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Optimum Drill Bit Selection for Horizontal Wells Utilizing Neural Network Model

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Abstract
An artificial neural network is a computational system of networks and consists of a simple element called neurons or nodes that simulates human intellectual processes, like learning, training, making decisions, and solving problems with multiple variables and a high number of hypotheses. Utilizing rate of penetration data and other drilling parameters, an artificial neural network model was developed to select the optimum drilling bits in the current study. The suggested model was programmed using MATLAB. The neural network adopted a two-layer structure with a sigmoid transfer function employed in the hidden layer and the output layer. The hidden layer consists of three neurons, whereas the output layer holds one neuron. The data on the rate of penetration, other drilling parameters, and formation characteristics were collected from horizontal wells of one of the Iraqi fields. Preprocessing involved cleaning, normalization, and handling of missing values to ensure data quality. The neural network was trained with a backpropagation algorithm and validated on a separate dataset. The performance evaluation results using the R-squared coefficient demonstrated good agreement between actual and predicted rate of penetration values, with an R-squared coefficient value of 0.9982 when using nine neurons, which indicates that improved prediction accuracy is a result of increasing the number of neurons in the hidden layer.

Keywords: Neural network; neuron; rate of penetration; drilling; bit; cost.

Introduction
Drilling bit selection is principal characteristic of a well drilling cost. It requires careful analysis of the factors affecting performance. Historical well data and well logs are contributing factors to analyze the actual performance of preceding drillings and the effect of geological formations. Artificial neural networks can be applied as advanced analytical techniques to develop accurate forecasting models for optimum bit selection, considering the factors that influence the decision [1]. The durability of the bit governs its potential to operate for further periods in the well without replacement. Optimal performance for the bits requires operating them in the well for a certain period; otherwise, repeated replacements can cause a break in drilling operations, consequently, additional costs. To achieve effective penetration of different types of formations during drilling, it is essential to identify the geological formations characteristics and select designs adequate for hard, medium, or soft rocks to warrant lower resistance and higher productivity [2]. Cost calculation per foot is a fundamental factor in bit selection. Accurate cost analysis helps in decision-making to determine the economic feasibility of drilling operations compared with results from offset wells to ensure the highest operational efficiency at the lowest possible cost [3]. Moreover, specific energy is one of the vital factors to reflect the required energy to remove a unit volume of the drilled rock [4][5]. The present study aims to redefine conventional approaches to bit selection by leveraging the predictive potential of neural networks to improve horizontal well drilling performance with minimal stoppages and boost recovery.

2. Artificial Neural Networks

Artificial neural networks are powerful tools in artificial intelligence. Because they can learn from data and adapt to novel patterns, they can address problems regardless of limited data. Artificial neural networks are divided into two types: Supervised networks depend on labeled data to train models utilizing the backpropagation technique to reduce errors of prediction and increase accuracy, whereas unsupervised networks, depends on unlabeled data to detect clusters or patterns [6].

2.1.1. Biological Neural Networks

Biological neurons are one of the sophisticated cells in the nervous system that play a main role in data processing and transmitting signals in the brain [7]. A neuron is composed of dendrites, which represent branched extensions that pick-up signals from interconnected cells, and the cell body, which gathers and analyzes neural signals, while the axon transmits the processed signal to the outputs [8]. Synapses are considered electromechanical contacts between neurons, and as conjunctions, the neurons receive the signals from a large number of other neurons at the synapses, and the dendrites of other neurons are linked together at synapses [9]. A schematic of a biological neuron is shown in Figure 1.

