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A comparative study on the prediction of unconfined compressive strength for the sandstone formations based on well logging data

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ABSTRACT

Unconfined Compressive Strength (UCS) is a crucial geomechanical parameter commonly used in petroleum engineering and geology to evaluate rock integrity and its response to stress. Therefore, accurate measurements or estimation of UCS values is essential for efficient reservoir management and operational planning due to their significant role in evaluating wellbore stability, constructing fracture stimulation, and implementing well control techniques. However, to precisely ascertain the values of UCS, it is important to acquire rock samples from the specified region of interest. Unfortunately, retrieved cores typically extend only to the reservoir section and often exhibit significant discontinuities. Moreover, the core extraction process is both time-consuming and costly. Therefore, selecting the most appropriate correlation to estimate the UCS profile for the study area is crucial. In this context, a field case study was conducted in southern Iraq to develop reliable and straightforward mathematical models—namely, multiple regression analysis (MRA) and artificial neural networks (ANN)—for sandstone formations, using well-logging data to generate the UCS profile. The results demonstrate that both ANN and MRA models effectively predict UCS values when compared to empirical correlations from the literature and actual UCS measurements. Moreover, the ANN model outperforms the MRA model, achieving a higher coefficient of determination (R^2) of 0.99, compared to 0.84 for the MRA. This study ultimately presents efficient and cost-effective methods that integrate conventional well logs to predict the UCS profile accurately.

KEYWORDS

Mechanical rock properties, UCS, ANN, multiple regression analysis, well logging

I. INTRODUCTION

Rock mechanical characteristics are essential for mitigating drilling hazards and optimizing reservoir productivity. Unconfined Compressive Strength (UCS) is one of the most critical mechanical properties of rock, with numerous applications in reservoir stability analysis, geological modeling, and petroleum engineering. It specifies the ultimate axial compressive stress a rock specimen may endure before breaking, in the absence of lateral confinement (Tariq et al., 2017). Additionally, it is an essential measure of the mechanical behavior and strength of rock, particularly in subsurface strata where activities such as drilling, fracturing, and extracting oil and gas are carried out (Attewell and Farmer, 2012; Issa and Hadi, 2021).

Several issues arise during drilling operations, including wellbore instability, formation damage, and uncontrolled fracturing. These problems may arise from inaccurate characterization of unconfined compressive strength, which can result in increased operational expenses and non-productive time (NPT) (Issa et al., 2025b). Consequently, geomechanical modelling, investigations of fracture propagation, and reservoir simulations rely heavily on accurate UCS data (Zoback, 2007). Understanding the UCS of sedimentary rocks, such as sandstone and shale, is crucial due to their abundance in oil reservoirs (Jin et al., 2018). Sandstones frequently serve as reservoir rocks because of their high porosity and permeability, whereas shales typically act as cap rocks or, in unconventional formations, as source rocks. Additionally, various physical and geological factors influence the distinctive behaviour of shale and sandstone when exposed to unconfined loads. Some of these factors, including diagenetic history, anisotropy, mineral composition, cementation, porosity, and moisture content, must all be considered (Bell, 2007). For example, quartz-rich sandstones generally exhibit higher UCS values due to their hardness and the interlocking nature of their grains, while clay-rich shales tend to be weaker and more sensitive to moisture

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variations; when saturated, shale displays plastic behaviour and rapidly loses strength (Chandler and Apted, 1988). Therefore, accurate UCS measurements are vital for assessing borehole stability, predicting formation failures, and enhancing hydraulic fracturing designs.

Static (direct) and dynamic (indirect) techniques are commonly employed to measure unconfined or uniaxial compressive strength (UCS) values. In dynamic methods, well-logging and geophysical data are used to estimate UCS values. Conversely, static procedures, laboratory tests, specifically uniaxial or triaxial compressive strength tests, are conducted on suitable cylindrical core samples extracted from the target depth (Issa et al., 2023b). The stress-strain distortion profiles generated during these tests enable the determination of UCS values, other strength parameters, and elastic properties (Barree et al., 2009). However, during the drilling of the productive section, extracting cores and conducting triaxial compressive tests are both highly expensive and time-consuming. Consequently, due to the significant costs associated with obtaining and analyzing core samples, only a limited number of specimens are usually collected from specified intervals of the reservoir (Abdulraheem et al., 2009; Khaksar et al., 2009).

In the mid-2000s, the accessibility of greater datasets and enhanced processing capabilities enabled the development of more advanced ANN models. Researchers commenced the integration of a broader array of input variables, encompassing petrophysical logs, mineralogical composition, and mechanical properties. In 2009, utilized artificial neural network models were employed to estimate the unconfined compressive strength of sandstone formations, employing inputs such as sonic velocity, density, and porosity. These models demonstrated considerable enhancement compared to traditional regression methods, underscoring the capability of artificial neural networks in managing the nonlinear interactions intrinsic to rock characteristics. More recently, the utilization of ANN has transformed the prediction and estimate of UCS in geomechanical research. In contrast to conventional empirical correlations that typically rely on a limited set of parameters, ANN models can integrate a wide array of geomechanical and petrophysical input variables, including porosity, density, sonic velocity, Young's modulus, Poisson's ratio, and brittleness indices (Hussein et al., 2025). This multi-parameter technique enables ANNs to more effectively capture the intricate, nonlinear relationships that govern rock strength compared to traditional methods.

