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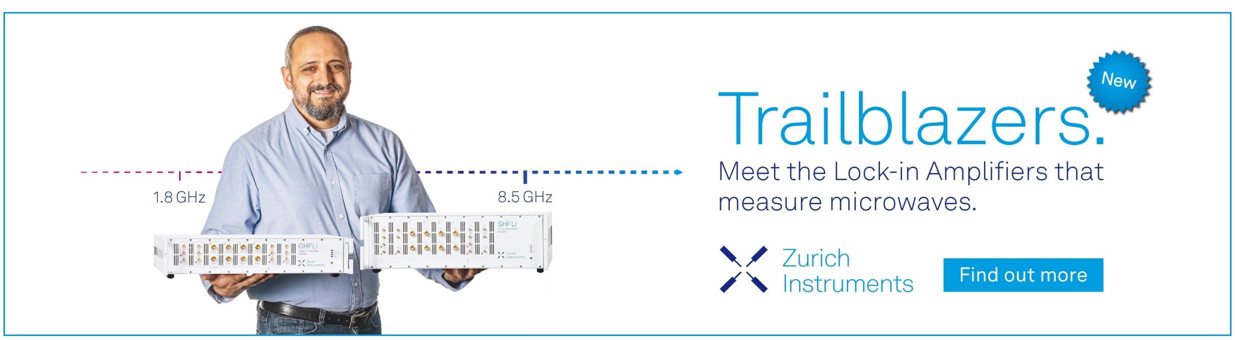

Total Organic Carbon (TOC) Prediction Using Machine Learning Methods Based on Well Logs Data

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Abstract. Evaluation of a source rock can use several parameters, one of which is the determination of Total Organic Carbon (TOC). The determination of TOC is a method that relies on expensive laboratory testing and is limited by the availability of rock samples. TOC prediction using well log data can be performed on most oil and gas wells, which can provide information regarding organic content and continuous data recording. So, the prediction method using well log data is an ideal method to determine TOC in source rock units. The purpose of this study is to predict the TOC value using a well log by applying the machine learning method with the Multi-Layer Perceptron Artificial Neural Network (ANN) technique. Eighteen data samples from the Talang Akar Formation were used for training and testing the MLP-ANN model. The well log data used to predict TOC are density log (RHOB), transit time (DT), deep resistivity (ILD), gamma-rays (GR), and neutron porosity (NPHI), and produce a high correlation (R^2 0.87 and the mean absolute percentage error (AAPE) 10%) against the resulting MLP-ANN model. The TOC prediction technique carried out will help a geophysicist (geophysicist and reservoir geology) to evaluate the source rock in an oil and gas field without the need to have a large number of source rock sample data.

INTRODUCTION

Shale gas is an alternative resource to conventional natural gas and has become a popular resource in oil exploration and production, especially in recent years. This type of resource makes the evaluation of source rock very important to do. Especially in shale, evaluation related to the quality and potential of hydrocarbons is very important and the Total Organic Carbon (TOC) content is the most important parameter. In general, the TOC values contained in the source rock are measured directly in the laboratory, but this method is very limited because it depends on the number of core samples and the cost of analysis is very expensive. The source rock has a specific response to rock density (RHOB), transit time (DT), gamma-rays (GR), and resistivity values (ILD/LLD), which makes it useful for distinguishing surrounding rocks [1-4]. So that the well log data can be used for the evaluation of the source rock. TOC prediction using well logs can provide continuous evaluation of the source rock or target formation in the borehole.