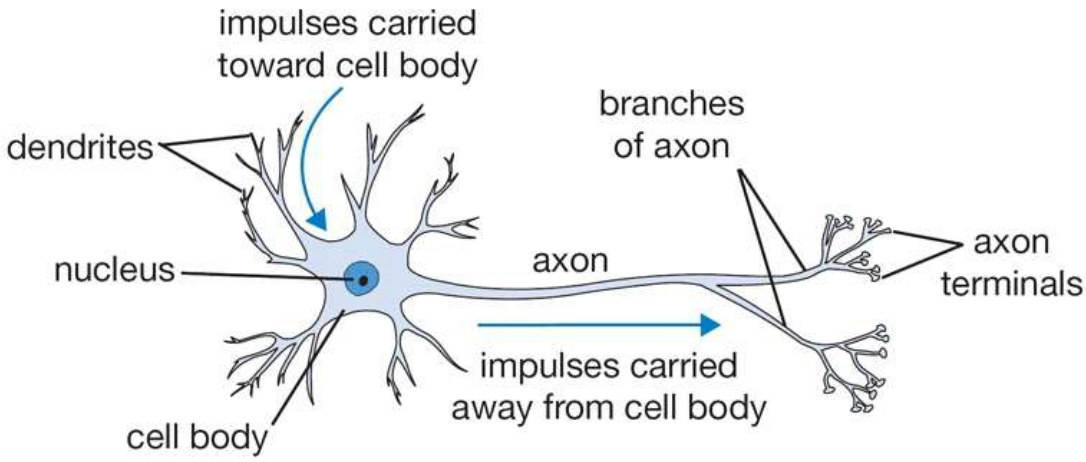

Figure 1. A schematic of a biological neuron. [10]

2.2. Artificial Neural Network Structure

2.2.1. Neuron

An artificial neuron is the basic unit of an artificial neural network, consisting of inputs, weights, an activation function, and outputs. The inputs are multiplied by the weights, the output is summed to form the local receptive field, and then passed through the activation function to determine the final output [11].

$$y_i=\sum_{i=1}^{n} W_i X_i \qquad (1)$$

y_i= sum of the weighted signals.

W_i= connection weight between neurons.

X_i= input value from the neuron in the previous layer.

One or more hidden layers lie between the input and output layers of the network, processing incoming signals before passing them on. These layers contain bias neurons that add bias values to the weighted inputs to improve model performance.

$$y_i=\sum_{i=1}^{n} W_i X_i + b_i \tag{2}$$

The output is passed through a nonlinear activation function to transform the pure inputs into processed outputs, giving the model a nonlinear nature that allows it to represent complex relationships between variables. Figure 2 shows the architecture of the artificial neural network, and Table 1 lists the most distinguished activation functions and their properties [12].

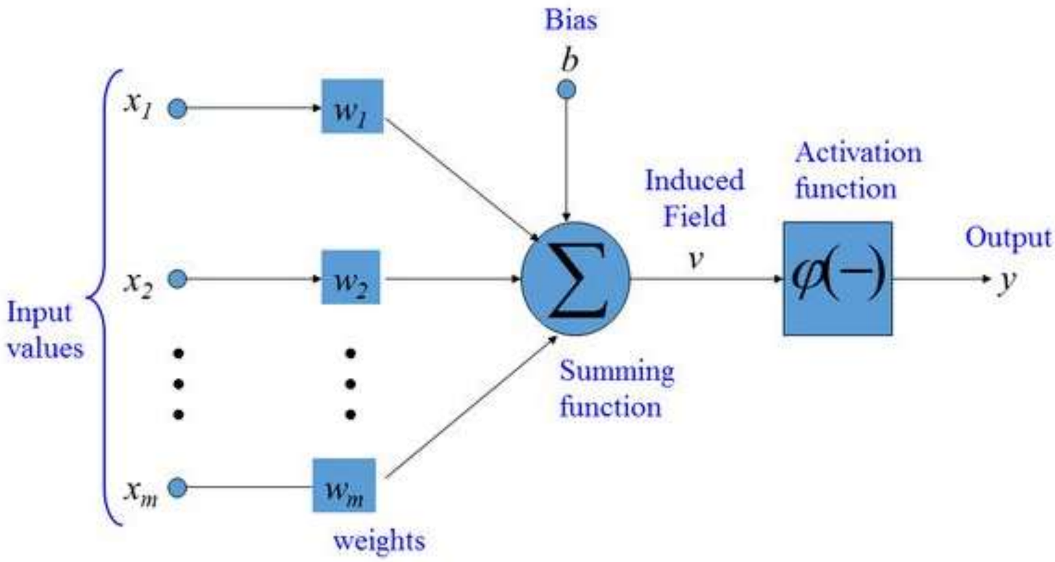

Figure 2. Simple Artificial Neuron. [13]

Table 1. Types of Activation Functions [5].

