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Employing well logging data to generate a synthetic model of the formation rock density applying the ANN approach

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ABSTRACT

The first challenge in conducting seismic surveys, petrophysical evaluations, assessments of the mechanical rock characteristics, and stress analyses in oil and gas fields is to ascertain the bulk density. It is a physical characteristic of rocks assessed in the laboratory on rock specimens or acquired from oil and gas wells through logging equipment. However, the rock samples are difficult to extract along the interested intervals to construct a rock density profile due to the cost and time-consuming. Additionally, most of the logging tools, especially the bulk density log, are usually not implemented in the shallow depth of the drilled borehole sections. Therefore, this study was motivated to synthesize bulk density from other well-logged data, i.e., gamma ray, neutron porosity, and sonic compressional waves. Two mathematical models of bulk density were created exploiting a dataset from a single well, employing artificial neural networks (ANNs) and multiple regression analysis (MRA) as predictive techniques. The outcomes indicated that the ANNs and MRA are comparable in predicting bulk density; however, the higher determination coefficient (0.92) and smaller root mean square error (0.063) of the ANNs illustrate superior accuracy compared to the MRA. Eventually, this study offers efficient and cost-saving approaches that combine traditional well logs to synthesize the rock density.

KEYWORDS

Artificial neural network; multiple regression analysis; bulk density, well logging

I. INTRODUCTION

The complex attributes of oil and gas reserves present a challenge in the petroleum industry. The absence of reliable information predics reservoir parameters complicated (Bukar et al., 2019). The bulk density log is a kind of well logging tool that shows how dense the rocks are around a borehole. In other words, the density log contributes to distinguishing various lithologies along the geological column. Each rock type has a distinct density, and density logs can differentiate among them (Ghawar et al., 2021). One of the most significant variables in determining rock characteristics is rock bulk density. Several estimation techniques depend on rock parameters, which are intimately related to calculating formation rock density; these include predicting sand production and evaluating wellbore stability (Hadi et al., 2020).

Throughout the various phases of the petroleum industry, from discovery to exploitation, bulk density is regarded as a crucial factor because it provides important insights into the geomechanical and physical characteristics of rock formations that may contain gas or oil reserves. Moreover, petrophysical logs are highly accessible and practical tools for acquiring information concerning these characteristics (Issa, Hadi, et al., 2025). This technique offers continual data regarding formations, in contrast to the information derived from laboratory analyses of core specimens. In addition, the expenses associated with executing petrophysical logging in wells are considerably lower than those required for performing laboratory tests (Issa et al., 2024). According to various well logs, the bulk density log is crucial, as it offers essential information for different areas of study, including reservoir characterization (Eberli et al., 2003), geophysics (Phadke et al., 2000; Waluyo et al., 1995), and geomechanics (Asoodeh & Bagheripour, 2014; Chang et al., 2006; Eaton, 1975). As for the geomechanical parameters, including in-situ stresses (vertical stress and maximum and minimum horizontal stresses), formation pore pressure, and mechanical rock properties (strength and elastic rock parameters). Accurately identifying these characteristics is critical for

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developing and implementing hydrocarbon extraction, while incorrect evaluation of these properties may lead to flawed decision-making and inappropriate field development procedures (Issa et al., 2023). Moreover, to carry out any activity, it is necessary to develop a consistent profile of the geomechanical properties. Nevertheless, the process of recovering rock samples from various depths within the reservoir and carrying out laboratory testing is costly and time-consuming. To overcome these challenges, bulk density in conjunction with sonic logs is occasionally utilized to assess these properties (Issa, Issa, et al., 2025).

A wide variety of research efforts have recently been published in the scientific literature, seeking to determine the relationship between bulk density and diverse petrophysical properties of rocks. It is important to note that many factors affect bulk density, not all of which are included in empirical relations. Furthermore, these correlations applay solely to a specific location or lithological type (e.g., Castagna et al., 1993, Brocher, 2005, and Gardner et al., 1974). Additionally, many researchers have employed machine learning techniques, such as artificial neural networks (ANNs), to develop various models that address the complex issues associated with the petroleum industry. These models are applicable at diverse stages, i.e., exploration (e.g., Ross, 2017), drilling (e.g., Elzenary et al., 2018), production (e.g., Tariq, 2018), and reservoir (e.g., Hamam & Ertekin, 2018) in addition to a synthetic model of well logs based on traditional well logging data. Finally, many of these investigations have substantially advanced the petroleum industry by developing prediction models that address challenges arising from missing or discontinuous data (Akinnikawe et al., 2018; Hussein et al., 2025; Long et al., 2016).

