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SYNERGISTIC PREDICTION OF PENETRATION RATE IN BOUKHADHRA MINING USING REGRESSION, DESIGN OF EXPERIMENTS, FUZZY LOGIC, AND ARTIFICIAL NEURAL NETWORKS

The comparative analysis of predictive methodologies highlights the original contribution of this study in optimizing the prediction of Rate of Penetration (ROP) in mining drilling operations. The emphasis on employing advanced Artificial Neural Networks (ANN), fuzzy logic, and linear regression models provides new insights into enhancing predictive accuracy and operational efficiency in mining practices. This study aims to quantify the effects of three pivotal drilling parameters: compressive strength, rotational pressure, and thrust pressure on the rate of penetration, a critical performance metric in mining drilling operations. Additionally, the study seeks to develop and evaluate advanced predictive methodologies for predicting ROP. The effects of compressive strength, rotational pressure, and thrust pressure on the rate of penetration were investigated through a Design of Experiments (DOE) approach. Initially, the main effects and two-way interactions among these variables were identified using DOE. Subsequently, three predictive methodologies: linear regression, fuzzy logic, and artificial neural networks, were developed and evaluated to predict ROP based on the identified factors. The evaluation of predictive methodologies revealed that the ANN model demonstrated superior accuracy in predicting the ROP, achieving over 95 % accuracy. Additionally, the fuzzy logic model provided effective handling of nonlinearities in the data, while the linear regression model offered initial insights into the relationships between the variables. The application of advanced predictive methodologies: artificial neural networks, fuzzy logic, and linear regression to optimize the prediction of rate of penetration in mining drilling operations offers precise insights into drilling parameter interactions, enhancing operational efficiency and supporting informed decision making in mining practices.

Keywords: *drilling, mining, rate of penetration, design of experiments, fuzzy logic, artificial neural network.*

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1. Introduction

Rate of penetration (ROP) is essential in determining drilling efficiency and managing operational costs. A decrease in ROP leads to a long drilling process, resulting in important economic losses [1]. On the other hand, exceeding the ideal ROP results in several operational issues, such as important vibration, fast bit overheating, and tear of the bit [2].

These drilling malfunctions require frequent stops to replace the bit, which in turn leads to an increase in drilling duration and costs [3]. The important role of ROP has led to a wide range of studies and research projects, and it is the primary motivation for the authors conducting the present study. This topic has attracted significant attention in recent years, not only in terms of concepts and theoretical definitions, but also for its practical applications [4].

Numerous ROP correlations have been proposed over the years as part of on-going efforts to predict the ROP. Initially, an empirical correlation was introduced for diamond bits, taking into account lot of drilling parameters such as formation characteristics and drill bit configuration parameters. This correlation considered factors like effective formation strength, hydraulic horsepower (HHP), rotational fluid loss, speed, and average weight on bit (WOB) per square inch, as influencing factors on ROP [5]. Later on, a ROP correlation was developed based on geological data, the factors incorporated in this correlation was the depth interval, the mud weight and viscosity, the rotational speed, the bit torque, and the conditions of the bit [6]. ROP was predicted also using two different correlations under distinct conditions, incorporating the presence of rock mechanical properties and its absence [7]. These correlations take into account variables such as friction angle, WOB, bit rotational speed, mud flow rate, hole depth, resistivity logs, and neutron porosity hydrogen index. Subsequently, Regression analysis was employed to predict ROP in different geological layers. These correlations relate ROP to several important factors [8]. A correlation was developed to predict the rate of penetration (ROP) by integrating controllable factors such as compressive strength (UCS) and uncontrollable factors like: Push pressure (PP) and rotation pressure (RP). The study focused on these specific factors to enhance the accuracy of ROP predictions in mining drilling operations, reflecting the dynamic interaction between the drill mechanism and the different rock properties [9].

The concept of fuzzy sets was pioneered in 1965, marking a significant advancement in the field of handling uncertainty and imprecision [10]. Fuzzy logic (FL) utilizes an inexact approach for reasoning, where deduction are approximations rather than precise. This technique is particularly effective in processing data that may be lacks completeness, precise, or reliability. FL shares a strong resemblance with the concept of fuzzy sets, which deals with collections of elements defined by ambiguous boundaries where membership varies in degree [11]. Fuzzy systems are commonly utilized to describe uncertainty resulting from imprecise data or a lack of adequate input factors, both of which significantly impact the outcomes. An item or property can be classified into one of several ambiguous groups; each assigned a specific level of membership. Fuzzy set theory suggests incorporating a truth value that falls between 0 to 1 for dealing with non-crisp variables. This approach employs a membership function to establish the relation between a truth value and its variable, where the function assigns a value from 0 and 1 that represents the «degree» of membership. Several forms membership functions are applicable in practice, such as triangular, trapezoidal, Gaussian, bell-shaped, sigmoidal, and S-curve waveforms [12]. The knowledge base includes the definitions of linguistic variables, their associated terms as fuzzy sets, and fuzzy production rules, representing all the knowledge required to solve the problem. Fuzzy rules are established based on past experience and knowledge that has been gathered over time.

The Fuzzy Inference System (FIS) is designed to map given inputs to outputs, employing a structured approach. It integrates logical operations, a set of «If-Then» rules, and the development of membership functions. The system comprises five principal components: the Fuzzification Interface, Rule Base, Database, Decision-Making Unit, and Defuzzification Interface. The Fuzzification Interface converts input data into degrees that align with linguistic values. The Rule Base contains different fuzzy «If-Then» rules, which utilizes a database for the appropriate membership functions. The decision-Making Unit is responsible for the inference operations. Finally, the Defuzzification Interface converts the fuzzy output into precise results. Numerous defuzzification techniques are utilized, including those based on the centroid of an area, the bisector of an area, the mean of maxima, the smallest of maxima, and the largest of maxima. Among these, the centroid of an area method is the most frequently used for defuzzification.

The application of fuzzy logic to solve real-world problems across various domains has been extensively documented in many studies demonstrating the utility of the aggregated output membership function [13]. The Sugino-type constitutes another category of fuzzy «If-Then» rules. This configuration is recognized as the Adaptive Neuro-Fuzzy Inference System (ANFIS), which integrates elements of both fuzzy logic and neural networks. ANFIS harnesses the strengths of both methodologies in a robust method [14]. It utilizes both of backpropagation and least squares methods to learn and adjust the membership functions, thereby enabling the fuzzy system to train and model data accurately [15]. Numerous models have been developed to estimate drilling penetration rates, yet none have proven reliable due to the complexity of the drilling operations. This has led to a growing reliance on artificial intelligence (AI) in mining drilling operations, due to its ability to incorporate unknown parameters effectively in model development.