Activation Functions	Mathematical Function
Logistic (Sigmoid)	$f(x) = \frac{1}{1+e^{-x}}$
Linear	$f(x) = x$
Tanh, Hyperbolic Tangent	$f(x) = \tanh(x)$
Tanh	$f_{(x)} = \tanh(1.5x)$
Sine	$f_{(x)} = \sin(x)$
Symmetric Logistic	$f_{(n)} = \frac{2}{(1+e^{-x})} - 1$

Gaussian	$f_{(n)} = e^{-x^2}$
Gaussian - complement	$f(x) = 1 - e^{-x^2}$

2.2.2. Artificial Neural Network Architecture

Artificial neural network architectures are classified based on the arrangement of their layers and the direction of information flow through the network. They are classified into three main types: feed-forward networks, which include single-layer and multi-layer networks; recurrent networks, which feature circular connections that allow information to be stored across time; and specialized networks, such as adversarial networks and Jordan networks, which are used for specific application purposes [14].

2.2.2.1. Multi-Layer Perceptron (MLP)

The multilayer perceptron (MLP) is a featured artificial neural network architecture. Its ability to model complex relationships between variables makes it an ideal choice for achieving accurate results in many applications. A multilayer perceptron has an input layer, one or more hidden layers, and an output layer. The input layer distributes the input elements without carrying out any computations. Every hidden layer conducts a weighted sum utilizing an activation function. The output layer implements a weighted sum using an activation function to realize the result. Figure 3 shows a typical architecture for a multilayer neural network [15].

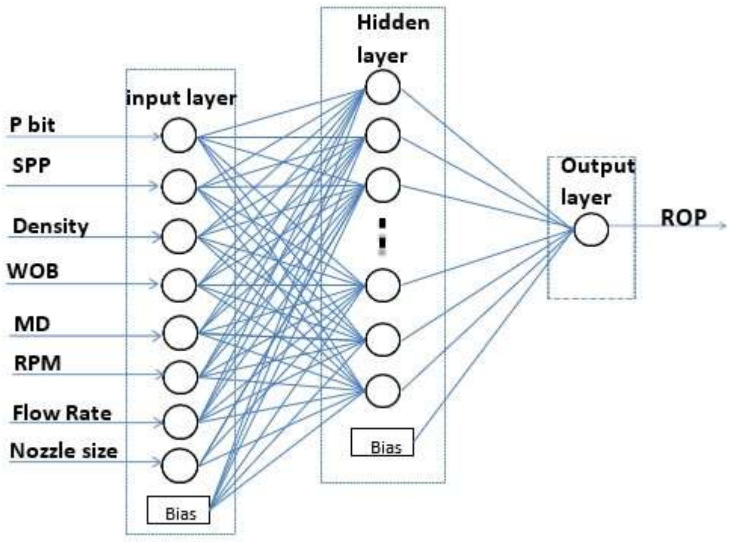

Figure 3. Typical neural network structure of a multilayer perceptron [15].

3.1. Materials and Methods

3.1.1. Case Study

One of the Iraqi oil fields was selected as a case study for the current article. The studied oil field consists of multiple oil zones. Figures 4 and 5 show the studied region and well structure. Tables 2 and 3 illustrate the data for a chosen well with a drilling bit report.