The UCS magnitude is critical in geomechanics applications, particularly in addressing wellbore instability, sand production predictions, and hydraulic fracturing. To effectively implement these applications into field development plans, it is essential to establish a continuous UCS profile across the area of interest. Numerous empirical correlations have been documented in the literature to estimate UCS values specifically for sandstone formations. These correlations rely on geophysical well logs and geomechanical data (e.g., Freyburg, 1972; McNally, 1987; Vernik et al., 1993, Moos et al., 1999, and Chang et al., 2006). Table 1 illustrates a set of the most important empirical correlations published in the literature that are used to establish UCS profiles for sandstone formations. Furthermore, the empirical relationships and predictive models outlined in Table 1, along with those found in the scientific literature, serve as a reasonable alternative for estimating rock strength when well-core specimens are unavailable. However, it is important to point out that these correlations only apply to specific rock types, depths, ages, or basins. Therefore, without proper validation, using them in other oil and gas fields or different rock types may yield unreliable results. Consequently, this study was motivated by the need to construct reliable and straightforward mathematical models—specifically multiple regression analysis (MRA) and artificial neural networks (ANN)—through a field case study conducted in southern Iraq. Moreover, ANNs offer superior predictive accuracy, the capacity to model nonlinear relationships, and robustness to noisy input data. MRA, conversely, offers transparency, simplicity of implementation, and the capacity to establish clear mathematical relationships among variables. The complementary advantages of these two methodologies provide a more comprehensive assessment of UCS prediction efficacy.

In this study, models were developed using conventional well logging data, including rock bulk density (RHOB) and compressional (DTc) and shear (DTs) sonic wave measurements, to generate unconfined compressive strength (UCS) values for sandstone formation. The predictive performance of each model was evaluated using two distinct metrics: the coefficient of determination (R^2) and the root mean square error (RMSE). The Zubair Formation, a critical reservoir within the X field, primarily consists of sandstone and shale intervals, and served as the focus of this study. This research aims to forecast UCS using a dataset obtained from specific lithological units under specified laboratory conditions. Therefore, applying the generated models to rocks with significantly different geological properties or testing conditions may limit their applicability. Furthermore, although the dataset size is sufficient for developed models, it may not fully encompass the entire variability present in broader geological contexts.

Table 1. Demonstrate the empirical relations for sandstone formation using UCS.

Eq. no.	Equation (MPa)	Developed region	Reference
1	$UCS = 0.035V_p - 31.5$	Thuringia, Germany	(Freyburg, 1972)
2	$UCS = 1200\ exp(-0.036\Delta t)$	Bowen Basin, Australia	(McNally, 1987)
3	$UCS = 254\ (1 - 2.7\varphi)^2$	Sedimentary basins worldwide	(Vernik et al., 1993)
4	$UCS = 0.2787E_{sta}^2 + 2.4582E_{sta}$	-	(Lacy, 1997)
5	$UCS = 2.28 + 4.1089\ E_{sta}$	Worldwide	(Bradford et al., 1998)
6	$UCS = 1.745 \times 10^{-9}\ \rho\ V_p^2 - 21$	Cook Inlet, Alaska	(Moos et al., 1999)
7	$UCS = 277\ exp\ (-10\varphi)$	-	(Chang et al., 2006)
8	$UCS = 3.87\ \exp(1.14 \times 10^{-10}\ \rho\ Vp^2)$	Gulf of Mexico	(Chang et al., 2006)
9	$UCS = 1.4138 \times 10^7\ \Delta t^{-3}$	Gulf Coast	(Fjar et al., 2008)

Where V_p is the compressional wave velocity, Δt is the sonic compressional wave, ρ is the bulk density, E_{sta} is the static Young's modulus, and φ is the porosity.

