Chemical Engineering Research Bulletin 23 (2023)
Available online at http://banglajol.info/index.php/CERB
DOI: https://doi.org/10.3329/cerb.v23i10.78502

Special Issue on the 7th International Conference on Chemical Engineering (ICChE), 2023
ISSN: 2072-9510 (Open Access)

ARTIFICIAL NEURAL NETWORK-BASED PREDICTIVE MODEL DEVELOPMENT FOR RESERVOIR ROCK PERMEABILITY

Mohammad Islam Miah[1*], Abrar Bin Enayet[1] and Mafruha Akhter Ovi[2]

[1]Department of Petroleum and Mining Engineering, Chittagong University of Engineering &Technology, Chattogram-4349, Bangladesh.

[2]Department of Basic Sciences, Primeasia University, Dhaka-1213, Bangladesh.

[*]E-mail**:** islam.m@cuet.ac.bd

Abstract

Rock permeability is an important parameter for reservoir quality assessment of any hydrocarbon reservoir. The traditional methods for determining permeability include core analysis and well-test techniques. These approaches are time-consuming and costly. As a result, various studies have been conducted to predict rock permeability using core and log data with machine learning approaches. The aims of the study are to investigate the performance of data-driven predictive models in determining rock permeability and analysis of model accuracy. In the study, 260 log data sets from a gas field in the Bengal basin are adopted to forecast the reservoir rock permeability using an artificial neural network (ANN). Using the most suitable parameters, the data set was divided into three distinct categories such as 60% for training, 20% for testing, and 20% for validation. The most common two algorithms of Levenberg-Marquardt (LM), and Bayesian regularization (BR) have been applied in determining permeability to train the ANN-based model. The LM algorithm training procedure delivers the best match between the target and predicted values of permeability using the predictor variables (such as sonic travel time, gamma ray, bulk density, formation resistivity, and neutron porosity, compared to the BR-based optimized ANN network strategies. For instance, the LM algorithm provides an excellent outcome, which has a correlation coefficient (%) and average absolute percentage error of 89.90 and 6.54, compared to the BR algorithm of 67.55 and 10.93 for testing data sets, respectively. The studied procedures of the ANN-based model can be applied to predict the penetration rate of drilling, reservoir rock quality assessment and oil recovery prediction for reservoir simulation studies.

Keywords: Data analytics, Machine learning, Model accuracy, Rock permeability, Reservoir characterization

1. Introduction

Permeability is a significant reservoir property that is crucial for groundwater and hydrocarbon exploration. This characteristic is used in reservoir modeling and simulation to create static and dynamic models, as well as to estimate reserves and create hydrocarbon recovery processes [1]. Traditionally, core sample analysis can be used to directly evaluate these reservoir parameters. Data from wire-line logs are nearly always available for all well in a field and tend to give a solution to the problem with absence of unity in core information. Other issues with the wire-line log include lack of information during logging and excessive temperature, pressure, and corrosion of the subsurface media, malfunctioning tools, and operator errors that restricted the logging performance. Nowadays, machine learning techniques with an artificial neural network (ANN) has been known as an effective tool at predicting attribute of reservoir from subsurface data including well-log data[2]. ANN model uses critically important processing unit, which are artificial neurons coupled to one another to create a flow of information. Through a network of neurons, the data is processed in this manner [3]. Because it is simpler than other neural structure, the feed-forward artificial neural network is the most commonly utilized ANN structure in the petroleum operations. A list of studies with machine learning techniques (such as ANN, support vector machine, random forest) have been done to predict the reservoir properties in oil and gas engineering [4]. To full fill the knowledge gaps, the main objectives of the study are to investigate the performance of data-driven predictive models and analysis of model accuracy in determining rock permeability.

*Corresponding Author: islam.m@cuet.ac.bd

2. ANN-based Model Development and Evaluation Metrics

The artificial neural network (ANN) model act as similar to human body brain in the case of simplification of a mathematical problem. ANN models have a specific architectural form inspired by the biological nervous system. The model development of ANN including network structure design, number of hidden layers, network simulation, weigh factor and bias terms is designed by training and testing method. This network can solve the problems by creating a pattern classification then predicting the value according to input parameter and then lastly by controlling and optimizing the model. According to the design of ANN network, the classification and simulation of predicted model can be different. ANN model can be divided into three groups namely- static, dynamic and statistical. The static type of ANN model most commonly known as multilayer perceptron neural network. ANN models can also be combined with other optimization techniques for better prediction. ANN employs robust, complicated, and continuous correlation to provide an analytical approximation of such non-linear interaction by modelling. An ANN is consisting of an input layer, hidden layers and corresponding output layer. The data is received the input signal from input data, and the signal is passed through the hidden layers. On the behavior of hidden layers and transfer function the output layer provides the predicted result of the input value. To perform a multilayer perceptron (MLP) based model, the number of hidden layers is selected as trial and error method [5]. The best predictive model performance is evaluated by selecting the minimum value of mean squared error. The permeability prediction model is developed based on the available log data as predictor variables with bulk density, neutron porosity, formation resistivity and gamma-ray log. The model performance indicators are root mean square error (RMSE), average percentage relative error (AAPE), maximum absolute relative percentage error (MAPE), and correlation coefficient (R^2) are applied to find the best model to obtain rock permeability prediction. The mathematical equations for all model performance indices are listed below [6]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_{m,i} - Y_{p,i}\right)^2} \quad (1)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_{m,i} - Y_{p,i}\right)^2}{\sum_{i=1}^{n}\left(Y_{m,i} - Y_{t,mean}\right)^2} \quad (2)$$