It is noteworthy that the density log measurements of the most drilled borehole sections are not recorded in shallow depths. Thus, the present study was motivated and conducted based on data extracted from oil wells located in southern Iraq to synthesize the rock density for the unlogged intervals in the area of interest, depending on the conventional well logging data. Robust and straightforward mathematical models, namely multiple regression analysis and artificial neural networks, were established using data derived from traditional wireline logs to generate synthetic bulk density for different formation lithologies. Finally, the predictive ability of each model was assessed using two distinct metrics: the coefficient of determination (R^2) and the root mean square error (RMSE).

II. Materials and Methods

A. *Area of Study*

The current study was conducted in an oilfield located in southern Iraq to estimate bulk density by utilizing well logging data (DTc, GR, and NPHI). The research employed two mathematical models: Artificial Neural Networks (ANN) and Multiple Regression Analysis (MRA). Data from two wells were used in this study; the first well served to construct the models, while the second well was utilized to validate the developed models. The geological layers of the southern Iraq fields consist of a complex sequence of sedimentary strata that extend from the Jurassic to the Cretaceous and Tertiary periods. These sedimentary deposits include various types of rocks, such as sandstone, limestone, and shale (Fig. 1). These formations are essential for the development of geological structures that contain oil and gas. Finally In this investigation, the area of interest was expanded from the surface to a depth of 1800 m, as shown in Fig. 1.

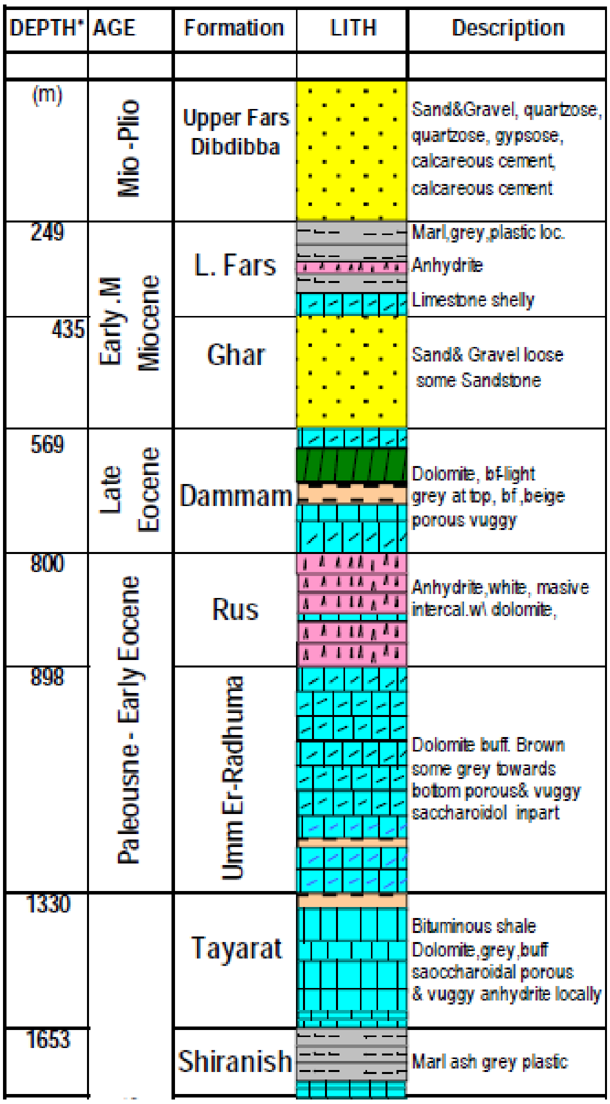


Fig. 1. Illustrate the area of study.