II. Materials and Methods

A. Problem Statement and Research Methodology

An investigation was conducted on the final drilling documents related to the time breakdown assessment for several vertical and deviated wells drilled to reach the target depth, specifically the Zubair formation. According to the data presented in Fig. 1, non-productive time (NPT) associated with borehole instability accounted for approximately 40% of the total drilling time in the Zubair formation. Additionally, the primary instability challenges identified during the analyzed period, based on NPT investigations, included issues such as sticking of the drill string and well logging equipment, as well as borehole wall collapse. In severe cases, these challenges may require fishing activities or redirection of the borehole trajectory. Furthermore, to overcome these issues, a geomechanical model is usually constructed along the area of interest in most oil and gas fields to identify the optimum drilling fluid density (mud weight window) and wellbore trajectory. A critical parameter in developing this geomechanical model is the unconfined compressive strength (UCS), which provides a reliable indicator of the formation rock strength. In other words, the UCS value helps predict whether shear failure will occur. Accurate determination of UCS values requires rock samples from the specific area of interest. Unfortunately, in the majority of instances, the extracted cores are confined solely to the reservoir portion and exhibit significant discontinuity. Additionally, core extraction is time-consuming and costly. Therefore, to establish a UCS profile for the study area, it is essential to select the most suitable correlation. This study was initiated to address this need, culminating in a field case study in southern Iraq aimed at developing reliable and straightforward mathematical models (MRA and ANN) to generate the UCS profile.

This study employs a research methodology that utilizes existing data from various databases. To execute this process effectively, data preparation and analysis were carried out to standardize and filter well-logged data, which was essential for establishing a logical connection between the input data and the output function. These logs are crucial for calculating the Unconfined Compressive Strength (UCS) in this research. Subsequently, two mathematical models, namely Multiple Regression Analysis (MRA) and Artificial Neural Networks (ANN), were developed for the area of interest, specifically the sandstone interval of the Zubair Formation, using conventional well logging data, including rock bulk density and compressional and shear sonic wave measurements. Two distinct metrics, the coefficient of determination (R^2) and the root mean square error (RMSE), were employed to validate the constructed models. Finally, to achieve more accurate results, a comparison was conducted between the developed models, the empirical correlations outlined in Table 1, and the actual UCS profile for the area of interest.

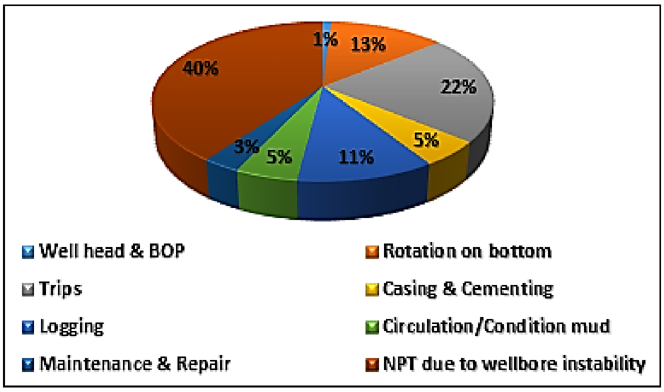


Fig. 1. Presents the time breakdown analysis for one well (Issa et al., 2023a).

B. Data Analysis for Developing Models

Data analysis refers to the steps used to analyze the gathered information from a collection of data to build models through statistical techniques. The goal is to establish a logical relationship between the input data and the output function. Moreover, the data analysis proceeded to reveal which input parameters have a major impact on the output function. Well logging data extracted from a single well located in southern Iraq was utilized to achieve the aims of this investigation. Fig. 2

presents the relationship between the input data and the output function. As a result, well-logged data, such as caliper (CALI), bulk density (RHOB), compressional (DTc) and shear (DTs) sonic waves, gamma ray (GR), and neutron porosity (NPHI), were analyzed (Fig. 2). These parameters served as inputs for the developed ANN and MRA models, while the UCS is defined as the output. Additionally, the data analysis identified the input parameters that significantly affect the output function. In this study, depth, RHOB, DTc, and DTs were selected as the input parameters for both models.

C. It is worth mentioning that different statistical techniques and visual inspections were performed to detect and handle outliers or anomalous data points. Identified outliers were removed to ensure data integrity and mitigate their impact on model training and predictive accuracy. Additionally, high-frequency noise and outliers in the logs were detected and eliminated based on statistical criteria, including standard deviation and interquartile range. These steps ensured that the input variables were clean, reliable, and suitable for developing accurate predictive models of UCS. Fig. 3 presents the histograms and statistical evaluations of the datasets used for ANN and MRA model development.

D. ANN and MRA Models

An artificial neural network (ANN) is a machine learning model designed to mimic the structure and function of biological neural networks found in the brain (Anemangely et al., 2019). The primary purpose of ANNs is to solve complex problems that traditional modelling techniques struggle to address (Issa and Abd-Alameer, 2025). In the oil and gas sector, ANNs are increasingly employed to tackle various challenges related to optimizing operations throughout the entire lifecycle of oil and gas fields, from exploration to abandonment (Alkinani et al., 2019).

In this study, a fully interconnected three-layer neural network architecture was employed to implement the developed models. Four input parameters were incorporated: depth, bulk density (RHOB), compressional sonic wave (DTc), and shear sonic wave (DTs), which impact the output function (UCS), as depicted in Fig. 4. This figure also illustrates the three layers of the network design: input, hidden, and output layers. Basic processing neurons are interconnected across these layers to ensure full connectivity. Furthermore, five neurons were specifically selected for the hidden layer to enhance accessibility (Fig. 4). An iterative technique is typically used to determine the optimal number of neurons. The construction of the ANN model generally consists of three stages: training, validation, and testing.