Previous researchers such as Fertl and Rieke (1980) [5] and Fertl and Chilingar (1988) [6] have initiated a TOC evaluation technique using well log data, namely utilizing GR spectral logs in identifying organic-rich rocks and looking for relationships between total GR ratios, U, and Th-K. Schmoker and Hester (1983) [7] introduced the log RHOB approach in estimating TOC, and it is often used in shales. Mendelzon and Toksoz (1985) [8] have another point of view, namely by using a multivariate method to find a quantitative relationship between well log data and TOC values based on core samples which produce a regression equation with a high correlation coefficient. Carpentier et al. (1991) [9] had the idea of obtaining an estimate of the TOC content in situ based on the transit time of the sonic log (DT) and resistivity using the CARBOLOG method. The method explains that the shale layer rich in organic material has the characteristics of a long transit value and a high resistivity value. However, it requires TOC (core)

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data for calibration [10]. In addition, the DlogR technique was introduced by Passey et al. (1990) [11] which performed an overlay between the porosity log and the resistivity log to predict the TOC value qualitatively and quantitatively. Kamali and Mirshady (2004) [12] have a new idea in determining the TOC value in shale gas by combining the DlogR method and the Neuro-Fuzzy approach [13]. Passey et al. (2010) [14] then updated their findings by including organic-rich rocks that have a high maturity level as a calibration of the DlogR method and identify source rocks that have a good maturity level in shale gas. Integration between DlogR and neural networks in predicting TOC values was carried out by Bakhtiar et al. (2011) [4] to evaluate the source rock. So the DlogR technique is a well log-based technique that is most often used in evaluating TOC values. However, the DlogR technique has problems such as having to choose a baseline manually, the TOC value is quite difficult to determine and regionally has variations. Artificial intelligence systems and neural networks have carried out the prediction of TOC, especially in recent years. Kadkhodaie-Ilkhchi et al. (2009) [15] applied machine learning to predict TOC values from well log data or rock physics. An artificial intelligence method based on well log data was also applied by Khoshnoodkia et al. (2011) [16] to determine the TOC value of the Gadvan formation. Some things that must be considered in using neural networks in TOC calculations are that the calculations involve many parameters and are very complex, so choosing the relevant parameters is very important and generally complicated.

TOC predictions in most cases were obtained by reconstructing the multiregression method. In recent years, several direct TOC estimation techniques have been introduced using well logs (geochemical logs). This technique can display TOC values directly without complex calculations [17-18] but is only found in certain wells.

Machine learning (ML) and artificial intelligence (AI) are techniques that combine computing and human intelligence to obtain precise solutions to complex and nonlinear problems [19]. Several journals in the last two decades have published many articles related to AI and ML for regression correlation and multivariable classification. The development of computational techniques in the field of reservoir characterization, utilizing AI-based correlation techniques [20-21], as well as in engineering, and geomechanics. This correlation is also applied to the field of petroleum geochemistry which can be seen in the work of Rahaman and Vasant (2020) [22]. In recent years, a multi-layer perceptron (MLP) artificial neural network (ANN) has been used to predict porosity values by researchers [23]; researchers have also used MLP-ANN to predict permeability [24].

Based on the previous explanation, the prediction of TOC values in shale rich in organic material can be done using well log data. However, the model obtained does not yet have high accuracy unless it has a lot of core data in predicting TOC. Thus, this study aims to predict TOC using well logs in Talang Akar organic material-rich shales using the MLP-ANN technique. This research will utilize ML and evolutionary algorithms to obtain an optimal model.

METHODS

Several conventional well logs such as RHOB, DT, ILD, GR, and NPHI, were used to predict the TOC value, especially in the Talang Akar shale, which had previously been trained on the MLP-ANN model. Some of these well logs were used to estimate TOC (MLP-ANN model training) because of their proven high accuracy (R^2 more than 0.6), especially in evaluating source rock. The target zone has 18 core data samples and log data. The well log data that will be used to reconstruct the model in the target zone can be seen in Figure 1 (columns 2-5). The process of optimizing the ML model is continued until the prediction TOC matches the core rock data as reflected by the minimum AAPE average value and the highest correlation coefficient (R^2). The trained and optimized ML model was then validated using another formation in the same well (Gumai organic material-rich shale).