An artificial neural network (ANN) is a computational model inspired by the structure of biological neural systems, employed to address computational problems that challenge unmanageable linear computing methods [16]. An ANN is composed of multiple layers, with a basic requirement of three layers: input, hidden, and output layers. Each layer consists of units known as neurons, which are the core components of each layer, essential in processing information within the ANN system. Transfer functions interconnect these layers, while data training is done using specialized algorithms. Furthermore, the links between neurons across various layers are established by constants known as model weights [17]. It is essential to adjust the number of neurons to avoid overfitting or underfitting, which can degrade performance, or can lead to inadequate model training. During the training phase, the system employs backpropagation to adjust errors and process data from the input to the output layer. To enhance model efficiency, the predicted outputs are then compared with actual data, and weights and biases are adjusted to minimize errors in the output estimations [18].

In various studies, artificial neural networks (ANNs) were employed to predict of ROP in drilling operations. A model used 500 data points with nine inputs. The data set was split into 90 % for training and 10 % for testing, achieving correlation coefficients between 0.902 and 0.982. Another approach focused on enhancing ROP prediction by analyzing previous drilling data with six key factors, and reported a determination coefficient (R^2) of 0.8, indicating a significant correlation between predicted and actual ROP measurements [19]. Researchers have employed ANNs to predict ROP in drilling. One study integrated Genetic Algorithm into ANN, using 330 data points across ten different parameters. The model was tested with 20 data points, reporting a coefficient of determination (R^2) of 0.9402 for training and 0.7401 for testing. Another approach involved analyzing offset well data using ANN, incorporating 21 inputs. 75 % of its data were splitted into training, with the remaining divided equally for testing and validation, resulting in a correlation coefficient (R) of 0.916 and a mean square error (MSE) of 0.015, using two ANN layers [20]. In recent studies ANNs were applied to enhance the prediction of the rate of penetration (ROP) in drilling operations. One approach used 5000 data points with 11 factors, splitting them into 75 % for training and 25 % for testing. The results gave a coefficient of determination (R^2) of 0.91 for training and 0.90 for testing, with RMSE = 1.51. Another method utilized a multi-layer ANN combined with a Genetic Algorithm (GA) to optimize the ROP model using a dataset of 332 across ten parameters. High correlation coefficients of 0.957 for training and 0.962 for testing were reported.

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The aim of this study is to develop predictive models for the rate of penetration in blast hole drilling at Boukhadra's open cast mine (Algeria). Our structured approach includes four pivotal stages: operational testing on different geological layers, gathering detailed operational data, analyzing this data statistically using design of experiments and regression model, and construction of accurate predictive models by application of fuzzy logic and Artificial Neural Network. These models are designed to optimize the prediction of rate of penetration in drilling operations, improve efficiency and enhance the drilling precision.

2. Materials and Methods

2.1. Overview on the Boukhadra mine. The Djebel Boukhadra, situated in eastern Algeria, lies 45 km north of Tebessa City and just 13 km from the Algerian-Tunisian border (Fig. 1). The region, part of the mountainous Atlas Saharan series, hosts the Boukhadra iron deposit, notable for its straightforward NE-SW anticline structure. Mining operations at Boukhadra are conducted using two methods: open pit mining, employing half-trench techniques, and underground mining via sublevel stopping. Iron ore is transported from the mine site to a gyratory crusher using trucks, after which the crushed ore is moved via a belt conveyor to a homogenization station for further processing.

At the Boukhadra open cast mine, diverse geological layers are present within the working area. The performance of drilling in these various formations is evaluated based on the penetration rate of a blast hole. The data used in the study come from direct, controlled measurements at the mine site. ROP was measured using a stopwatch to accurately track the time required for the drill process, enabling real-time assessment of drilling efficiency. The penetration depth records are obtained from the digital displays on the drilling machines. The penetration rates are then calculated using the following equation:

$$ROP = \frac{H}{t} = \frac{Depth\ of\ the\ blasthole}{time},\ \text{m/min}. \quad (1)$$

The field drilling tests were conducted using an ATLAS-COPCO ROC-L8 drilling machine (manufactured in Sweden), equipped with a 160 mm diameter button bit and drill tubes of a 70 mm outer diameter. Drilling parameters were maintained constant during the drilling process.

In our study, let's focus on two critical parameters of the drilling machine: Thrust pressure (TP) and rotational pressure (RP). Thrust pressure, ranging from 30–110 bar, refers to the axial force applied to the drill string. The interaction between the drill bit and the rock face generates friction, which influences the cutting and removal of rock material. Increased thrust pressure can enhance the cutting action, potentially increasing ROP up to a certain threshold, beyond which it may cause bit wear or failure. Rotational pressure, ranging from 30–70 bar, also plays a significant role in the drilling process. Although its effect on ROP is positive, it is not as pronounced as that of thrust pressure. Our findings indicate that the mean ROP increases slightly with higher rotational pressure, suggesting that rotational pressure contributes to the rate of penetration, albeit to a lesser extent compared to thrust pressure.

Fig. 1. Location map of the study area

2.2. Laboratory assessments and field studies. In drilling of blast holes, Compressive strength is a vital mechanical property of rocks. The compressive strength was measured using a compression testing machine (results in Table 1).

Table 1

Independent factors and levels used in the experimental design for ROP case in Boukhadhra mine

Factors	Level	
	–1	+1
Compression Strength, MPa	8	52
Rotational Pressure, bar	30	70
Thrust Pressure, bar	30	110

2.3. Design of Experiments (DOE). To thoroughly investigate the impact of compressive strength, thrust pressure, and rotational pressure on the ROP, a full factorial design was selected. This design allows for the evaluation of the main effects of each factor as well as their interactions.

The full factorial design for three factors, each at two levels (–1, +1 for Compression Strength (MPa), Rotational Pressure (bar), Thrust Pressure (bar)) as described in Table 1, results in 23 experimental runs, enabling a comprehensive analysis of the factors and their interactions.

The experimental data were analyzed using MINITAB software. The software facilitated the calculation of main effects, interaction effects, and the generation of an empirical regression model. Design of experiments (DOE) was conducted to identify the significance of each factor and their interactions. The regression equation derived from the DOE analysis is as follows:

$$ROP = -1.275 + 0.0539 \cdot CS + 0.01709 \cdot TP + \\ + 0.04932 \cdot RP - 0.001384 \cdot CS \cdot RP, \qquad (2)$$

where ROP is the rate of penetration, CS is the Compressive Strength, TP is the Thrust Pressure, RP is the Rotational Pressure, and $CS{\cdot}RP$ is the interaction term between Compressive Strength and Thrust Pressure.

2.4. Development of the fuzzy model. This section details the development of a fuzzy model, using the Mamdani algorithm, for predicting ROP at Boukhadra mine. The model was implemented using the fuzzy logic toolbox in MATLAB version 7.6 (R2016b). It comprises three input variables: compressive strength (CS), rotational pressure (RP), and thrust pressure (TP), with ROP as the output variable. Fig. 2 provides a visualization of these input and output variables within the MATLAB interface.

In the model, triangular membership functions were chosen to characterize the input and output variables due to their ease of use and processing reliability. These functions, as expressed in Equation (1), convert linguistic terms into numerical values ranging from 0 to 1:

$$Triangle(x,a,b,c) = \begin{Bmatrix} 0, & x \le a, \\ \dfrac{x-a}{b-a}, & a \le x \le b, \\ \dfrac{c-x}{c-b}, & b \le x \le c, \\ 0, & x \ge c, \end{Bmatrix}, \qquad (3)$$

where a, b, and c represent the parameters of the linguistic value, and x indicates the range of the input parameters. Fig. 3 illustrates the membership functions for various input and output variables. Furthermore, Table 2 outlines the linguistic variables, their corresponding linguistic values, and the associated parameters.