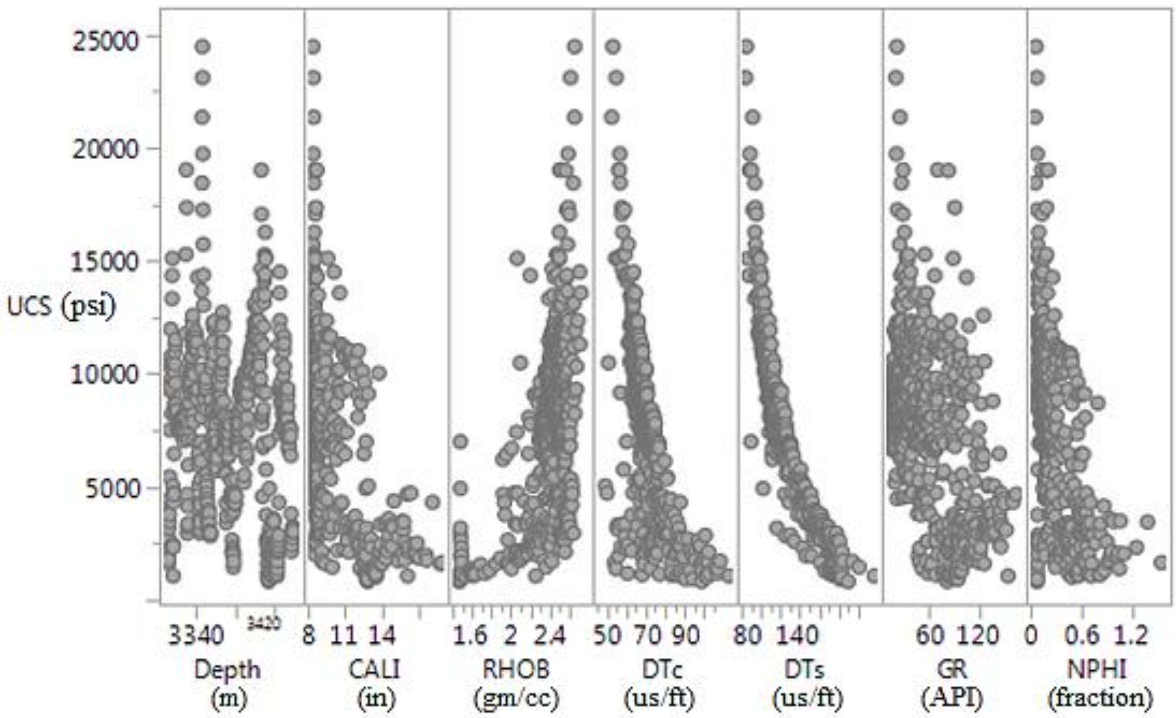
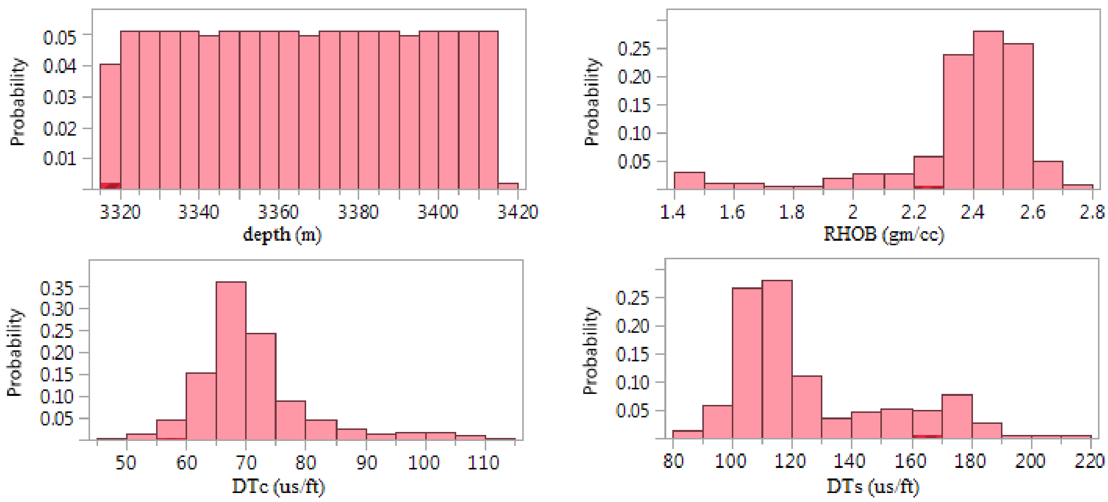


Fig. 2. Evaluation of the UCS using quantifiable data from well logs.