The well log data selected for the TOC value prediction training were analyzed. The analysis is in the form of looking at the comparison between conventional well logs and TOC values measured in the laboratory. The data used to train the ML model, TOC, were highly correlated with RHOB, while moderately associated with DT, ILD, GR, and NPHI.

The five well logs were selected based on their relationship to the TOC values in the core rock, and the five logs will also be used to train the ML model. For example, the estimated ILD of the measured value is influenced by the richness of kerogen in the source rock [25]; DT decreased with increasing TOC [26]; GR is widely used by several researchers in predicting TOC [27]; the more kerogen increases, the RHOB decreases; and NPHI are sensitive to the presence of organic matter even in small amounts and must be corrected for inorganic matter to find out [11]. The explanation above illustrates that the five well logs can be used to develop the TOC model in this research.

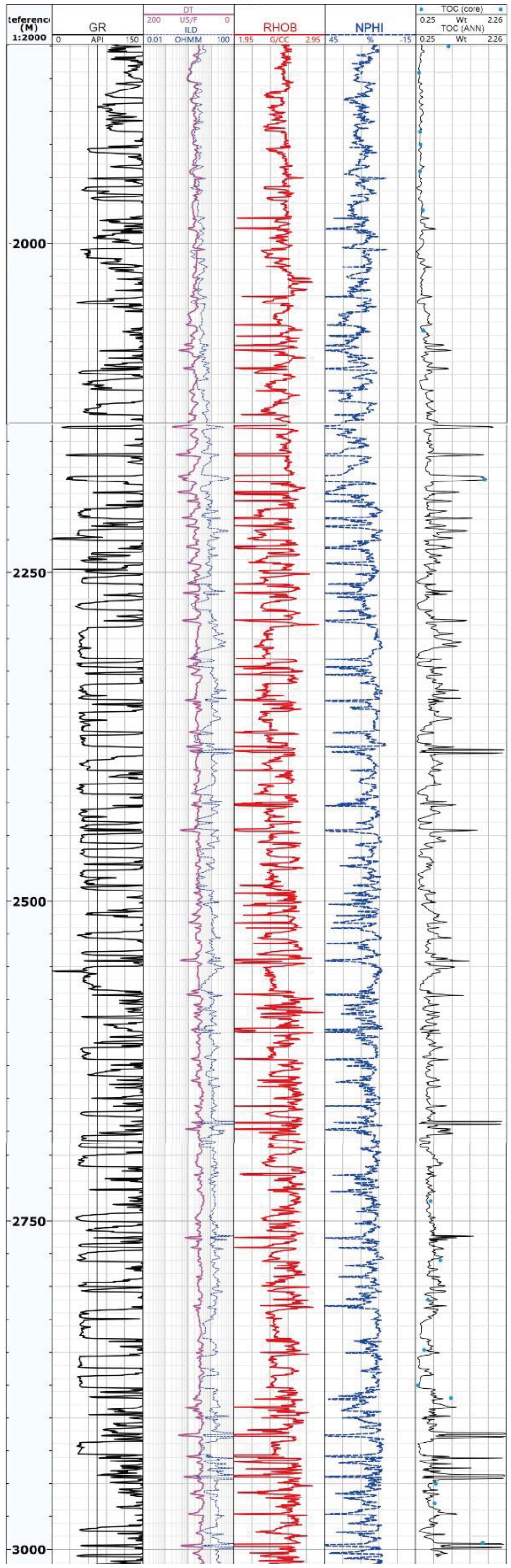

FIGURE 1. Some well log data on the Talang Akar shale formation used to reconstruct the ML model (columns 2-5, start from left) and TOC MLP-ANN prediction compare versus TOC core (column 6).

Principles of MLP-ANN

Multilayer Perceptron (MLP) is a popular supervised learning technique in ANN whose architecture has been used for several forecasting problems in the literature [24]. It is a distributed mathematical model inspired by the behavior of the human brain and nervous system. MLP consists of three layers; input layer, hidden layer, and output layer. The hidden layer may have one or more activation functions [28]. The input for this research is five conventional well logs, while the output is Total Organic Carbon. Figure 2 shows a schematic diagram of the MLP-ANN and the respective neural network architecture.