B. *Problem Statement and Methodology*

The missing recording of the bulk density measurements due to the well logging job did not implement a density log for the shallow depths of the drilled borehole sections, or it may be to avoid the borehole problems that are associated with lowering logging tools inside the wellbore. However, the absence of the bulk density measurements can lead a reduction in the accuracy of several applications that are strongly associated with the bulk density measurements, including but not limited to geomechanical applications, i.e., determination of in-situ stresses, pore pressure, stimulation jobs, wellbore stability analysis, and sand production prediction. Thus, several techniques, such as extrapolated methods or empirical correlations based on well logging data, were introduced in the literature that may be used to solve these issues, but these methods have uncertainty; additionally, these correlations are specialized to a specific location or lithological type. Consequently, a field case study in southern Iraq was implemented to propose reliable mathematical models to overcome these challenges. This research employs a methodology (Fig. 2). It effectively utilizes existing databases by applying conventional well log data to generate synthetic bulk density.

Data analysis involves the processes used to extract information from a dataset and then apply it to create models using statistical methods. Its goal is to ensure a logical relationship between the input data and the output function. In this study, well logging data from two wells in southern Iraq were used to achieve the research objectives. As a result, well-logged data, such as sonic compressional wave, gamma ray, and neutron porosity, were analyzed (Fig. 3). These parameters serve as inputs for the developed ANN and MRA models. At the same time, the bulk density is defined as the output. Additionally, the data analysis identified the input parameters that significantly affect the output function, as depicted in Fig. 3.

C. *Artificial Neural Networks (ANNs)*

One form of machine learning model is the artificial neural network, which attempts to mimic the brain's biological neural networks in terms of both structure and function(Anemangely et al., 2019; Gharbi & Mansoori, 2005). The primary objective of ANNs is to tackle complex problems that traditional modelling methods fail to tackle because of the problem's complexity (Liu et al., 2021). In the oil and gas industry, artificial neural networks are currently employed to address several difficulties related to the enhancement of oil and gas field operations that extend from the exploration phase to the abandonment phase (Alkinani, 2019). Generally, the neural network consists of several key components, including the input layer, weights, transfer or activation function, hidden layer, and output layer. Each layer connects to the next through neurons. The model features one hidden layer containing three neurons. The transfer function, also known as the activation function, plays a crucial role in controlling the processes within each model neuron. The tangent sigmoid function was selected as the nonlinear transfer function for this study because it can limit the potential output from a neuron to approximately [-1, 1]. This capability is achieved by differentiating the outputs for both the hidden layer and the output layer. In machine learning, various algorithms are utilized, including support vector machines, supervised back-propagation neural networks, and genetic algorithms. This study employed a back-propagation neural network (BPNN) as a supervised learning algorithm, which is particularly effective at addressing complex problems that may be challenging for traditional machine learning techniques to solve. The fundamental basis of a Backpropagation Neural Network (BPNN) is to gradually minimize the model's total error, ideally reaching zero during the learning process. This is achieved by iterating and readjusting the connection weights among the input, hidden, and output layers of the network. One type of BPNN algorithm is the Levenberg-Marquardt (LM) algorithm. This algorithm is advantageous because it is generally faster and more reliable than other BPNN algorithms, allowing it to effectively manage situations where the relationship between input and output variables is nonlinear. Before presenting the input-output data to the Levenberg Marquardt (LM)-Artificial Neural Network (ANN) model, all input data (DTc, GR, and NPHI) were normalized within the range of [-1, 1] using Eq. 1. In this equation, X_{norm} represents the normalized value of the input parameter, X denotes the input parameter, and X_{min} and X_{max} indicate the minimum and maximum values of the input parameters, respectively. This normalization step enhanced training stability and accelerated the convergence process. In this investigation, early stopping was implemented to automatically halt training when there was no significant improvement in model accuracy after several consecutive iterations, which helps to prevent overfitting. Additionally, training parameters, including the initial damping factor, were configured to permit adaptive adjustments throughout the training process. Regarding hyperparameter optimization, the selection of the number of neurons was based on trial and error. Configurations ranging from 1 to 10 neurons were evaluated, and it was found that three neurons yielded the optimal results (Fig. 4).