The subsequent phase of the FIS involves developing the «If-Then» rules to describe the fuzzy relationships between the input and output fuzzy variables. In this study, 35 rules were formulated to build the rule base of the fuzzy model, based on expertise of professionals and data collected from the mine (measured data).

Fig. 4 illustrates a fuzzy «If-Then» rule editor featuring 10 rules from the model in the MATLAB interface. These rules integrate different levels of input variables to generate an output, following a logical. Each rule is given an equal weight of 1, ensuring that all rules have the same impact on the output when their conditions are met. Additionally, the rules are covering various input level combinations to enable the system to handle a wide range of scenarios.

In the final stage, the fuzzy set results are converted into crisp values again through the defuzzification process. In this model, the centroid of area (COA) method, a widely used defuzzification technique, was employed to obtain the crisp value using the following equation:

$$Z_{COA} = \frac{\int_Z \mu_A(z) z \, dz}{\int_Z \mu_A(z) \, dz}, \qquad (4)$$

where $\mu_A(z)$ denotes the aggregated output membership function.

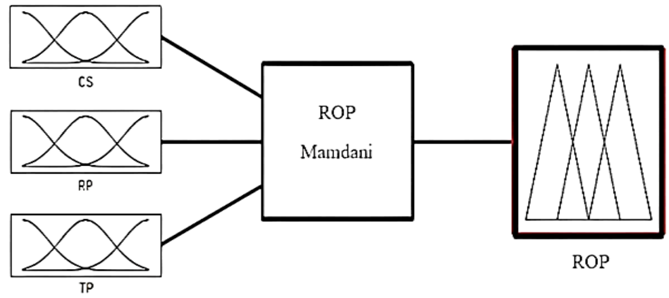


Fig. 2. Input and output variables of the fuzzy model

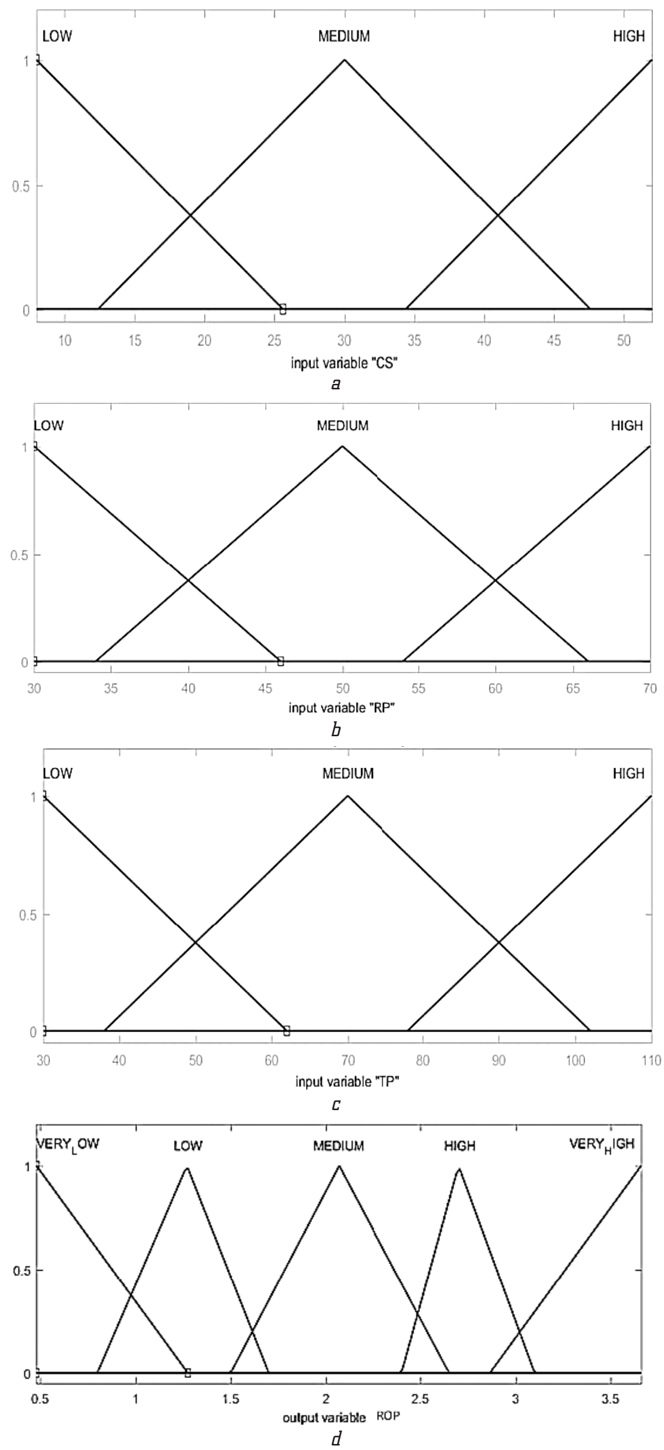


Fig. 3. Graphical representation of triangular membership functions of: *a* – Compressive strength, *b* – Rotational pressure, *c* – Thrust pressure, *d* – ROP

Table 2

Membership functions and their input and output parameters

Variables	Linguistic variables	Range	Linguistic values	Parameters
Input	Uniaxial Compression Strength (UCS)	[8 52]	Low	[8 8 25.6]
			Medium	[12.4 30 47.6]
			High	[34.4 52 52]
	Rotational Pressure (RP)	[30 70]	Low	[30 30 46]
			Medium	[34 50 66]
			High	[54 70 70]
	Thrust Pressure (TP)	[30 110]	Low	[30 30 62]
			Medium	[38 70 102]
			High	[78 110 110]
Output	Rate of Penetration (RoP)	[0.48 3.66]	Very low	[0.48 0.48 1.27]
			Low	[0.8 1.27 1.7]
			Medium	[1.5 2.07 2.65]
			High	[2.4 2.7 3.1]
			Very High	[2.86 3.66 3.66]

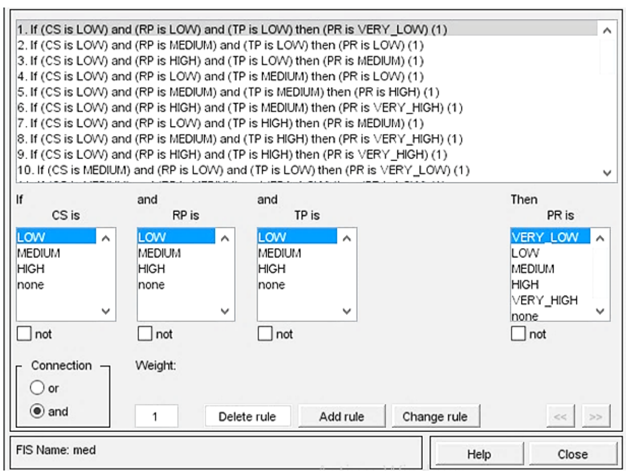


Fig. 4. Fuzzy logic rules

The developed fuzzy model can estimate the rate of penetration ROP when supplied with accurate input data. For example, as illustrated in Fig. 5, with input parameters of a compressive strength of 30 MPa, rotational pressure of 50 bar, and thrust pressure of 70 bar, the model predicts an output ROP of 2.73 m/min, compared to the measured ROP of 2.61 mm/s.