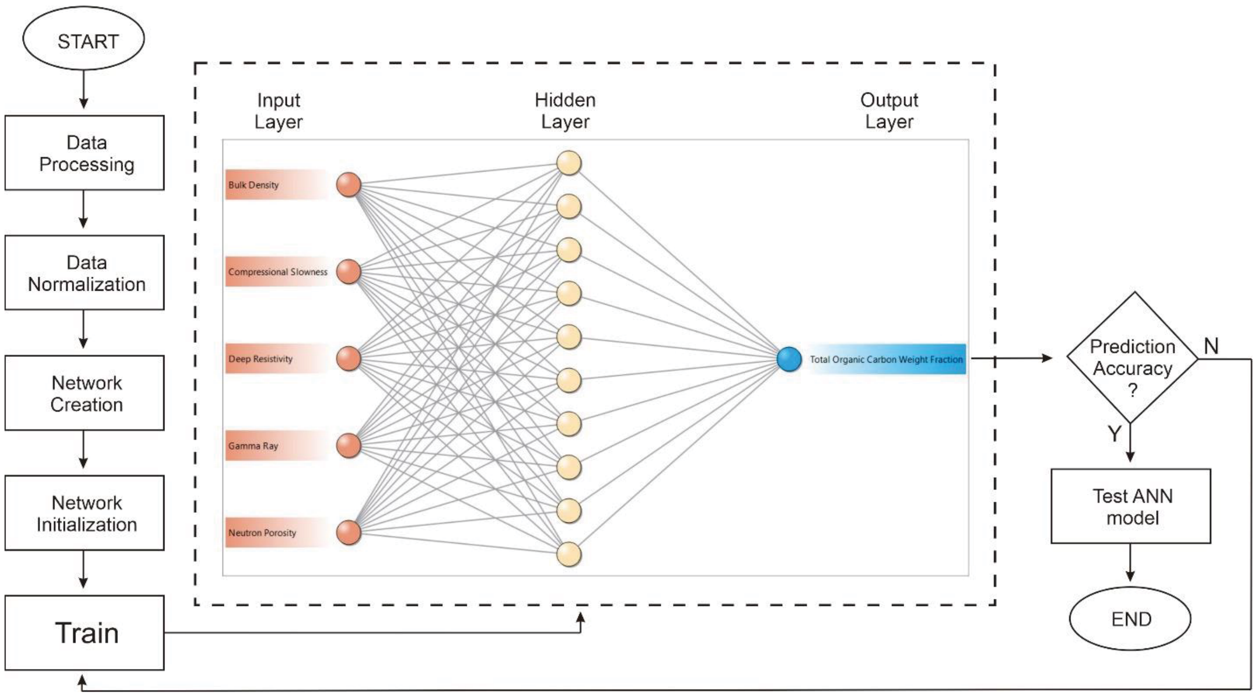

FIGURE 2. The schematic diagram for MLP-ANN.

RESULTS AND DISCUSSION

Figure 1 shows that the MLP-ANN model predicts TOC content with high accuracy with R^2 0.87 and AAPE 10.0% (after validation). Another data set from the same well was used to test the MLP-ANN model using invisible data. TOC values range from 0.3-1.8 Wt%, while RHOB values range from 2.0-2.8 g/cc, and DT values range from 49-124 us/ft. ILD values range from 8-171 ohm.m, then GR values range from 31-173 ^{o}API, and NPHI ranges from 2 to 45%. The test interval zone is the same as the training interval. In Figure 3 it can be seen that the TOC prediction using the MLP-ANN model produces high accuracy (R^2 0.98), especially in the training process. After validation, the MLP-ANN model from several well log data can be concluded that it is feasible to be used to predict TOC. 15% of the data sample is used randomly to assess the generalizability of the reconstructed network so that it is not overfitting. The lowest mean squared error (MSE) shown in Figure 4 is 49, this value indicates the optimal number of iterations. The results obtained at the test stage were analyzed for each evaluation. Network training and performance testing should be appropriate. If only the training stage is seen (eg has a high correlation), then the overfitting effect needs to be considered, and the model is not feasible to choose.