$$AAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left(Y_{m,i} - Y_{p,i}\right)}{Y_{m,i}} \quad (3)$$

$$MAPE = Max.\left|\frac{\left(Y_{m,i} - Y_{p,i}\right)}{Y_{m,i}}\right| * 100 \quad (4)$$

In the above-mentioned equations, n denotes the total number of data points, Y_m denotes the measured variable, $Y_{m,\ mean}$ is the mean value of Y_m, and Y_p indicates the predicted output variable, k.

The accuracies of the data-driven models have been analyzed in the scale of the high or low value of statistical parameters, whereas the lower values of RMSE, AAPE and MAPE, and higher magnitudes of R^2 imply a predictive model with a greater precision. The Levenberg-Marquardt (LM) back-propagation, and Bayesian regularization (BR) algorithms are used as training algorithm to train the predictive models in this study. In Fig. 1, a simplified flow chart depicts the ANN model development steps to obtain the output results of rock permeability.

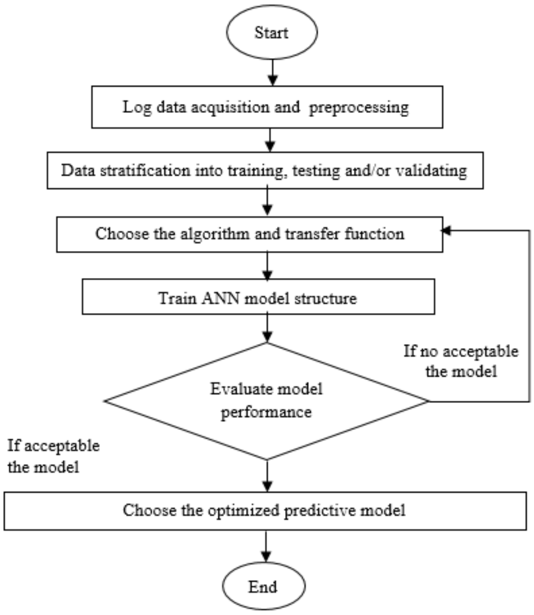

Fig. 1: The flowchart of ANN model development steps.

3. Results and Discussion

To predict the reservoir rock permeability with ANN model, 260 log data are obtained from various fields of Bengal basin, Bangladesh. In this study, the five input parameters are sonic travel time (DT), gamma ray (GR), bulk density (RHOB), formation resistivity (RT), and neutron porosity (NPHI), while the output parameter is rock permeability (k). The statistical analysis for the collected data is presented in Table 1. The minimum and maximum value of GR of sandstone lithology is 76.28 and 126.12, while standard error (STE) and standard deviation (STD) values are 0.25 and 4.02 respectively. The permeability is used as output parameter in the ANN-based model development process and minimum magnitude with a value of 10.63 mD and maximum of 138.21 mD with a low standard error of 1.63. Among these parameters, the bulk density and neutron porosity value have less complexity and less error compared to other parameters such as sonic travel time, gamma ray, formation resistivity, and permeability. The descriptive statistics value with mean, median, and variance of these parameters are shown in Table 1. The data set is divided into 60% for training, 20% for each phase of testing and validation using the optimum parameters, which included 50 neurons and five hidden layers in the training and testing process. An input layer, five hidden layers, and an output layer are present in the ANN. The input layer will receive input data, which will be transmitted through the hidden layers using a mathematical function known as an activation function. Using its activation function, every neuron in the hidden layers will compute the input from the layer before it produces an output. The final hidden layer's output will be sent into the output layer. The ideal structure of MLP-ANN is trained with two methods in this study, namely, LM, and BR to generate a MLP network. The performance of applied model is generated in Figures 2, and 3. Based on RMSE, AAPE, R^2, and MAPE values, the LM-based algorithms perform better than BR-ANN, which shown in Table 2.

Table 1

Descriptive statistical analysis of well-log data and rock permeability.