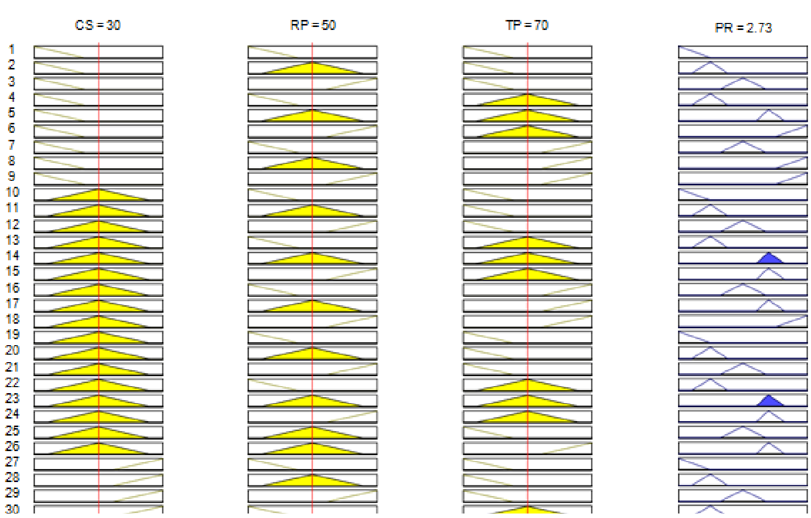


Fig. 5. Fuzzy rule viewer of the fuzzy model

2.5. Artificial neural network method. In this section, it is possible to utilize ANN to predict ROP in mining operations by considering the same three primary factors: compressive strength, thrust pressure, and rotational pressure. ANNs are adept at modeling the complex, non-linear interactions between these factors and the ROP, offering the potential for more accurate and reliable predictions than those achieved through conventional statistical methods.

2.5.1. Data collection. In this study, over 114 data points over three months, covering a wide range of conditions, were collected including those used in previous models (fuzzy logic and DOE). To improve model accuracy, it is possible to use data augmentation algorithms to generate additional data by slightly altering the original dataset. This increased the training data, improved the model's generalization and reduced overfitting.

2.5.2. ANN architecture. Fig. 6 presents the neural network structure employed in this study, illustrating the configuration of the input layer with three input factors (compressive strength, thrust pressure, and rotational pressure), the weighted summation of these inputs, the application of the Rectified Linear Unit (ReLU) activation function, and the error evaluation process used to predict ROP.

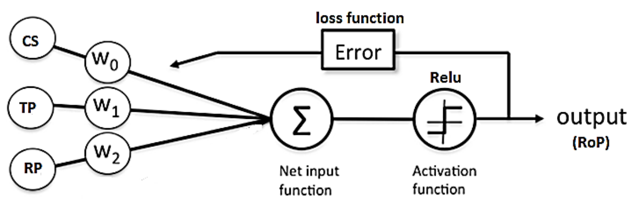


Fig. 6. Architecture of a neural network employed in this study

2.5.2.1. Input layer. The input layer consists of three neurons, each corresponding to one of the independent variables: compressive strength, thrust pressure, and rotational pressure. These neurons receive the input data and transmit it to the hidden layer.

2.5.2.2. Hidden layers. The architecture includes one hidden layer with ten neurons. The configuration of hidden layers and the number of neurons were selected based on preliminary experiments and a review of relevant literature. The weighted sum of its inputs is transformed by each neuron in the hidden layer using an activation function. It is possible to choose ReLU activation function due to its capability to introduce non-linearity and prevent the vanishing gradient problem.

2.5.2.3. Output layer. The output layer includes a single neuron that generates the predicted rate of penetration. This layer utilizes a linear activation function to produce continuous prediction values.

2.5.3. Training the ANN

2.5.3.1. Data preparation. The dataset was divided into training (70 %), validation (15 %), and testing (15 %) sets to assess the model's performance on unseen data. Input data were scaled using the min-max normalization technique to ensure that each feature had an equal impact during training. This normalization process transformed the data to a range of [0, 1].

2.5.3.2. Training process. The ANN was trained using the backpropagation algorithm, which consists of two essential steps:

1. *Forward Pass:* Input data is fed through the network to obtain predictions.
2. *Backward Pass:* The error between the predicted and actual values is determined using the Mean Squared Error (MSE) loss function. This error is then propagated back through the network to update the weights using gradient descent optimization.

The learning rate, batch size, and the number of epochs were carefully adjusted to achieve optimal results. The Adam optimizer, known for its efficiency in finding the best learning rate automatically, was used to make these adjustments.

2.5.4. Validation and Testing. To evaluate the model's behaviour and performance, let's use a k-fold cross-validation technique with k set to 5. This process involved dividing the data into five parts and conducting five separate tests, each time using a different part for testing and the remaining parts for training. This strategy ensures that the model behave well across different data subsets and prevents overfitting to a specific dataset.

3. Results and Discussion

3.1. Design of experiments

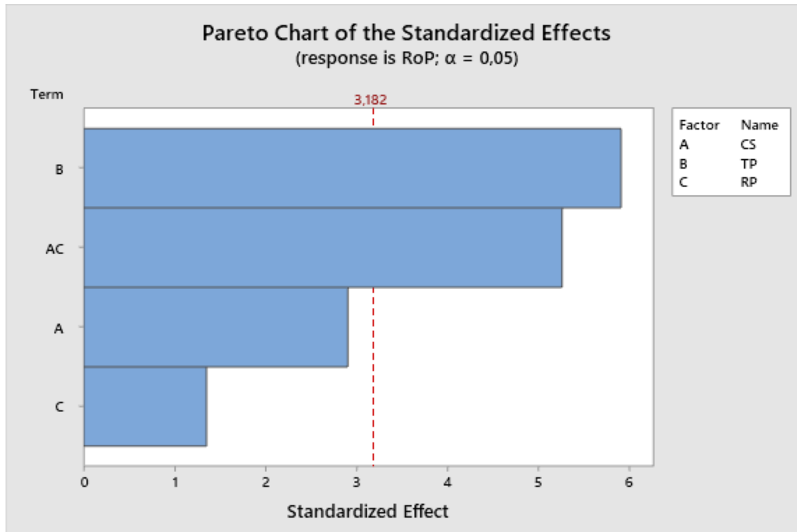
3.1.1. Effect of various factors on penetration rate. Fig. 7, *a* shows the Pareto chart which illustrate the standardized effects of various factors used in this study and their interactions on the response variable ROP with a significance level set at $\alpha=0.05$.