CONCLUSION

In this study, the well log data-based ML model based on the MLP-ANN technique was reconstructed to predict the TOC value, in particular several well logs such as resistivity logs, gamma-rays, transit time, neutron porosity, and density. The model was reconstructed and tested using data on the Talang Akar shale interval zone, which was then validated using data on the Gumai organic material-rich shale interval. The ML model shows a high correlation, both in the Talang Akar and Gumai organic material-rich shale intervals. The model is adequate for estimating TOC using the well logs used in this study (R^2 0.87 and AAPE 10%).

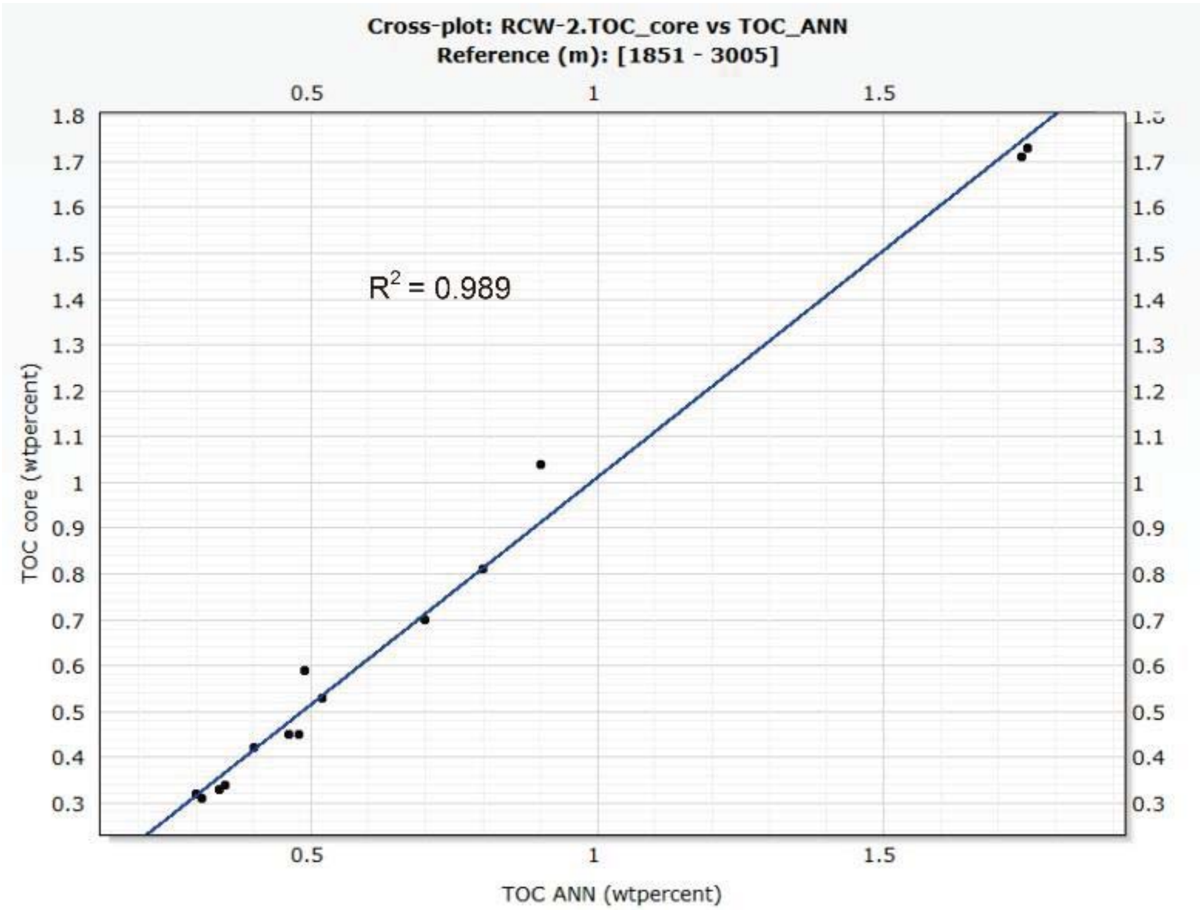

FIGURE 3. The correlation coefficient for the prediction of TOC values at the training stage (18 samples) used the MLP-ANN technique.

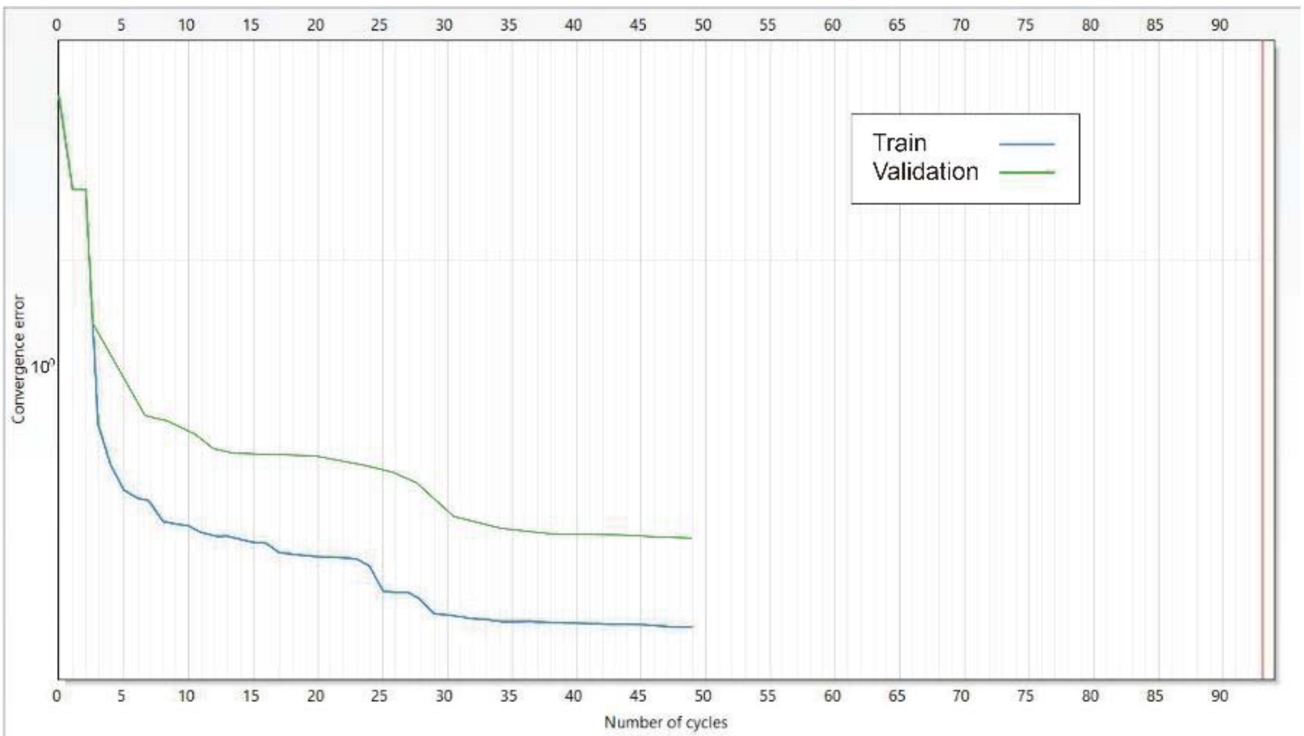

FIGURE 4. Training and validation errors.

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