$$X_{norm} = 2\left(\frac{X-X_{min}}{X_{max}-X_{min}}\right) - 1 \tag{1}$$

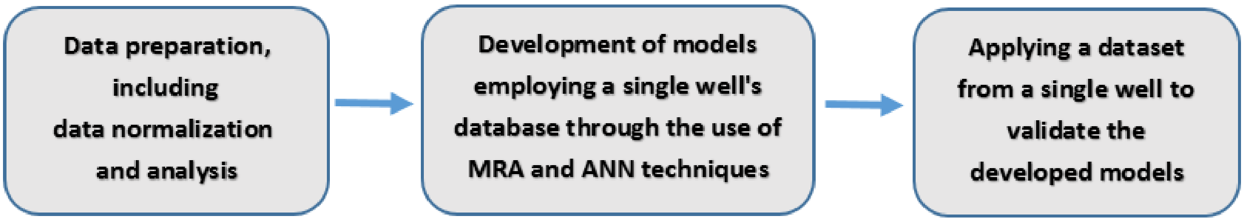
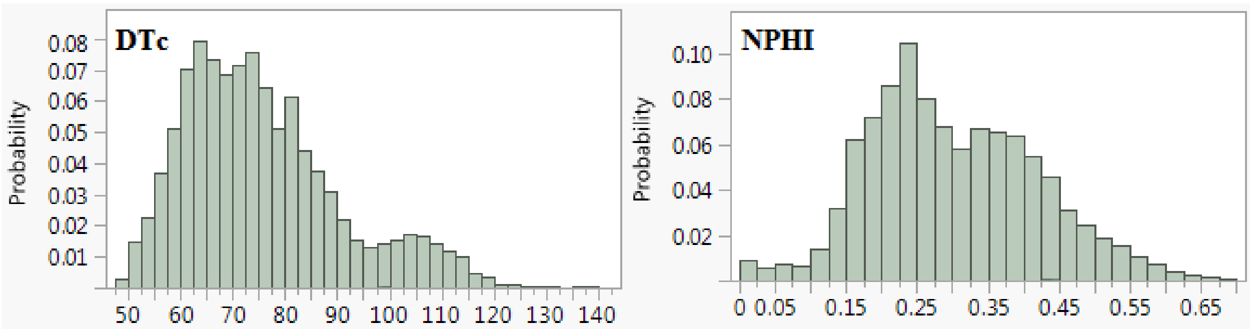
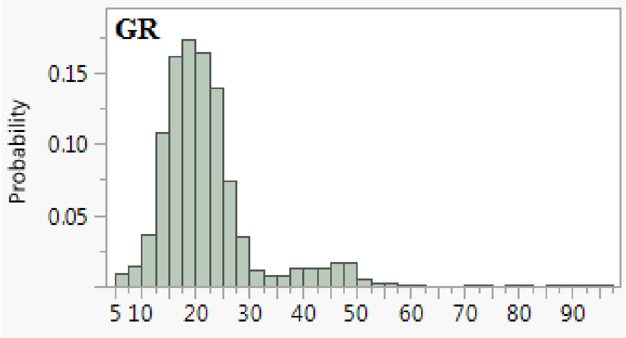


Fig. 2. Flowchart of the research methodology





Statistical Summary	DTc	GR	NPHI
Mean	75.439832	21.66826	0.2998341
Std Dev	14.870171	8.6550653	0.1167227
Std Err Mean	0.1667756	0.0970704	0.0013091
Upper 95% Mean	75.766756	21.858543	0.3024003
Lower 95% Mean	75.112908	21.477977	0.2972679
N	7950	7950	7950

Fig. 3. Shows the statistical analyses of the input data.

In this study, a fully linked three-layer neural network architecture was used to execute the procedure of the developed models, and three parameters, i.e., sonic compressional waves (DTc), gamma ray (GR), and neutron porosity (NPHI), influencing bulk density measurements (RHOB) were included. There are three layers to the network design depicted in Fig. 4: input, hidden, and output. Simple processing neurons related across layers provide full connectivity between them. Moreover, in the hidden layer, three neurons were specifically chosen to guarantee accessibility (Fig. 4). Finally, the development of the ANN model typically involves three steps, i.e., training, validation, and testing. As for the training, the fundamental operation of an artificial neural network is the training process. It enhances the efficiency of the ANN by assessing the output value concerning the target value within the ANN model. The backpropagation neural network (BPNN) approach, which employs the Levenberg-Marquardt methodology, was introduced in the present study (Fig. 4). The BPNN algorithm was selected due to its capability to iterate and modify the connection weights for the network's input, hidden, and output layers, typically yielding acceptable outcomes. Regarding the validation, the training dataset undergoes cross-validation in order to prevent over-fitting in the ANN model. Randomly, 70% of the raw datasets were set aside for training purposes, and 30% were set aside for validation purposes. This split was done to facilitate the research. Finally, the last stage in evaluating the ANN model's performance during the learning process is the testing method. A rise in the testing operation's error rate will result in the termination of the training operation.