Pareto chart in Fig. 7, *a* indicates that factor B (TP) has the most significant influence on the response variable. This is followed by the interaction between A (CS) and C (RP), and then by factor A (CS) alone. Factor C (RP) on its own, does not indicate a statistically significant impact on the response variable at $\alpha=0.05$.

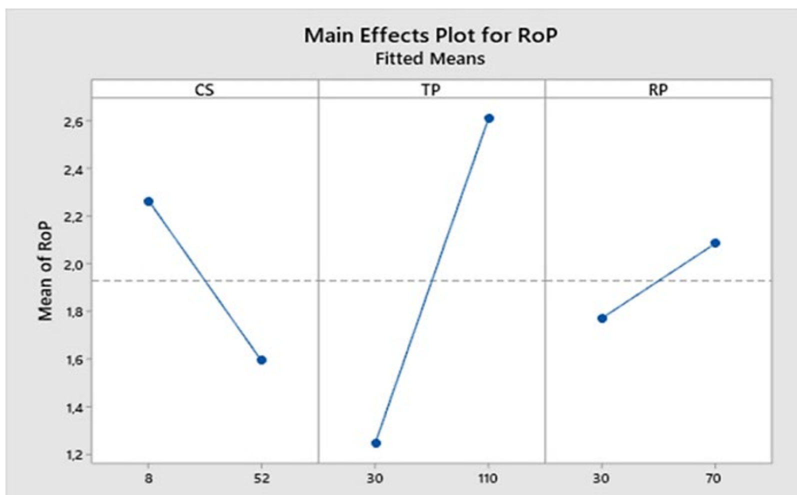
The main effects plot in Fig. 7, *b* illustrates the fitted means of the response variable, rate of penetration (ROP), at varying levels of the three used factors: Compressive Strength (CS), Thrust Pressure (TP), and Rotational Pressure (RP). The plot shows two levels of compressive strength, where the mean ROP decreases as compressive strength rises from 8 MPa to 52 MPa. This reveals that higher compressive strengths correlate with a lower rate of penetration, indicating that harder materials are more challenging to penetrate.

In contrast, the plot indicates a notable increase in the mean ROP as thrust pressure increases from 30 kN to 110 kN. This aligns with the findings from the Pareto chart, highlighting thrust pressure as the most significant factor on RoP. Higher thrust pressure evidently results in a higher rate of penetration, implying that increased force more effectively penetrates the material.

The influence of rotational pressure on ROP is positive but less significant compared to thrust pressure. The mean ROP increases slightly as rotational pressure increases from 30 bar to 70 bar, indicating that although rotational pressure contributes to the rate of penetration, its impact is not as significant as that of thrust pressure.



a



b

Fig. 7. Analysis of factorial effects on response variable: *a* – Pareto chart of standardized effects; *b* – main effects plot of various factors

This analysis of the Main Effects Plot reveals how each used factor affects the ROP, highlighting their varied impacts on the drilling process in Boukhadhra mine.

3.1.2. Analysis of the interaction plot for RoP. Fig. 8 presents the interaction plot, showing how various factorscombine to the mean rate of penetration (ROP). Each graph shows the mean RoP for two factors at specific levels while holding the third factor constant.

Non-parallel lines in the case of CS with TP and CS with RP plots indicate significant interaction effects, with increased thrust pressure (110 bar) and rotational pressure (70 bar) resulting in higher ROP, particularly at lower compressive

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strength (8 MPa), Fig. 8. The same interaction effects are observed in the case of TP with CS plot. In contrast, in case of TP with RP and RP with TP plots show nearly parallel lines, indicating little to no interaction effects.

These interactions indicate that higher thrust and rotational pressures generally increase ROP, especially at lower compressive strengths. Contour plots further illustrate these interactions by varying two factors while keeping the other one constant.

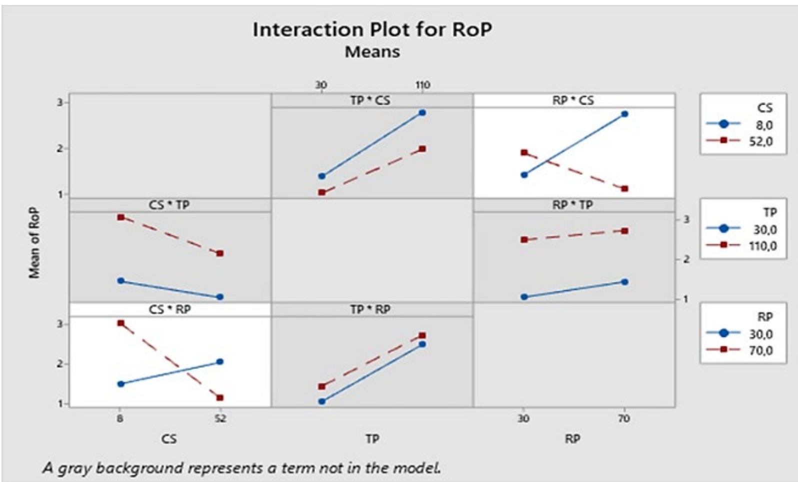

Fig. 8. Interaction plot for various factors

3.1.3. Analysis of the contour plots for Rate of Penetration (RoP). Contour plots reveal the relationship between three continuous variables: Rate of Penetration (ROP), Thrust Pressure (TP), Rotational Pressure (RP), and Compressive Strength (CS), Fig. 9. Contour Plot 1 (Fig. 9, *a*) shows that increasing both TP and RP generally lead to higher ROP. Contour Plot 2 (Fig. 9, *b*), with RP fixed at 50 bar, and indicates that higher TP and lower CS result in higher ROP. Contour Plot 3 (Fig. 9, *c*), with TP set at 70 bar, indicates that higher RP and lower CS leads to greater ROP. Thrust Pressure has a significant impact on ROP, as confirmed by the Pareto chart and main effects plot.

3.1.4. Penetration rate prediction using Multiple Regression Analysis (MRA). Regression equations are essential for predicting the Rate of Penetration (ROP) in drilling operations, as they reflect the effect of Compressive Strength (CS), Thrust Pressure (TP), and Rotational Pressure (RP). These equations help enhancing drilling parameters for better efficiency. For instance, a regression model demonstrated the significant impact of these factors on RoP, highlighting the practical application of regression analysis in improving drilling performance through analytical insights [9].

