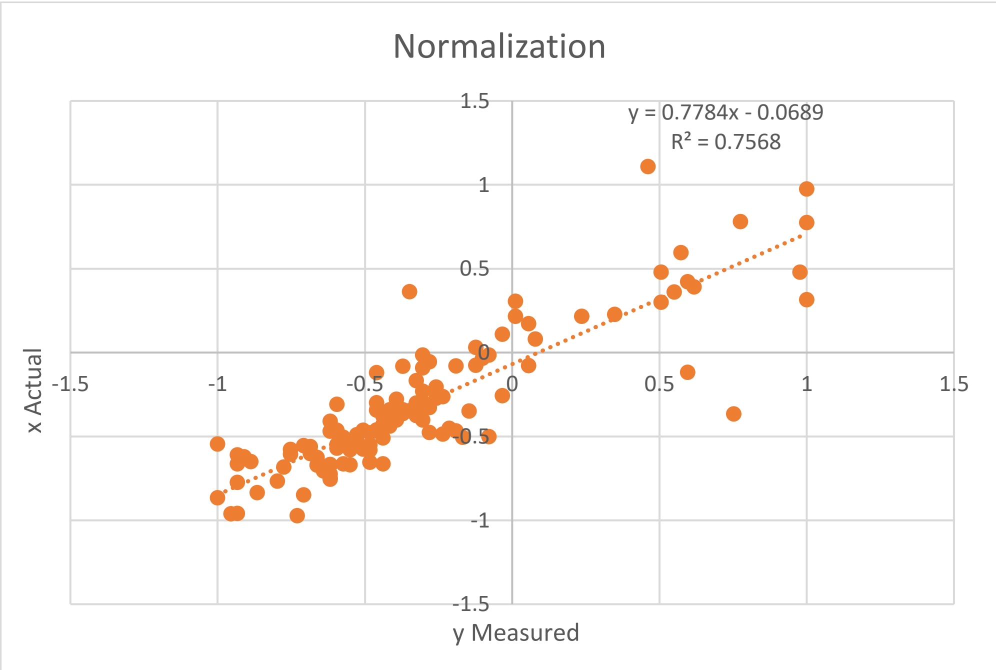

Fig. 5. Linear regression for the normalization of the swi model

The Reason for normalization is to show if the Model can be improved by adjusting the values to a scale of between -1 and +1 in this, case the Regression for normalization is lower than the Swi model meaning that the Model cannot be improved.

The Formula for Normalization is given as;

$$Xnorm = \left[2 \times \left(\frac{x - xmin}{xmax - xmin}\right)\right] - 1 \quad (3)$$

Where;

X = the value in question
Xmin = the smallest value in the data set
Xmax = the largest value in the data set

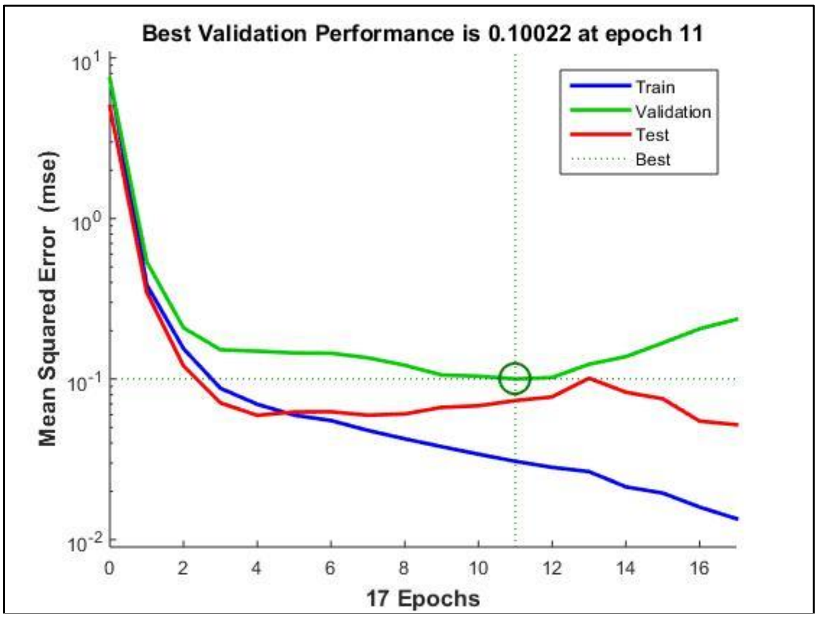

Fig. 6. Mean Squared error (MSE) against epochs for normalization

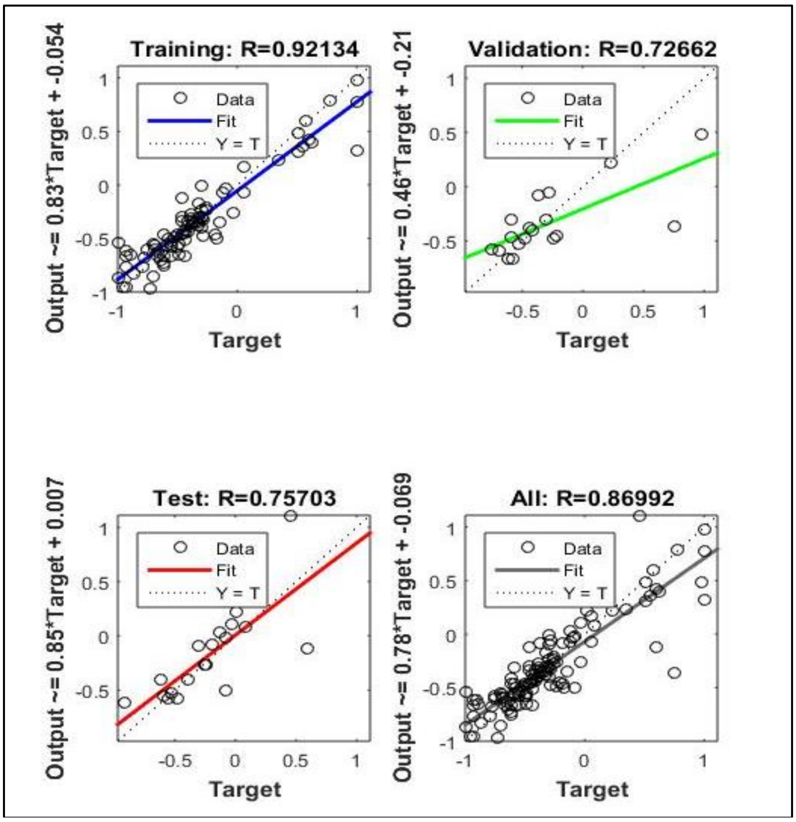

Fig. 7. Regression plot of the training, validation, test, and overall performance after normalization

4. CONCLUSIONS

MATLAB tools are used in the modelling and validation of Initial Water saturation in the Niger Delta. Interpreted well log data from the different field in Niger Delta Field is used as the input parameters for modelling Water Saturation. MATLAB, a complex mathematical software used in Modelling, Simulation and Optimization. This works shows the possibility in using Artificial Neural Network in deriving a Model for the Initial Water Saturation of any reservoir.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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