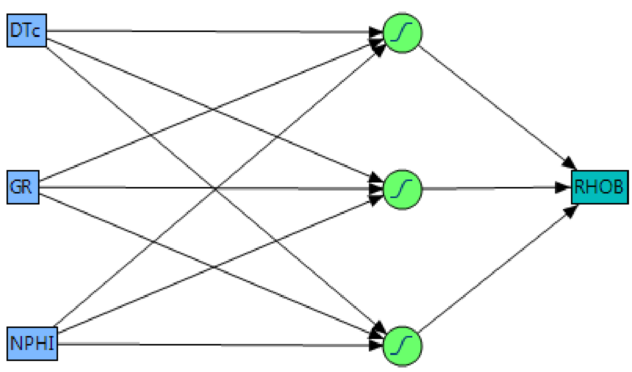


Fig. 4. The ANN architecture for the development of bulk density

D. Multiple Regression Analysis (MRA)

Regression analysis can be performed on datasets gathered within the reservoir, for instance, well logging or core sample measurements, in order to simulate the output function. Regression analysis, either simple or more complicated (also called multiple regression analysis), can be used (Issa & Hadi, 2021). An important statistical technique for determining the output function with several independent variables is the multi regression analysis. The sonic compressional wave (DTc), gamma-ray (GR), and neutron porosity (NPHI) are the independent parameters in this investigation. On the other hand, the bulk density (RHOB) was the dependent variable, which utilized the MRA.

III. Results and Discussions

According to the scientific literature, many studies have been published to determine the relationship between bulk density and various petrophysical parameters of rocks. However, empirical relationships often fail to account for many factors influencing bulk density. Additionally, these relationships are typically specific to a particular locality or lithological type. This study was conducted to develop robust mathematical models (MRA and ANN) tailored explicitly for the southern Iraqi oilfields. The aim is to address the issue of absent bulk density measurements, which arise from the lack of density logging in the shallow depths of drilled borehole sections. Furthermore, the study utilizes the ANN technique, which significantly diverges from existing literature by incorporating variables associated with the model's input layer (weights and biases), the hidden layer, and the output layer.

A. Model Development Employing MRA

A statistical analysis was conducted to ascertain the correlation and reduction of log characteristics. Partial regression leverage plots (Fig. 5) were employed to assess the reliability of the multiple regression model and to illustrate the individual impact of each predictor. These diagnostic plots facilitate the isolation of the impacts of each independent variable (DTc, GR, and NPHI) on the dependent variable (RHOB) while accounting for the other factors' effects. In each plot (**Fig.** 5a, b, and c), the horizontal axis represents the residuals of the chosen independent variable after removing the effects of the other two predictors. The vertical axis represents the residuals of the dependent variable (rock bulk density) after adjusting for the same other factors. Additionally, the slope of the fitted line in each graph directly corresponds to the partial regression coefficient of the associated variable. This graphical method elucidates the distinct contribution of each predictor to the model, identifies influential observations or outliers, and reveals potential multicollinearity concerns, if present. Moreover, to examine the correlation and reduction of well-logging characteristics, the P-value has been taken into consideration in the present investigation. In summary, bulk density is significantly influenced by each physical parameter when the P-value is below 0.0001, demonstrating the model's accuracy in forecasting bulk density. Fig. 5 shows how each physical characteristic affects the bulk density and the corresponding P-values. The blue line shows the mean output attribute, which is bulk density. Conversely, a 5% confidence range is shown by the red line. Furthermore, significant deviations of the mean bulk density from the confidence range make these physical characteristics crucial in the bulk density computation. As a result of the DTc and NPHI (Fig. 5a and Fig. 5c) creating high angles, the P-values for both of them are below 0.0001. Thus, these properties have a significant influence on the bulk density function. In contrast to the GR property (Fig. 5b), its P-value is equal to 0.0003; hence, it has the minimum effect on the bulk density. The constructed model (Fig. 5d) to predict the bulk density using multiple regression analysis is illustrated in Eq. 2. Ultimately, the model's statistical validity is evidenced by a P-value below 0.0001, highlighting the superior prediction accuracy of MRA in estimating formation bulk density using well logging data. The findings validated that each variable exerted a significant and distinct influence on density prediction. No indications of significant multicollinearity or concerning leverage points were detected. Consequently, the regression coefficients obtained from the model are deemed statistically robust and dependable. Additionally, the given model exhibits a determination coefficient (R^2) of 0.88 and the root mean squared error (RMSE) of 0.0751.