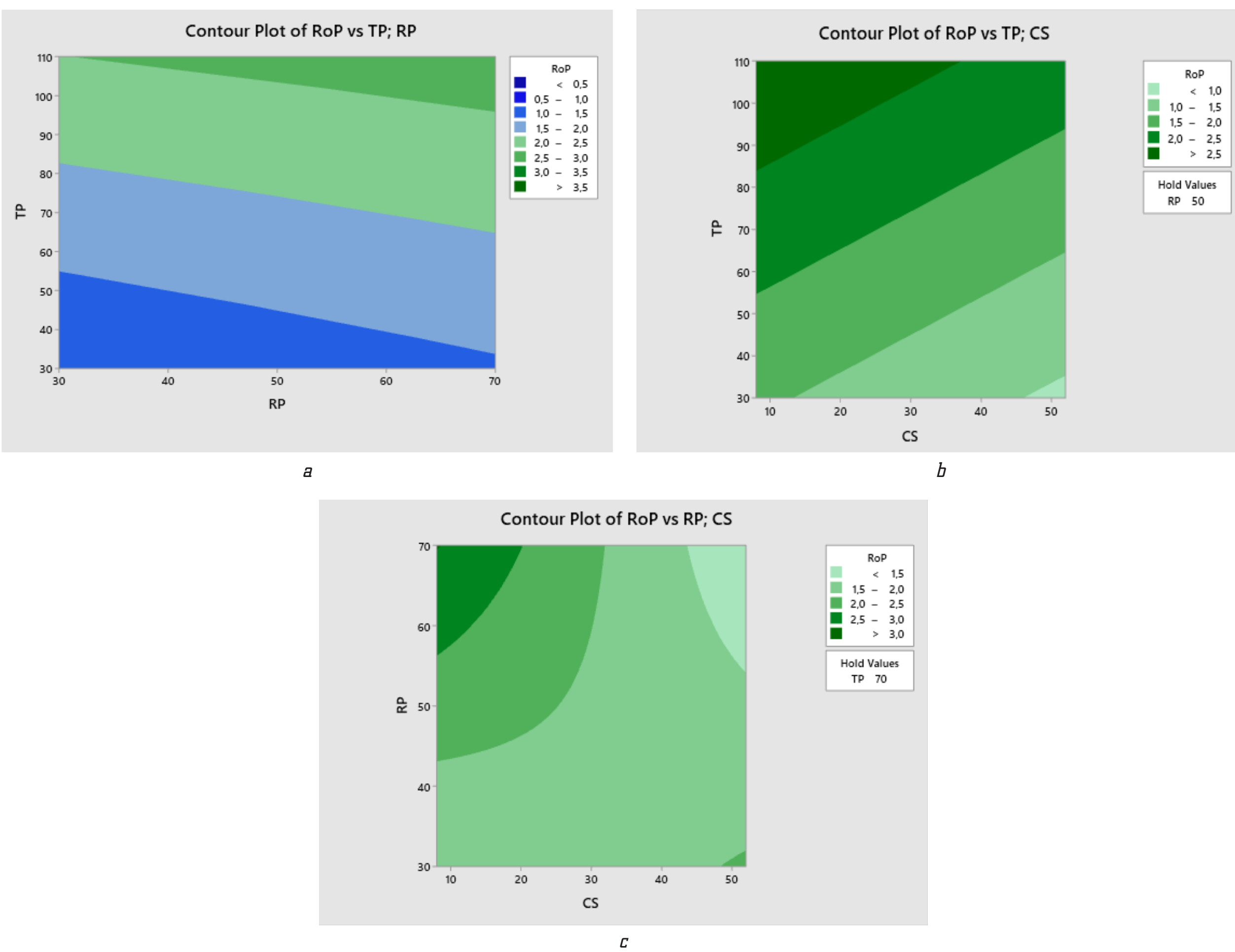

Fig. 9. Contour plots of factorial effects on response surface:
a – contour plot ROP vs TP, RP; *b* – contour plot of ROP vs TP, CS; *c* – contour plot of ROP vs RP, CS

The MRA was carried out with the same datasets and input parameters as previously mentioned.

The MRA prediction equation for ROP is:

$$ROP = -1.275 + 0.0539 \cdot CS + 0.01709 \cdot TP +$$
$$+ 0.04932 \cdot RP - 0.001384 \cdot CS \cdot RP.$$

This regression equation estimates the Rate of Penetration (*ROP*) based on the three factors: Compressive Strength (*CS*), Thrust Pressure (*TP*), and Rotational Pressure (*RP*), including an interaction term between *CS* and *RP*. The intercept (–1.275) serves as a baseline reference. For each unit increase in *CS*, *TP*, and *RP*, *ROP* increases by 0.0539; 0.01709; and 0.04932 units, respectively, showing positive relationships. The interaction term (–0.001384) indicates that increasing both *CS* and *RP* decreases *ROP* by 0.001384 units for each unit increase in their product, indicating a reduction in *ROP* when both *CS* and *RP* are high.

3.2. Fuzzy logic. When the fuzzy logic system receives crisp inputs for CS, RP, and TP, it evaluates the rules in the rule base to create a fuzzy output for ROP. This fuzzy output is then converted using the centroid defuzzification method to provide a single value prediction for the rate of penetration. This prediction can help understand or control the drilling process. The following three-dimensional plots illustrate the relationship between the inputs and the ROP prediction in the Boukhadra mining drilling operation.

3.2.1. Plot Interpretations

a) *First Plot (CS vs. RP)*. Fig. 10, *a* shows the relationship between Compressive Strength (CS) and Rotational Pressure (RP) with respect to the Rate of Penetration (PR). As CS increases, PR decreases, indicating that harder materials reduce the penetration rate. In contrast, higher RP increases ROP, suggesting that increased rotational pressure improves penetration. The slope of the surface as CS increases indicates a direct or nearly direct relationship between these factors and PR.

b) *Second Plot (RP vs. TP)*. Fig. 10, *b* illustrates the relationship between Rotational Pressure (RP) and Thrust Pressure (TP) with respect to PR. The curved surface indicates a nonlinear connection between these variables and the output. A peak in PR reveals an optimal combination of RP and TP that maximizes the penetration rate. Beyond this peak, increasing TP or RP does not further enhance PR, suggesting inefficiencies at excessive pressures.

c) *Third Plot (CS vs. TP)*. Fig. 10, *c* illustrates the combined impact of Compressive Strength (CS) and Thrust Pressure (TP) on ROP. The surface slopes downward as CS increases, confirming that harder materials decrease the penetration rate. Although PR increases with higher TP, the relationship is not linear. The non-flat surface indicates that the effect of TP on PR varies with different CS values, indicating an interaction between these variables.