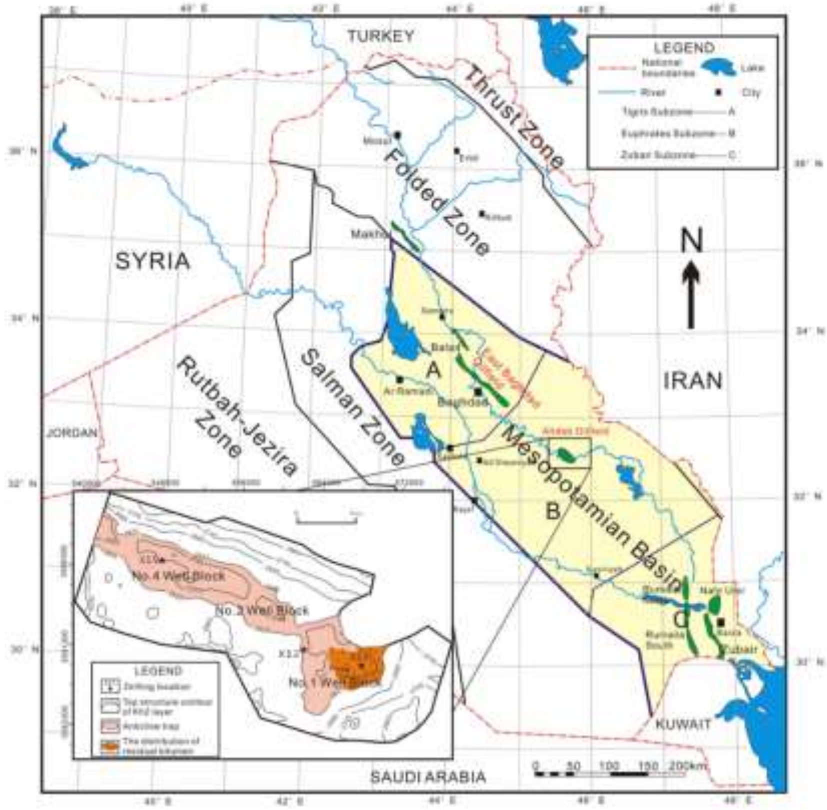

Figure 4. Oil field geographical location [1].