Summary statistics	depth	RHOB	DTc	DTs
Mean	3365.6016	2.378966	70.745139	125.06296
Std Dev	28.662141	0.2394744	8.9513897	25.271819
Std Err Mean	1.1233579	0.0093857	0.3508326	0.9904807
Upper 95% Mean	3367.8075	2.397396	71.434041	127.00789
Lower 95% Mean	3363.3958	2.3605359	70.056237	123.11804
N	651	651	651	651

Fig. 3. Histograms and statistical evaluations of the used datasets for ANN and MRA models development

The essential function of an artificial neural network (ANN) is the training process, which enhances the network's efficiency by comparing the output values to the target values within the model. This study developed a backpropagation neural network (BPNN) approach utilizing the Levenberg-Marquardt method (Fig. 4). The BPNN algorithm was chosen for its capacity to iteratively adjust the link weights across the input, hidden, and output layers, often producing satisfactory results. The training dataset was subjected to cross-validation to mitigate overfitting in the ANN model. Seventy percent of the raw datasets were allocated for training, while thirty percent were designated for validation. This division was executed to enhance the research. The testing procedure is the final phase in assessing the performance of the ANN model throughout the learning process. An increase in the error rate during testing will trigger the termination of the training process.

Multiple Regression Analysis (MRA) can be performed on datasets obtained from the reservoir, including well logging data and core sample measurements, to model the output function. Regression analysis ranges from basic to complex forms, such as multiple regression (Issa et al., 2025a). Multiple regression analysis is an essential statistical technique for determining the output function when multiple independent variables are involved. In this study, the independent variables examined include depth, bulk density (RHOB), compressional sonic wave (DTc), and shear sonic wave (DTs). The dependent variable for the multiple regression analysis (MRA) is the unconfined compressive strength (UCS).

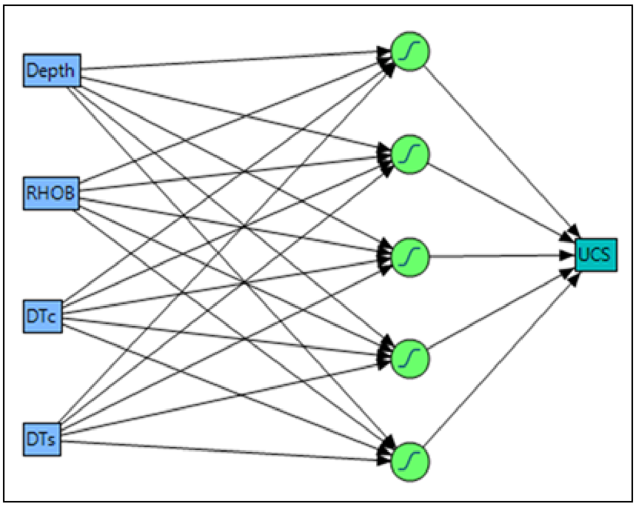


Fig. 4. The artificial neural network architecture for the establishment of UCS.

III. Results and Discussions

A. Model Construction Using MRA

A statistical analysis was conducted to assess the correlation and reduction of log characteristics. Fig. 5 displays partial regression leverage plots that examine the impact of specific physical properties—including rock bulk density (RHOB), compressional sonic wave (DTc), and shear sonic wave (DTs)—on unconfined compressive strength (UCS). This study investigates the correlation and reduction of well-logging characteristics while taking the P-value into consideration. In summary, UCS is significantly influenced by each physical parameter when the P-value is below 0.0001, which indicates the model's accuracy in predicting UCS. Fig. 5 illustrates how each physical characteristic impacts the UCS along with their corresponding P-values. The blue line represents the mean output attribute, which is the UCS, while the red line denotes a 5% confidence range. Significant deviations of the mean UCS from this confidence range highlight the importance of these physical characteristics in UCS calculations. The high angles associated with RHOB, DTc, and DTs (shown in Figs. 5a, b, and c) yield P-values less than 0.0001, indicating their substantial influence on the UCS function. In contrast, the P-value for measured depth is 0.00085, suggesting it has the least effect on UCS.

Equation 10 illustrates the constructed model (Fig. 5d), which employs multiple regression analysis to predict the unconfined compressive strength (UCS). The P-value below 0.0001 demonstrates the model's statistical validity and underscores the superior predictive accuracy of multiple regression analysis in estimating UCS based on well-logged data. Furthermore, the model exhibits a coefficient of determination (R^2) of 0.84, indicating that 84% of the variance in the actual UCS values is explained by the model. This signifies a strong fit between the model and the observed data. Additionally, the root mean squared error (RMSE) is calculated to be 1473.9 psi. This metric reflects the average magnitude of the error between the predicted and actual UCS values. To contextualize the significance of this RMSE value, it is compared to the approximate maximum UCS, which is about 25,000 psi (Fig. 5d). Based on the maximum UCS value (25,000 psi) and the RMSE (1473.9 psi), the estimated error percentage is 5.9%. This statistic indicates that the model's predictions deviate from the actual values by an average of 5.9%. Consequently, this percentage represents a relatively low level of error, highlighting the model's strong predictive accuracy.

$$UCS = 139.668 + 5.398\ Depth + 2768.977\ RHOB - 49.371\ DTc - 109.377\ DTs \tag{10}$$

Where *UCS* is the unconfined compressive strength (psi); *RHOB* represents the formation bulk density (gm/cc); *DTc* and *DTs* denote the compression and shear sonic waves (*us/ft*).