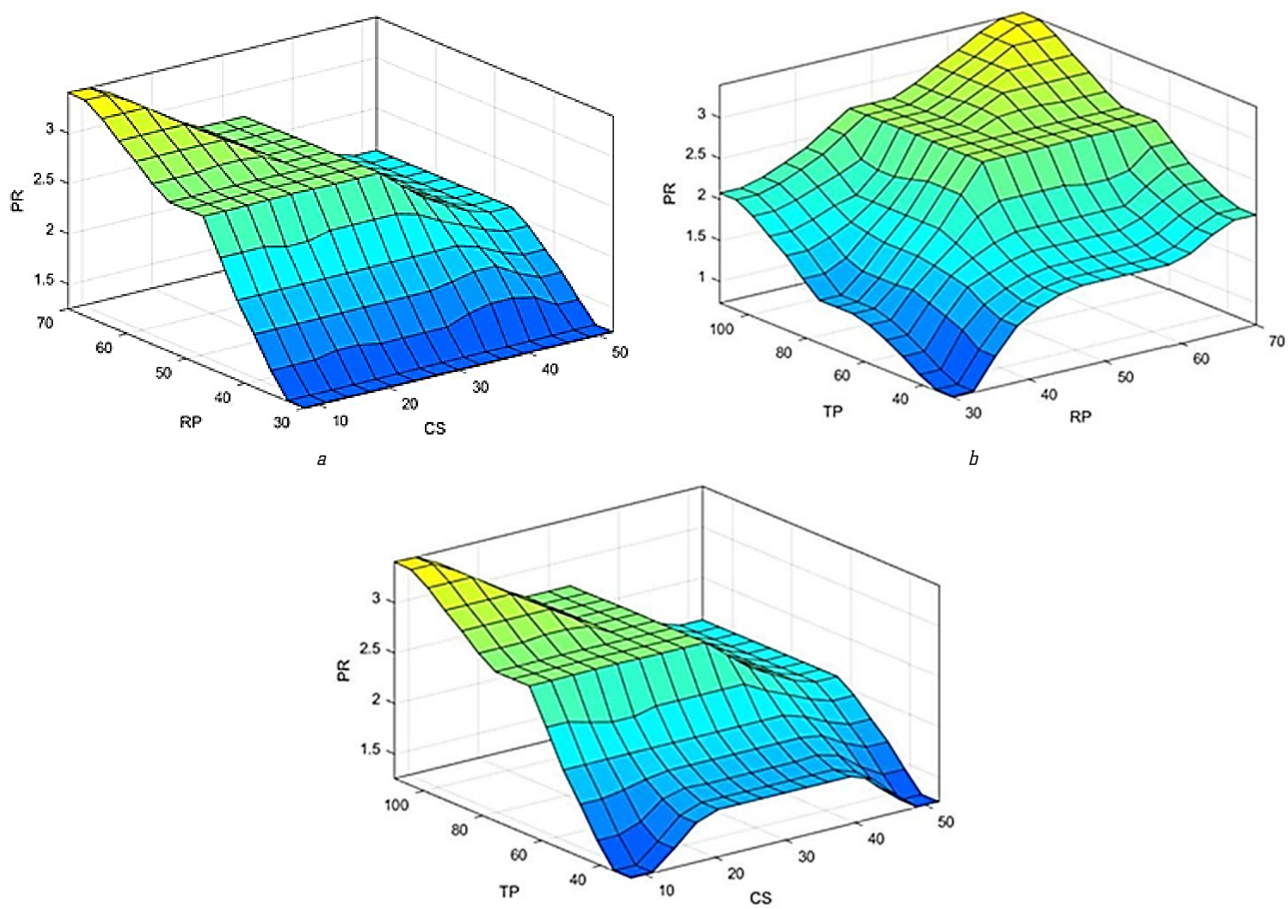

Fig. 10. Surface viewer of: *a* – penetration rate (PR) versus compressive strength (CS) and rotational pressure (RP); *b* – penetration rate (PR) versus (RP) and (TP); *c* – penetration rate (PR) versus (CS) and (TP)

3.3. Artificial neural network

3.3.1. Model training, validation and testing. The training process involved splitting the data into 70 % for training, 15 % for validation, and 15 % for testing to optimize the model's learning, validation, and testing performance. The training set, consisting of 70 % of the data, was used to adjust the neural network's weights and biases based on feedback from the loss function, creating a reliable dataset for detecting complex patterns. Fig. 11, *a* shows that the training data points are very close to the line, indicating high prediction accuracy and a high R^2 value, which reflects the model's effectiveness.

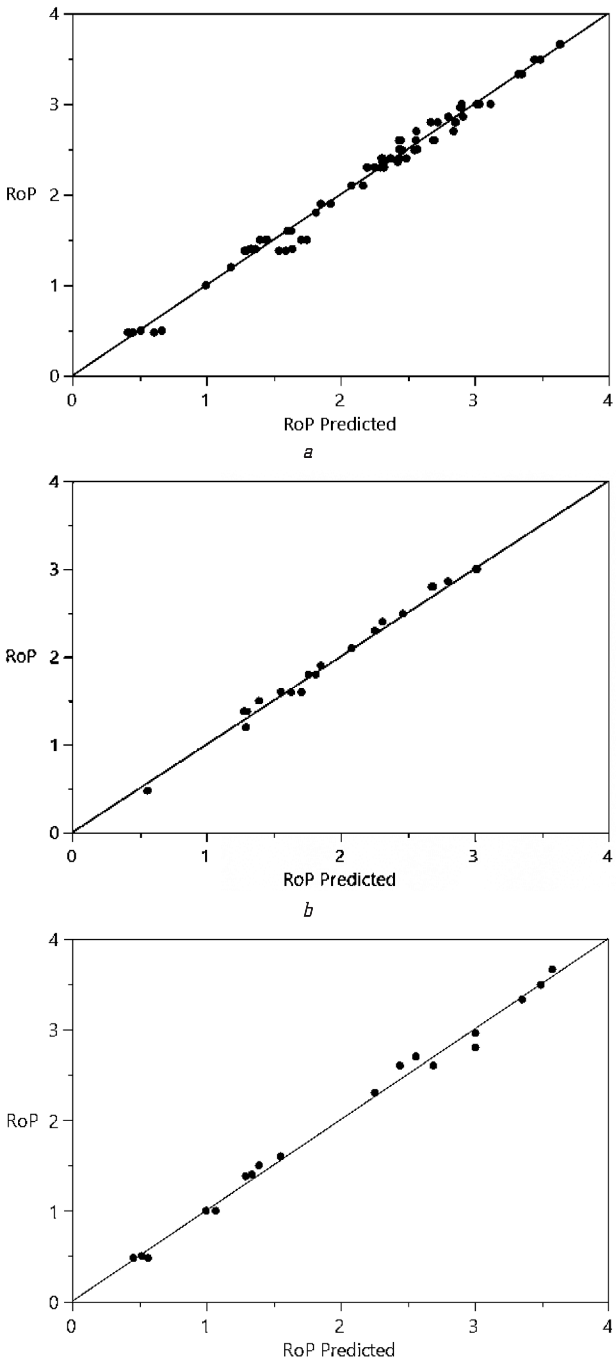

Fig. 11. Comparison of predicted and actual values across different data sets: *a* – training data step; *b* – validation data step; *c* – test data step

The validation set, consisting of 15 % of the data, offers an impartial evaluation of the model fit on the training dataset while adjusting the model parameters. This set is crucial for monitoring the model's performance during training, allowing for necessary adjustments without using the test set data. Reserving 15 % for validation ensures adequate statistical verification and adjustment of the model's performance, without reducing the data available for training. This proportion is sufficient to validate the model's effectiveness and detect issues like overfitting or underfitting. Fig. 11, *b* Validation Data Step shows points closely aligned with the line, indicating that the model generalizes well to unseen data in the validation set.

The test set, consisting of 15 % of the data, is essential for assessing the final model's performance. This data is never used during training and serves as a new dataset for evaluating the model's predictive accuracy on new data. Reserving 15 % to the test set ensures thorough testing of the model after training and validation, providing a balanced evaluation of its ability to generalize without reducing the training data size. Fig. 11, *c* Test Data Step shows that the test data points closely follow the trendline, with a slight divergence compared to the training and validation sets, which is expected as the test data represents completely new conditions, yet still demonstrates good predictive performance by the model.