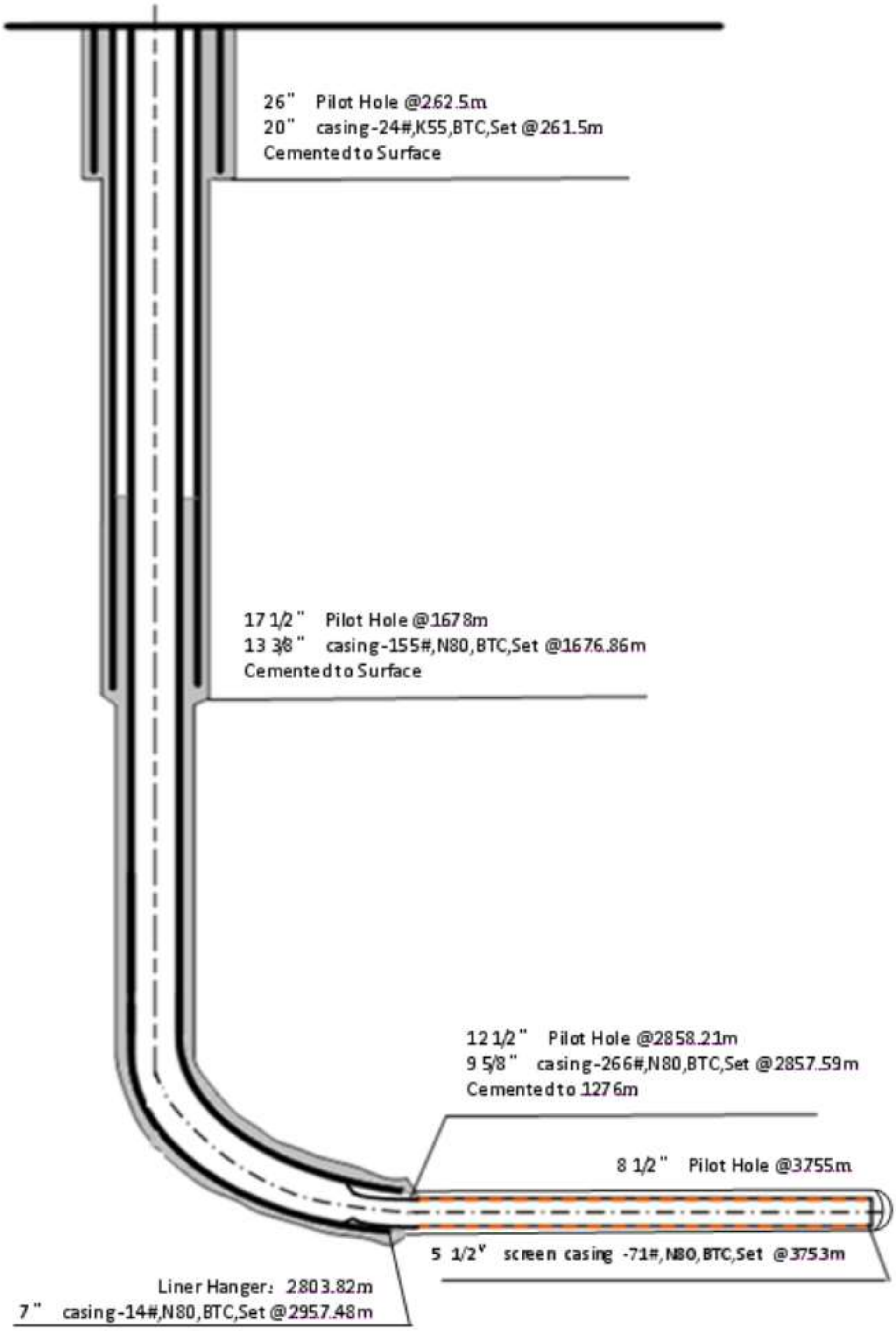

Figure 5. Well Structure Sketch.

Table 2. Well Data.

Well Name: X	Well Classification: Development well Well Type: Horizontal well
Design Depth:3758.96m	Actual Depth:3755 m
Maximum Inclination:90°	Maximum Displacement:1332.48 m
Well Completion Depth:2641.1 m	Target Zone: K2
Northing: 3595335.58 m	Ground Elevations: 16.02m
Easting: 560678.03 m	Completion Method: Perforated liner hanger
Primary Objectives: Y-2	Geographic Location: Location of proposed well is about 12.9km distant from the camp
Secondary Objectives: E-4, F-1, F-2b, N-1	Cement Job Quality: Competent