$$RHOB = 3.0562 - 0.00317\, DTc - 0.00036\, GR - 1.3877\, NPHI \quad (2)$$

Where, RHOB is the formation bulk density (gm/cc), DTc is the compression sonic wave (us/ft), GR is the gamma ray (gAPI), and the NPHI is the neutron porosity (fraction).

B. Model Development Employing ANN

A three-layer fully connected neural network structure was used to construct the models in this investigation. Three variables that affect bulk density measurements were incorporated into this structure. These variables are compression sonic wave, gamma-ray, and neutron porosity that make up the input layer. Iterative trial and error was employed during the learning and training processes to choose three neurons for the hidden layer. Then, the network was applied to construct the simulated RHOB model once the training operation had been finished.

Fig. 6 presents cross plots that depict the comparison between the actual and forecasted bulk density for both training and validation datasets. According to the performance metrics (R^2 and RMSE), the results indicated that the values of R^2 and RMSE are 0.92 and 0.063, respectively, for the training datasets. In contrast, they are 0.90 and 0.069, respectively, for the validation datasets.

Concerning the results shown above, when comparing the two models (MRA and ANN) for bulk density forecasting, the ANN model is more conservative than the MRA model. In other words, this conservative characteristic arises from the ANN's nonlinear learning capacity, which allows it to capture complex relations without excessively amplifying noise or fluctuations that might mislead simpler models like MRA. In contrast, the MRA model is defined by its strict linearity and sensitivity to multicollinearity, which can result in larger prediction intervals and greater sensitivity to outliers or variable combinations that diverge from the main data distribution. Thus, characterizing the ANN as more conservative suggests that it generates outputs that are steadier and less extreme, making it less prone to irregular or noisy data points and thereby improving its generalization abilities.