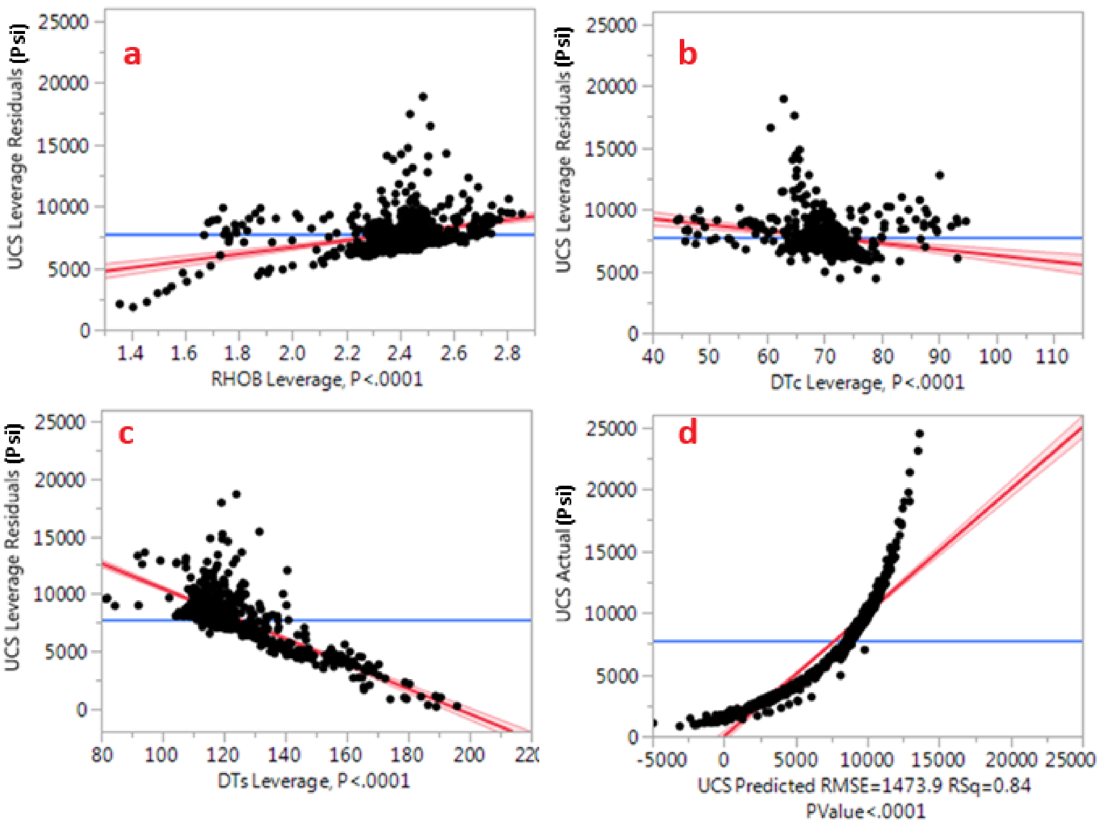


Fig. 5. Presents the predicted UCS model applying MRA.

B. *Model Development Utilizing ANN*

This study employed a three-layer fully connected neural network architecture to develop the ANN model. Four variables affecting UCS measurements were incorporated into the design. The input layer consists of the following variables, including measured depth, bulk density, and compression and shear sonic waves. This investigation utilized an artificial neural network model was constructed using a backpropagation neural network (BPNN) architecture optimized by the Levenberg–Marquardt (LM) algorithm. This approach was chosen for its proven efficiency in addressing nonlinear regression issues and its capacity for rapid convergence, making it particularly appropriate for forecasting geomechanical features such as UCS. The network structure featured a single hidden layer with five neurons, a configuration determined after extensive trials to achieve an optimal balance between model complexity and predictive performance. Initially, various network architectures with different numbers of neurons were evaluated, and their prediction accuracy was assessed using the Root Mean Square Error (RMSE) on both training and validation datasets. Networks with fewer than five neurons failed to adequately capture the nonlinear relationships between input parameters and UCS, leading to elevated RMSE values. In contrast, raising the number of neurons above five failed to provide a substantial enhancement in reliability, but it did elevate the risk of overfitting and computing complexity. The dataset was randomly divided into 70% for training and 30% for validation, following established practices in ANN modeling. The training subset was used for weight optimization via the LM algorithm, while the validation subset was employed to assess generalization and mitigate overfitting. Once the training process was completed, the network was used to create the simulated UCS model. Fig. 6 presents cross graphs that compare the actual and predicted UCS for both training and validation datasets. Performance metrics, specifically the coefficient of determination (R^2) and RMSE, indicate values of 0.99 and 12, respectively, for the training dataset, and 0.99 and 15, respectively, for the validation dataset. These results demonstrate that the ANN model predicts UCS with greater accuracy than the MRA model.