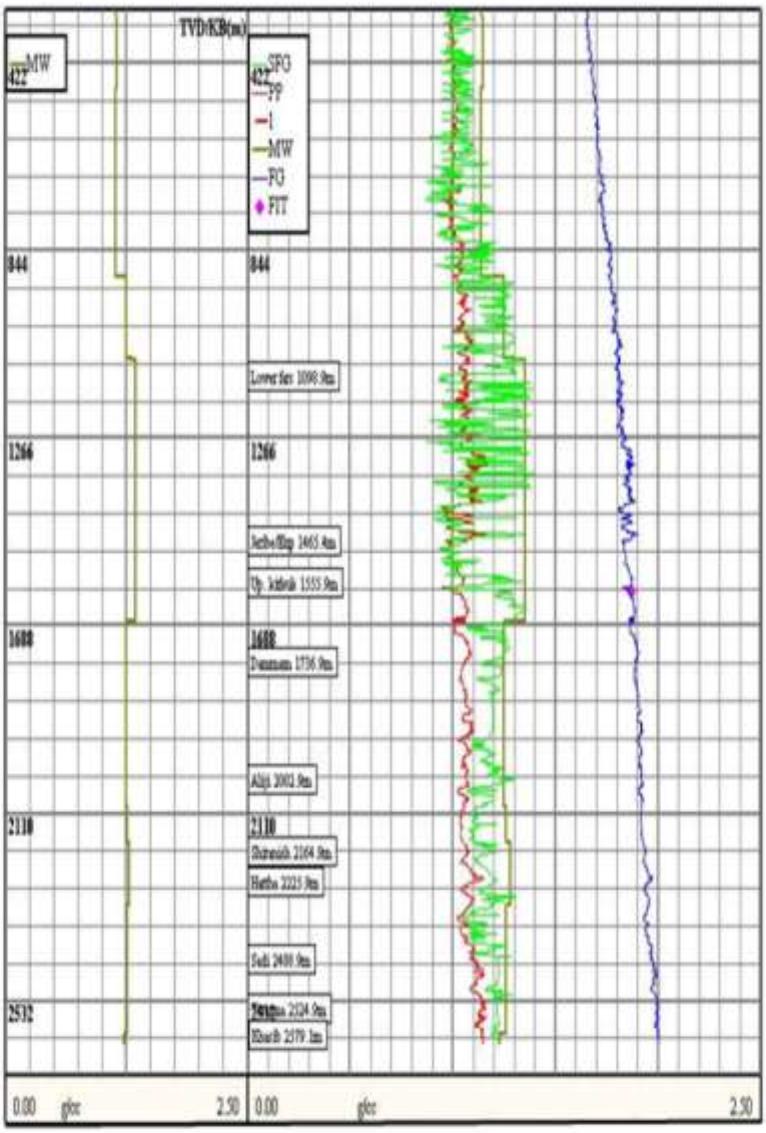

Figure 6. Formation pressure profile in well X.

Table 3. Drilling Bit report.

DEPTH, m		MTS, m	HRS, Hr	ROP, m/h	WOB, kN	RPM	Rate, L/S	PUMP, Mpa
IN	OUT							
12	262.5	250.5	35	7.16	10~90	65	52~53	12
262.5	323	60.5	10	6.05	40~50	65	48~52	7~12
323	509	186	19.5	9.54	50~80	65~100	50~53	12
509	1087	578	48.5	11.9	40	90	50~60	12
1087	1093.1	6.1	17	0.36	50~100	90	63	12~19
1093.1	1209.31	116.21	50	2.32	60~80	60~70	57~52	19~17.5
1209.31	1347.63	138.32	63	2.2	100~200	60~70	52	19
1347.63	1501.6	153.97	75	2.05	200	90	58	19
1501.6	1532.1	30.5	17.5	1.74	80	90	62	19
1532.1	1678	145.9	43.5	3.35	200	80~90	53~62	19
1678	1679.44	1.44	2	0.72	50	60		
1679.44	1681.81	2.37	0.12	19.75	40	100	36	7
1681.81	2045	363.19	71.5	5.08	40~200	60~90	46~50	15~16
2045	2095	50	44	1.14	150	motor	46	20
2095	2349	254	106	2.4	80	motor	43	18.2~21
2349	2630.74	281.74	94	3	60~70	motor	47	20~22
2630.74	2656	25.26	38	0.66	130~180	motor	47	20~22
2656	2858. 21	202.21	107	1.89	80	motor	46	20~22
2858.21	2890	31.79	28	1.14	120	motor	33	16.5
2890	3755	865	155	5.58	40~60	motor	33	18~19

3.2. Artificial Neural Network-Based Regression

Due to the complexity of system variables, achieving accurate predictions is a significant challenge. The artificial neural networks are an impactful tool to deal with them, which identify the accurate relationship between input and output parameters. Supervised neural networks were adapted in the presented study. Since the neural network model consists of three essential steps, which are training, validation, and testing. The applied data to develop the model were classified into three groups, with 70% of the data utilized for training, 15% for validation, and 15% for testing to guarantee the validity and consistency of the predicted results.