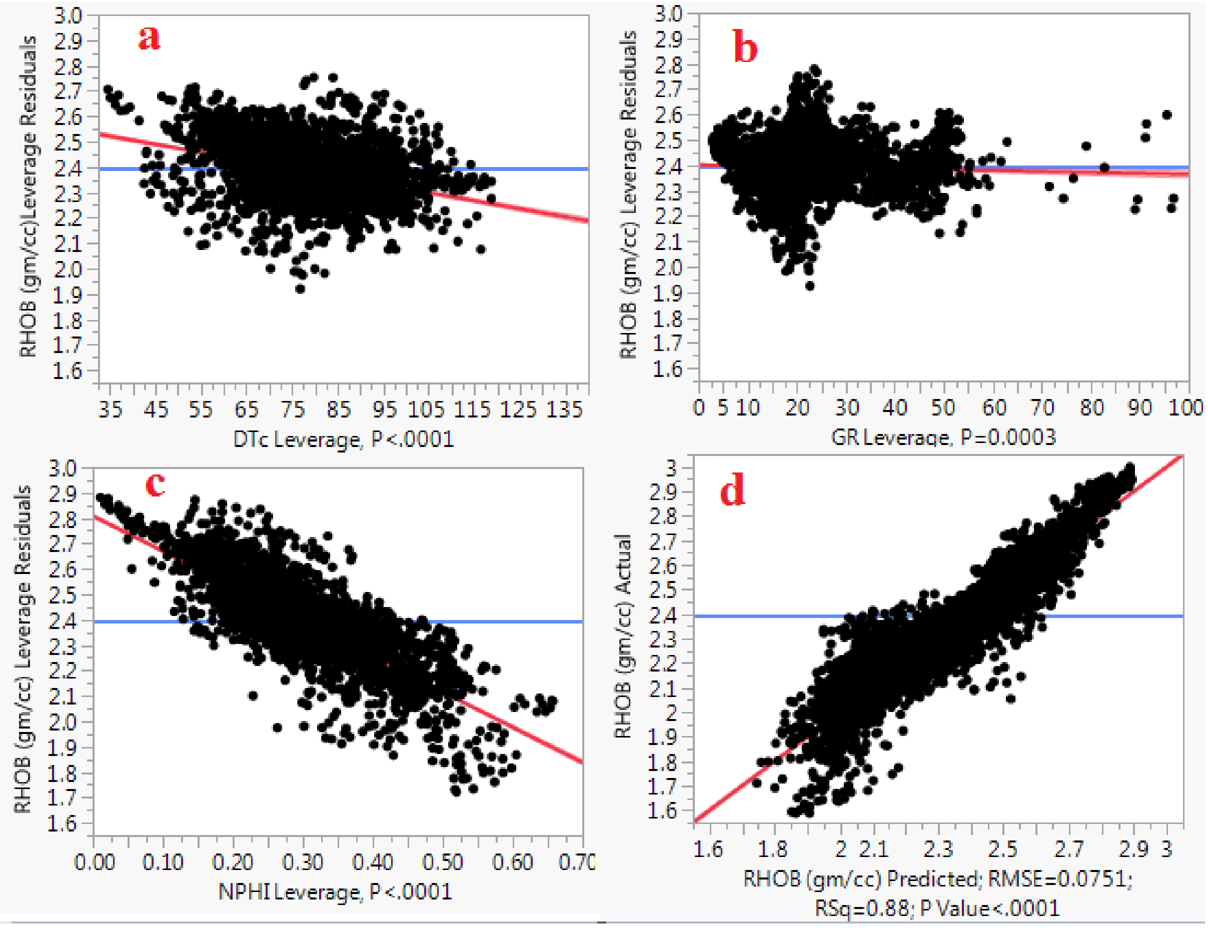


Fig. 5. Illustrates the bulk density model employing MRA

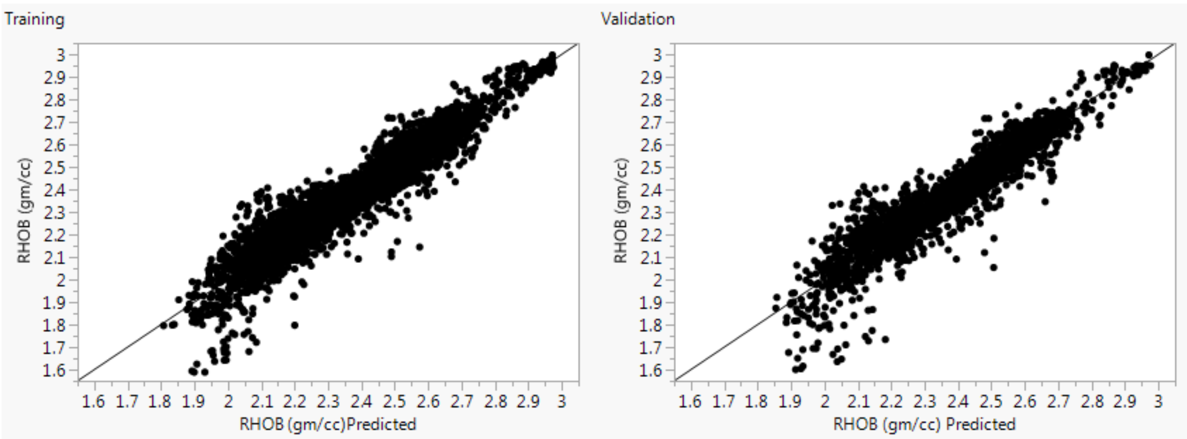


Fig. 6. Shows the actual and predicted bulk density for both training and validation datasets

The developed model for estimating bulk density using ANN (Fig. 6) was completed. Eq. 3 defines this model, which corresponds to the mathematical tangent sigmoid function. Ultimately, Eq. 3, in conjunction with the weights and biases of the ANN model detailed in Table 1, delineates the mathematical formulation of the constructed ANN model for precise prediction of formation bulk density.

$$RHOB_n = \left[\sum_{i=1}^{N} W_{2i}\left(\frac{2}{1+e^{-2(w1_{i,1}*DTc_n+w1_{i,2}*GR_n+w1_{i,3}*NPHI_n+b1_i)}}-1\right)\right]+b_2 \quad (3)$$

C. Validation of Developed Models

To determine the level of reliability of the produced models, they were compared with logging data from one well in the same area. The purpose of this comparison is to determine whether the research actually produces better results. To evaluate the dependability of the newly established models (MRA and ANN) in predicting the bulk density (RHOB), a thorough comparison between the continuous profile of the predicted bulk density by MRA and ANN with the actual reading profile of bulk density that was recovered from other wells has been implemented, as shown in Fig. 7.