3.3.2. Backpropagation learning algorithms. Backpropagation is a key learning algorithm for neural networks, involving a forward pass to generate outputs and a backward pass to calculate and propagate errors. These errors are used to update the network's weights and biases through an optimization technique. The goal is to minimize prediction errors by adjusting the model parameters, ensuring accurate correlation of inputs to outputs.

3.3.3. Evaluation and performance metrics. The performance metric used is the *R*-Squared Error (R^2), which measures the proportion of variance in the dependent variable predictable from the independent variables (Table 3). R^2 ranges from 0 to 1, with higher values indicating a better fit. The R^2 values are 0.9908 for training, 0.9883 for validation, and 0.9926 for testing, indicating excellent model performance across all datasets.

Table 3

R^2 error for each step of training process

Training		Validation		Test	
ROP		ROP		ROP	
Measures	Value	Measures	Value	Measures	Value
Rsquare	0.9908197	Rsquare	0.9883359	Rsquare	0.9926174

3.3.4. Prediction profiler. Fig. 12 presents the relationships between each input variable (CS, RP, TP) and the output variable (ROP). For Compressive Strength (CS), RoP initially decreases as CS increases and then stabilizes, indicating a nonlinear relationship. For Rotational Pressure (RP), a linear relationship is observed, with RoP increasing as RP increases. Similarly, for Thrust Pressure (TP), ROP increases with TP, though the relationship is slightly less linear, suggesting a limit beyond which the rate of increase in RoP slows down.

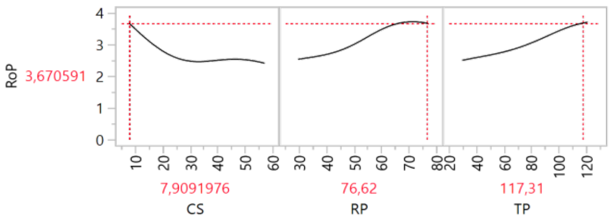

Fig. 12. Plots showing the relationship between each input variables and the output variable (ROP)

3.4. Evaluation of the predictive models. The methods' accuracies are compared in terms of RMSE (root mains square error), and it gave us these results (Fig. 13).

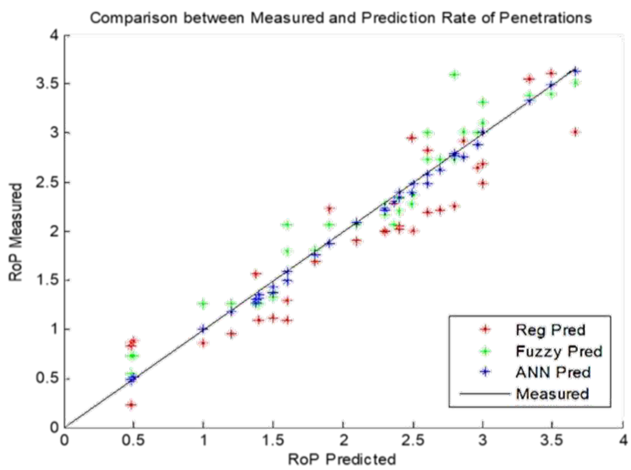

Fig. 13. Comparison between measured and prediction ROP

The following equation was used:

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \hat{x}_i\right)^2},$$

where n is the number of observations, x_i is the observed value, $\hat{x}_i$ is the predicted value.

3.4.1. RMS error analysis

3.4.1.1. RMS error between measured ROP and regression model predictions. The regression model's predictions show a moderate error compared to the actual measured ROP, with an RMS error of 0.37493. This indicates that the regression model is less accurate than other methods, due to its inability to effectively represent complex relationships or patterns in the data.

3.4.1.2. RMS error between measured ROP and fuzzy logic predictions. The fuzzy logic model shows a lower RMS error of 0.28354, suggesting it is more accurate in predicting the ROP compared to the regression model. Fuzzy logic systems are better at handling uncertainty and modeling complex processes, which explains the improved accuracy. However, some variation still exists between the fuzzy logic predictions and actual measurements.

3.4.1.3. RMS error between measured ROP and ANN predictions. The Artificial Neural Network (ANN) provides the most accurate predictions, with an RMS error of 0.069055. This relatively small error indicates high predictive accuracy, as ANNs are highly effective at identifying the fundamental patterns in the dataset that impact ROP. Their ability to model nonlinear and complex relationships contributes to this high level of accuracy.

3.5. Practical significance and conditions for using research. This study's findings and methodologies, particularly the predictive models developed for drilling operations, have the potential to be adapted and applied to various mining environments globally. By adjusting the models to different geological settings and mining conditions, these tools could significantly improve drilling efficiency and cost-effectiveness in mines worldwide. This potential for global applicability emphasizes the broader value of the research, reaching beyond its initial focus on the Boukhadra iron mine.

While the study provides valuable insights, there are several limitations that need to be acknowledged. Firstly, the accuracy of the models is heavily dependent on the quality and quantity of the available data, which could affect their reliability. Additionally, both Fuzzy Logic and Artificial Neural Networks (ANN) models are computationally intensive, which may pose challenges for practical implementation. Lastly, there is a risk of overfitting with the ANN model, where it may perform well on training data but struggle to generalize effectively to new, unseen data.

4. Conclusions

It is possible to conclude that for Boukhadra mining drilling operations, where the Rate of Penetration (ROP) is a crucial parameter, the Artificial Neural Network (ANN) model stands out as the most effective predictive tool. Through our comprehensive comparison involving regression models, fuzzy logic, and ANN, it is found that the ANN model consistently achieved the lowest Root Mean Square (RMS) error values. This indicates that its predictions are significantly closer to the actual measurements compared to the other methods.

The Regression Model produced an RMS Error of 0.37493, indicating a moderate level of prediction accuracy. In contrast, the Fuzzy Logic model demonstrated enhanced predictive performance with an RMS Error of 0.28354. Notably, the ANN model surpassed both, achieving the highest accuracy with a significantly lower RMS Error of 0.069055.

The ANN model's superior performance is attributed to its ability to capture complex, non-linear relationships between the factors influencing ROP, which traditional regression models and fuzzy logic systems might not adequately address. The adaptability of the ANN model make it particularly suited for the dynamic conditions encountered in mining operations.

Given these findings, the ANN model not only provides the most accurate ROP predictions but also offers a reliable basis for making informed planning and operational decisions. Its implementation in Boukhadra mining could lead to optimized drilling strategies, reduced operational costs, and improved overall efficiency. Therefore, it is possible to recommend adopting the ANN model for future predictive tasks in this context, ensuring better alignment with actual drilling performance and enhanced decision-making capabilities.

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Conflict of interest

The authors declare that they have no conflict of interest concerning this research, whether financial, personal, authorship or otherwise, that could affect the study and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

The paper has no associated data.

Use of artificial intelligence

The authors have used artificial intelligence technologies within acceptable limits to provide their own verified data, which is described in the research methodology section.

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