4. Results and Discussion

The artificial neural network (ANN) model was optimized utilizing the Levenberg-Marquardt (LM) algorithm by MATLAB code. Several cases were implemented utilizing tangent activation functions in layer one (hidden layer) and tangent functions in layer two (output layer) with different numbers (3, 5, 7, and 9) of neurons in the hidden layer in order to analyze whether increasing the number of neurons impacts the performance of the neural network. The figures (7, 8, 9, and 10) show predicted versus actual penetration rate (ROP) utilizing tanh activation function with various numbers of neurons.

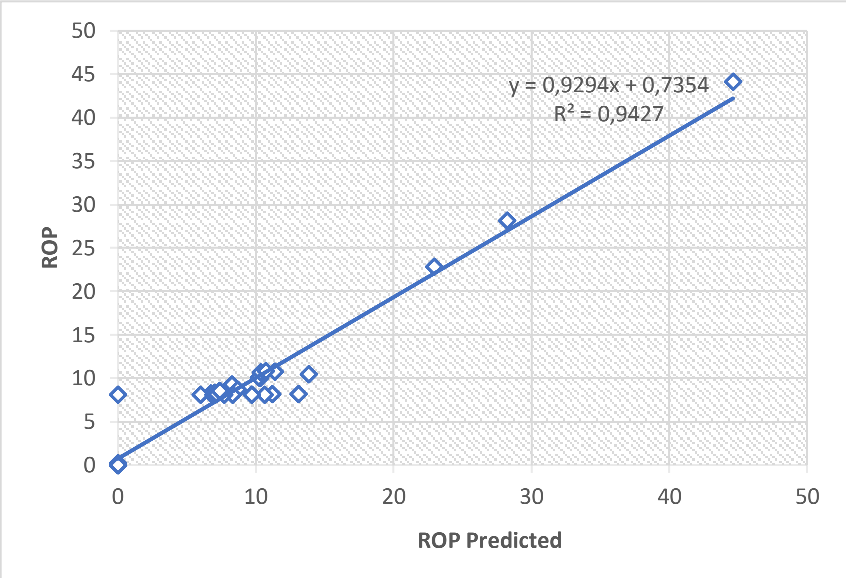

Figure 7. Predicted vs. actual penetration rates utilizing tanh activation function with 3 neurons.

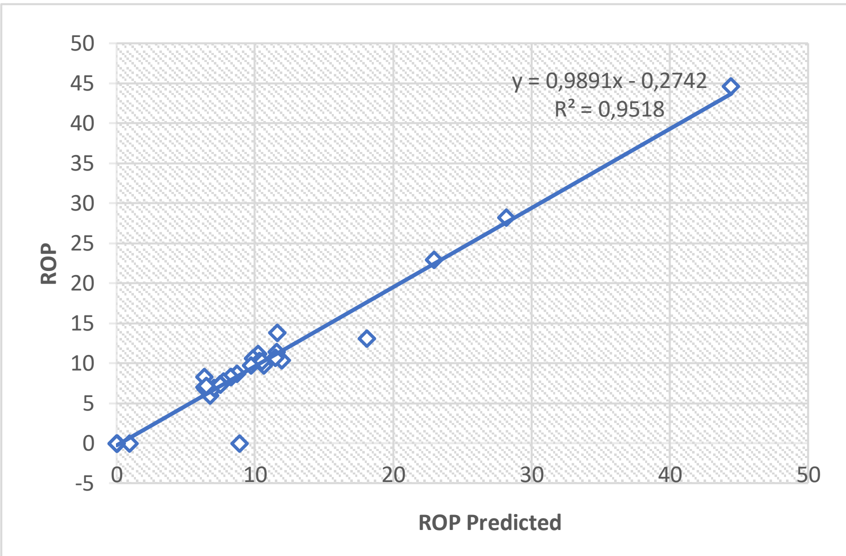

Figure 8. Predicted vs. actual penetration rates utilizing tanh activation function with 5 neurons