Parameters	Sonic Travel Time (DT) (µs/ft)	Gamma Ray (GR) (API)	Bulk Density (RHOB) (g/cm^3)	Neutron Porosity (NPHI) (%)	Formation resistivity (RT) (Ω-m)	Permeability (k) (mD)
Minimum	77.52	76.28	2.30	11.82	10.68	10.63
Maximum	97.40	126.12	2.51	20.38	39.70	138.21
Median	92.18	98.40	2.37	16.53	20.44	71.21
Mean	91.13	98.30	2.37	16.56	21.26	70.74
STD	4.02	9.29	0.039	1.46	4.89	26.42
STE	0.25	0.58	0.002	0.09	0.30	1.63
Variance	16.23	86.64	0.0015	2.14	23.97	698.41

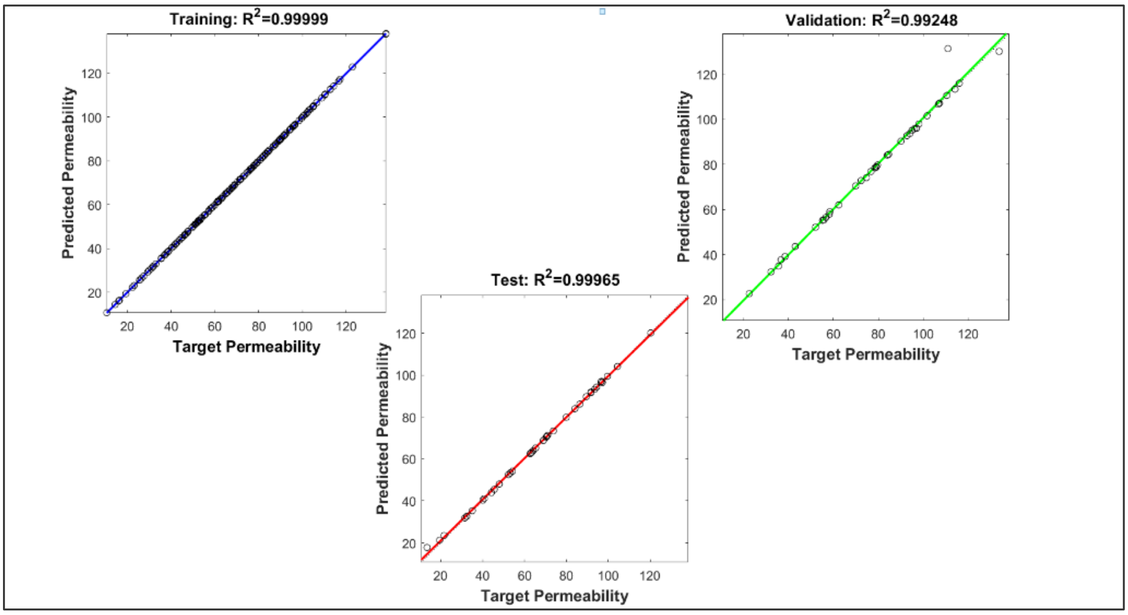

Fig. 2: ANN model performance of training, testing and validation with Levenberg- Marquardt algorithm.

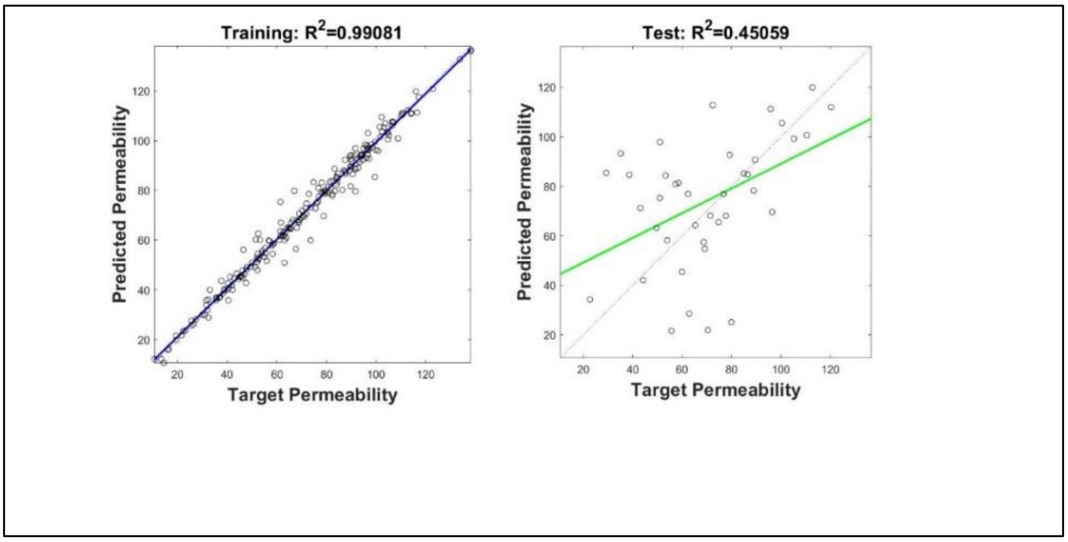

Fig. 3: ANN model performance of training and testing for Bayesian regularization algorithm

Table 2

Model evaluation of training algorithms used in the ANN model.