The model developed for calculating UCS using an artificial neural network has been finalized (Fig. 6). Equation 11 describes the constructed ANN model, which employs the mathematical tangent sigmoid function. Table 2 shows the details of the weights and biases of the ANN model. Finally, Equation 11 provides the mathematical framework for the model, enabling precise predictions of UCS.

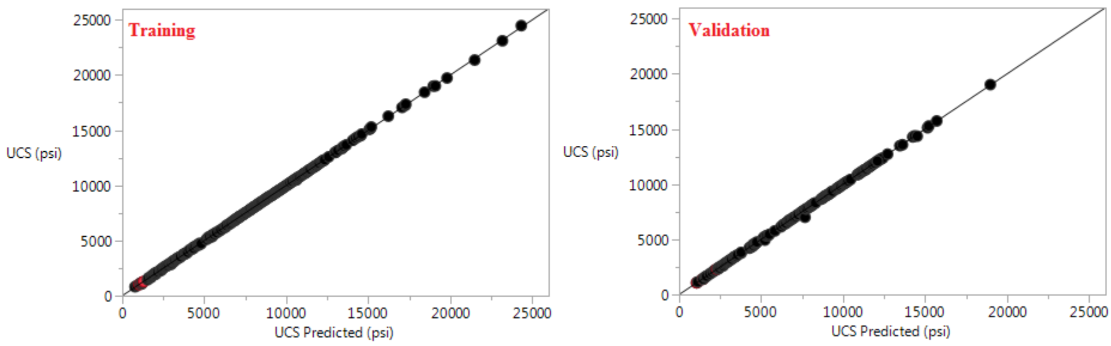


Fig. 6. Illustrates the actual and expected UCS for the validation and training databases.

$$UCS_n = \left[\sum_{i=1}^{N} W_{2i}\left(\frac{2}{1+e^{-2(w1_{i,1}*Depth_n + w1_{i,2}*RHOB_n + w1_{i,3}*DTc_n + w1_{i,4}*DTs_n + b1_i)}} - 1\right)\right] + b_2 \quad (11)$$

Where:

Table 2. The generated ANN model's biases and weights.

Hidden Layer Neurons(i)	Input-Hidden Weight (w_{1_i})				Hidden-Output Weight	Bias	
	Depth	RHOB	DTc	DTs	w_{2_i}	b_{1_i}	b2
1	0.00041	0.3489	0.0579	-0.0687	-34166.3	-1.1623	30085.7
2	-0.0004	-0.2108	-0.0592	0.0806	-5575.85	-2.0992	
3	-0.00053	-0.6395	-0.0049	-0.0172	-20869.3	2.2629	
4	-3.82e-5	0.5486	-0.0040	-0.0214	25353.2	-0.0354	
5	0.00019	0.8732	-0.0140	-0.0589	53774.04	0.9401	

C. Verification of Established Models

To evaluate the credibility of the generated models, comparisons were made with logging data from a single well located within the same research area. The aim of this comparison was to determine whether the research produced superior results. To examine the reliability of the newly developed models (MRA and ANN) in forecasting the UCS, a comprehensive comparison was conducted between the continuous profiles of the predicted UCS from MRA and ANN, as well as the empirical equations mentioned previously (Table 1), and the actual UCS readings.

Regarding the actual profile of the UCS measurements, core samples were collected from various depths within the study area to establish the UCS profile. These samples were subjected to triaxial tests to develop an empirical correlation between the UCS and the static Young's modulus (E_{sta}), as illustrated in Fig. 7. Equation 12 outlines the linear fit model, which has a coefficient of determination (R^2) of 0.84.