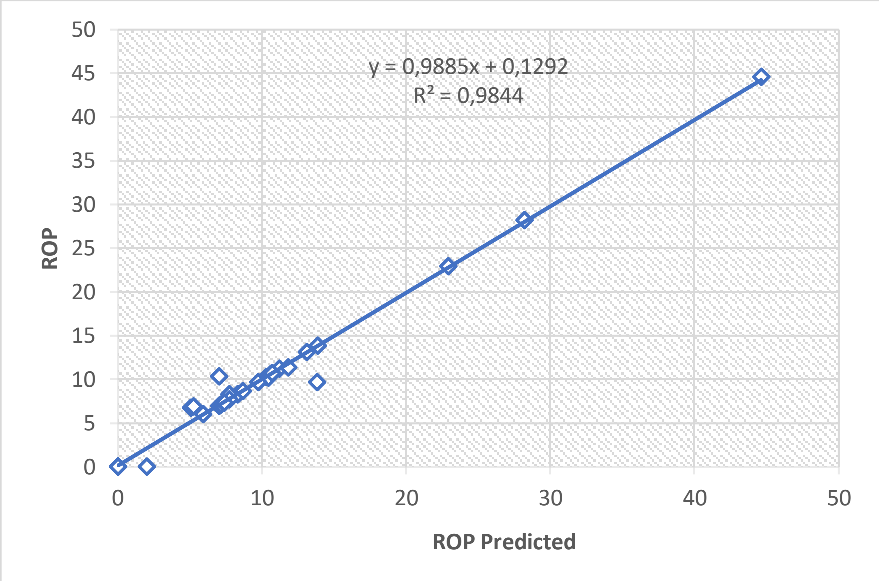

Figure 9. Predicted vs. actual penetration rates utilizing tanh activation function with 7 neurons.

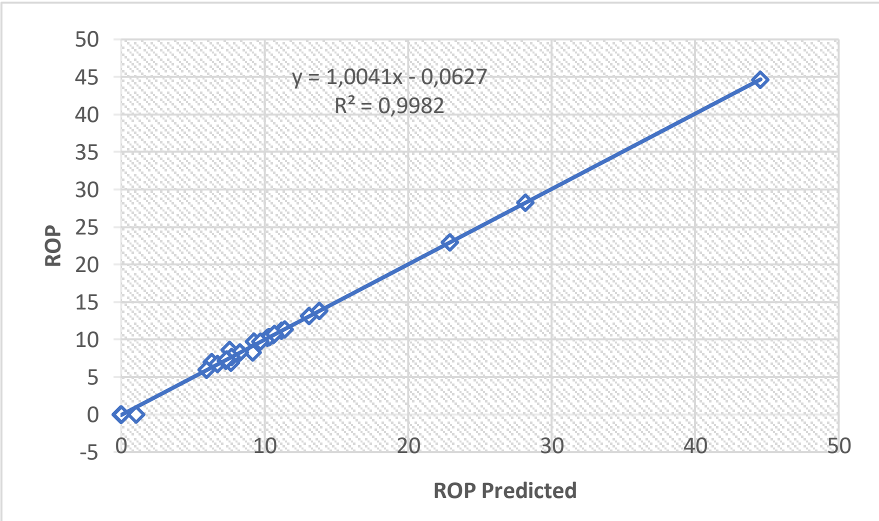

Figure 10. Predicted vs. actual penetration rates utilizing tanh activation function with 9neurons.

5. Conclusion

The suggested artificial neural network (ANN) model in the current study offers a valid and precise approach for drilling bit selection in the oil industry. Employing the ANN model for bit selection resulted in a considerable enhancement in rate of penetration compared to traditional bit selection methods. The high values of R-squared coefficient and convergent correlation between predicted and actual rate of penetration (ROP) showed the model's ability to optimize drilling efficiency, reduce operational costs, and decrease the risk of well defects.

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