Type of training algorithm	No. of epoch	R^2 Train (Test)	RMSE Train (Test)	AAPE Train (Test)	MAPE Train (Test)
LM-ANN	41	0.9957 (0.8990)	0.0417 (0.1606)	0.3625 (6.5371)	18.52 (26.3361)
BR-ANN	41	0.9047 (0.6755)	0.3250 (1.1220)	8.8690 (10.9260)	253.5968 (100.6753)

The combined curve demonstrates a strong relationship between the output and the target considering the R^2 value. According to Figure 2, the Levenberg-Marquardt training process offers the appropriate match between the output and forecast values of permeability compared to the other MLP-ANN network. An ANN model's validation performance is often measured using metrics such as mean squared error (MSE), and R^2. These metrics show how effectively the model generalizes to new, previously unseen data and can be used to compare multiple models or modifications of the same model. An excellent outcome is provided by the Levenberg-Marquardt algorithm, which has an R^2 of 0.9957 and an MSE of 2.84 compared to the Bayesian regularization value of R^2 and MSE is 0.9047 and 62.78 respectively.

Despite having nearly identical statistical parameter values with low MSE values, the BR-ANN model takes longer to compute than the LM-ANN model. The LM-ANN based model provide result of low AAPE of 0.3625 and 6.5371 for training and testing schemes respectively. The Levenberg-Marquardt algorithm is the selected model because of having low R^2 value of 0.9957 and 0.9047 for training and testing respectively. Table 2 and Figure 2 support the statement that the LM-ANN is the preferable model than BR-ANN algorithm-based models.

4. Conclusion

This paper focuses on developing the ANN-based model while predicting rock permeability using log data. The study's findings show that an ANN-based model can be useful for predicting rock permeability of hydrocarbon reservoir. In this study, ANN-based model performance has been analyzed by using value of statistical parameters including RMSE, AAPE, MAPE and R^2. The LM-ANN model RMSE and MSE value is 0.9957 and 2.84 while the other algorithm used in this study (BR-ANN) has value of 0.9047 & 62.78. The average percentage relative error (AAPE) for training is 0.3625, while the testing data is 6.5371. These results show the acceptance of proposed model. The results demonstrated that the created model with LM-ANN could estimate rock permeability properly depending on input factors such as rock type, porosity, and clay concentration. Experiment with different ANN structure, different activation functions, and different training algorithm that can help in identifying the model's ideal variables. Performance of a sensitivity analysis of predictor variables can help to determine how input factors affect the model's predictions. This can help identify critical factors and potential areas for improvement or further investigation.

Authorship Contribution Statement

Mohammad Islam Miah: Conceptualization, Data curation, Supervision, Formal analysis, Writing–review & editing. Abrar Bin Enayet: Investigation, Methodology, Software, Writing- original draft. Mafruha Akhter Ovi: Visualization, Writing – review & editing.

References

[1] Tahmasebi, P., & Hezarkhani, A. (2012). A fast and independent architecture of artificial neural network for permeability prediction. Journal of Petroleum Science and Engineering, 86, 118-126.

[2] Rezaee, M. R., Ilkhchi, A. K., & Barabadi, A. (2007). Prediction of shear wave velocity from petrophysical data utilizing intelligent systems: An example from a sandstone reservoir of Carnarvon Basin, Australia. Journal of Petroleum Science and Engineering, 55(3-4), 201-212.

[3] Chen, G., Meng, Y., Huan, J., Wang, Y., Xiao, L., Zhang, L., & Feng, D. (2022). A new predrilling reservoir permeability prediction model and its application. Journal of Petroleum Science and Engineering, 210, 110086.

[4] Miah, M. I., & Abir, M. A. N. (2022). Hybrid Connectionist Models to Investigate the Effects on Petrophysical Variables for Permeability Prediction. In Intelligent Computing & Optimization: Proceedings of the 4th IICO2021, (pp. 647-656). Springer International Publishing.

[5] Barzegar, R., Sattarpour, M., Nikudel, M. R., & Moghaddam, A. A. (2016). Comparative evaluation of artificial intelligence models for prediction of uniaxial compressive strength of travertine rocks, case study: Azarshahr area, NW Iran. Modeling Earth Systems and Environment, 2(2), 1-13.

[6] Miah, M. I. (2020). Predictive models and feature ranking in reservoir geomechanics: A critical review and research guidelines. Journal of Natural Gas Science and Engineering, 82, 103493.