The current findings endorse the idea that artificial neural networks and multiple regression analysis are effective methods for evaluating the bulk density. The models that possess have been developed to estimate the bulk density accurately. This precision is attained by integrating three frequently utilized well logs. Moreover, it can be concluded from Fig. 7 that both models (ANN and MRA) are reasonable in estimating the values of formation bulk density. In other words, these models successfully predicted the bulk density due to the satisfactory matching between predicted and actual bulk density as illustrated in the fifth track of Fig. 7. Finally, according to the performance metrics (R^2 and RMSE), the constructed ANN model outperformed the MRA model.

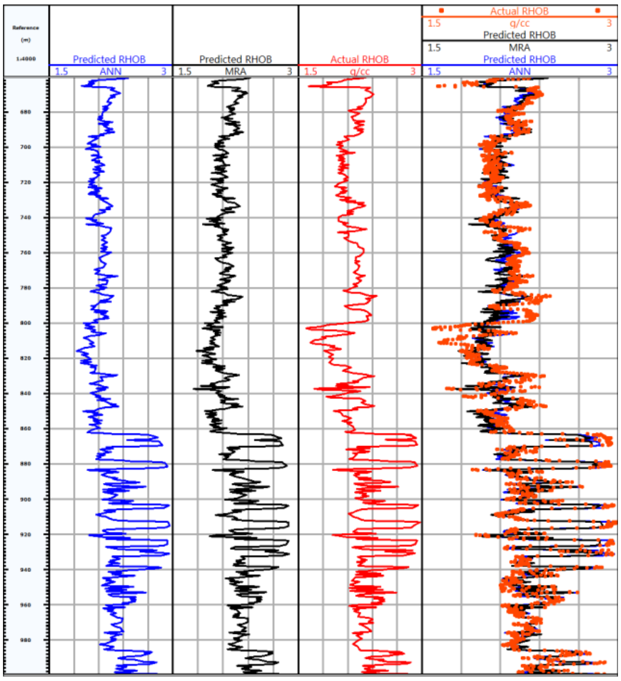


Fig. 7. Shows the validation of developed models with actual bulk density

IV. Conclusions

Formation bulk density is a critical characteristic for formation assessment. This study employed two models (ANN and MRA) to synthesize bulk density when well log data is unavailable or limited. These models were conducted using well-logging data that was obtained from one well located in southern Iraq. Thus, several applications related to bulk density computation can be performed (e.g., wellbore stability analysis, sand production prediction, drilling optimization, stimulation jobs, etc.). The following points briefly summarizes the conclusions of this investigation:

- This work presents straightforward, reliable, and advantageous approaches (ANN and MRA) for ascertaining bulk density through the utilization of well-logging data (DTc, GR, and NPHI).
- Regarding the performance metrics ($R^2$and RMSE), the ANN model exhibited superior performance (R^2 = 0.92 and RMSE = 0.063) compared to the model generated using MRA (R^2 = 0.88 and RMSE = 0.0751). This demonstrates the superiority of artificial neural networks in ascertaining bulk density in comparison to multiple regression analysis.
- The present study proposes a reasonable and adequate ANN model for predicting formation bulk density. It eliminates the need for expensive, commercially available software.
- In addition to demonstrating that well-logging measurements are dependable indicators for creating synthetic bulk density, this study recommends the significance of further investigations, considering the influence of other physical and mechanical rock properties on synthetic formation bulk density.

Finally, the generated synthetic bulk density can be used for diverse lithologies, as compared with studies published in the literature, which are specialized for specified formation lithologies. Moreover, when using these developed models in different regions, it is advisable to modify the data accordingly.

Table 1. Weights and biases of the developed ANN model

Hidden Layer Neurons (i)	Input-Hidden Weight (w_{1_i})			Hidden-Output Weight	Bias	
	DTc	GR	$NPHI$	w_{2_i}	b_{1_i}	$b2$
1	-0.18514	-0.16518	9.1933	0.101174	13.78159	3.511833
2	-0.01049	-0.03005	-0.8815	3.948866	0.673876	
3	-0.01582	-0.04993	0.135461	-2.41774	1.564944	

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