$$UCS\ (psi) = -3346.614 + 3390.9544\ E_{sta} \qquad (12)$$

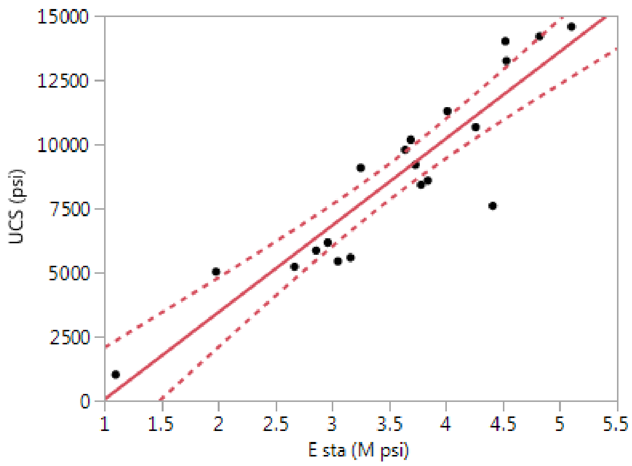


Fig. 7. Shows the relation between the UCS and static Young's modulus

In this study, the static Young's modulus was calculated from the dynamic Young's modulus (E_{dyn}) using a linear fit model (Equation 13). Additionally, the dynamic Young's modulus was determined as a function of the sonic transit time, as described in Equation 14. The determination coefficients (R^2) for Equations 13 and 14 are 0.76 and 0.90, respectively.

$$E_{sta}(\text{Mpsi}) = -1.227 + 0.9057\ E_{dyn} \qquad (13)$$

$$E_{dyn}(\text{Mpsi}) = 11.368 - 0.09102\ \text{DTc} \qquad (14)$$

The current findings indicate that artificial neural networks (ANN) and multiple regression analysis (MRA) are effective techniques for evaluating UCS. The developed models aim to accurately estimate UCS by utilizing three commonly used well logs. Fig. 8 also demonstrates the successful estimation of UCS values by both models (ANN and MRA). In other words, the strong correlation between predicted and actual UCS values, as shown in the fifth track of Fig. 8, further supports this accuracy. Finally, based on performance metrics such as R^2 and RMSE, the ANN model demonstrated superior performance compared to the MRA model.

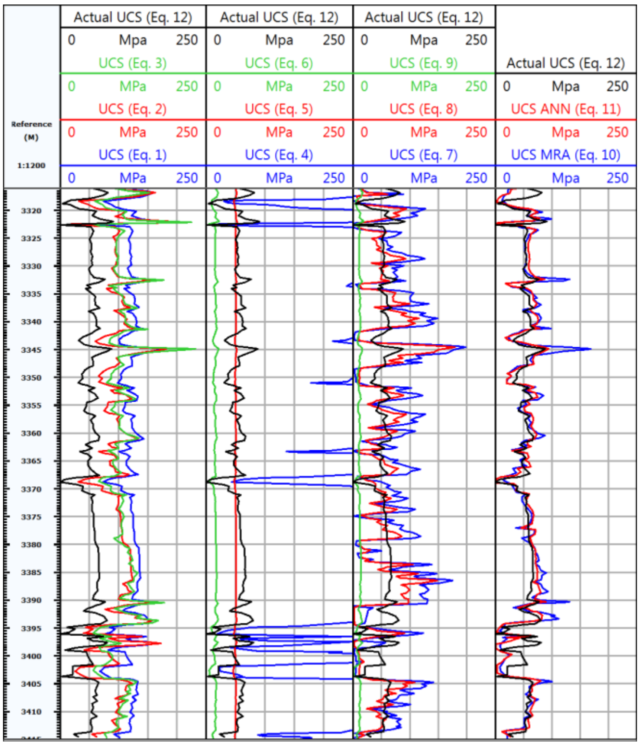


Fig. 8. Illustrates the verification of the proposed models against the actual UCS profile

IV. Conclusions

The UCS is a critical parameter for evaluating geological formations. This study employed two models—artificial neural networks (ANN) and multiple regression analysis (MRA)—to estimate the UCS of sandstone formations when actual measurements are unavailable or insufficient. The models were developed using well-logging data obtained from a single well located in southern Iraq. As a result, various applications related to UCS estimation can be implemented, including wellbore stability assessments, sand production forecasts, drilling optimization, and stimulation operations. The following points summarize the key findings of this investigation:

- This study introduces direct, dependable, and beneficial techniques (ANN and MRA) for determining the UCS using well-logging data.
- Based on the matching results, the ANN and MRA models demonstrate superior performance in predicting UCS compared to previous literature findings and actual UCS measurements.
- The results indicate that the ANN model outperformed the MRA-generated model based on various performance indicators. Specifically, the

value for the ANN model is 0.99, while the RMSE is 12 for the training dataset. In contrast, the MRA model has the value of 0.84 and an RMSE of 1473.9. This comparison highlights the advantages of using artificial neural networks over multiple regression analysis for predicting UCS.The present study develops efficient and practical ANN and MRA models for forecasting the UCS. Consequently, it reduces reliance on costly, commercially accessible software.

- This study demonstrates that well-logging measurements serve as reliable indicators for predicting UCS. Additionally, it highlights the need for further research to investigate how other physical and mechanical rock properties affect UCS values.
- The findings of this study pertain specifically to the oil fields in southern Iraq. However, to ensure accuracy when applying these results to other regions, it is essential to calibrate them using offset well data.

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