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Improvement of Drill Bit-Button Performance and Efficiency during Drilling: an application of LSTM Model to Nigeria Southwest Mines

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Abstract

The quarry operators and managers are having a running battle in determining with precision the rate of deterioration of the button of the drill bit as well as its consumption. Therefore, this study is set to find the best-performing model for predicting the drill bit button's wear rate during rock drilling. Also, the rate at which drill bit buttons wear out during rock drilling in Ile-Ife, Osogbo, Osun State, and Ibadan, Oyo State, Southwest, Nigeria was investigated. Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and adaptive moment Estimation-based Long Short-Term Memory (LSTM) machine learning approaches were used to create models for estimating the bit wear rate based on circularity factor, rock grain size, equivalent quartz content, uniaxial compressive strength, porosity, and abrasive properties of the rock. The performance of the models was measured using a new error estimation index and four other convectional performance estimators. The analysis of performance shows that the adaptive moment estimation algorithm-based LSTM model did better and more accurately than the other models. Thus, the LSTM models presented can be used to improve drilling operations in real-life situations.

1. Introduction

The use explosives for fragmentation of rock mass helps all other operations coming after drilling and blasting for improved productivity. It is also an important factor in determining mine productivity because it has a clear effect on how well mining equipment works and, on the mine's, overall profit. Drilling action is the process of making holes in rocks so that they break apart easier when they are blasted. The cost and output of blasting operations are directly tied to how well drilling operations are carried out [1]. Eshun *et al.* were of the opinion that drilling and blasting operations are two of the most important unit activities in any hard rock mine [2]. Different ways have been found around the world to make mining operations work at the optimum. These include drilling and blasting, using noiseless removal agents, and cutting, all of which require drilling [3, 4]. Drilling and blasting of rocks had been noted as an important part of Civil and Mining Engineering. The output of drilling and blasting depends on the person doing it, the rock, and the machine [5, 6]. The physical and mechanical properties of rocks change from one place to another. This is because the geology of the place where the rock mass is located and the makeup of the parent rocks [7, 8] affect how the rock behaves. Even when rocks are taken from the same place, their qualities can vary by a small or large amount due to the variety of the rock mass in place. The way a drilling machine works relies on the strength, grain size, pore spaces, and shape of the grains of the rock, all of these varied from place to place. These rock qualities can make a big difference in how well the

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drilling bit works, which determine how fast it wears [9, 10]. Abdulmalek *et al*. observed that the speed of bit penetration depends on the structure of the rock's minerals, the drilling machine, the rock's geo-mechanics, the driller, and the choice of drilling tools that are best for the rock [11–14]. Thus figuring out how fast the bit will wear is a very important part of mine planning, especially when the size of the grains, the strength of the rock, and the hardness of the rock are taken into account as separate factors [15]. Still, the rate of advance depends on how the drill bit and rock grains combine as the drill bit moves forward. When cutting into rock, the rate at which the drill bit wears out is an important factor that has a big effect on how much it costs and how far it will penetrate into the rock [16].

In the meantime, bit penetration rate mostly depends on rock characteristics (strength, abrasion, mineralogy, brittleness, and porosity), which cannot be controlled but can be found out through lab studies, and operational variables (drill bit diameter, rotational speed, thrust, air pressure, and drilling fluid pressure), which can be controlled and found out by drilling machine variables [17]. The research by Hoseinie *et al*. showed that the size of rock grains affects their mass and strength, which in turn affects how fast a drilling bit works [18]. The amount of material worn away from the drill bit per unit of time as the drill rod moves into the rock is called the "wear rate." Adebayo and Akande went on to explain that the rate of penetration is the length of rock that is cut through per unit of time, while the wear rate is the rate at which material is worn away from the bit's surface. This is used to predict how long the bit will last [19]. Duru's research showed that the shape of drill bit cones as the source of force penetration is also affected by the material's micro (texture, grain geometry, matrix material) and macro (strength, elasticity) qualities [20]. Luyckx and Love's work revealed that the abrasion resistance ability of the drill bit material and these properties of the rock control how fast the bit cone wears [21]. A good estimate of the rate at which the drill bit wears out helps plan rock mining projects and helps optimize drilling costs [22]. Drilling is the most expensive process, and knowing how fast drill bit wear is very important for improving the performance of drilling machines and the efficiency of blasting. Even though bit wear rate (WR) is the main factor that affects drilling penetration rate, operating economically and efficiently, it was noted that several theoretical models [23, 24] based on different parameters have been described in the literature. Plinninger *et al*. [25] said that tool wear happens under certain loads and temperatures because of a complicated system called tribology. They confirmed that removing rock is a microscopic and macroscopic process, like abrasion, adhesion, material stress or the brittle failure of tool materials. Many different things from the main fields of geology, tools, and transportation affect how quickly these things happen. Geologists, material scientists, mining engineers, and construction engineers have been studying these effects for decades. Major geological factors have been identified as rock properties, joint features, how rocks weather or change, the water situation, the makeup of different rock masses, and the underground stress situation. Saeidi [26] used image processing techniques in monitoring of bit wear, especially, WC/Co cemented carbide bits that are commonly used in rotary drilling in mining, civil and petroleum engineering. They acquired the image of the bits using a CCD camera. Their study revealed that bit wear in rotary drilling at surface mining operations correlate with various geological and operational parameters. Capik and Batmunkh [27] also predict bit wear during surface mine drilling operations. The wearing of bit depends on the button composition. Piri *et al.* [28] investigated the wear resistance of drill bits with tungsten carbide (WC) coating, DLC-Diamond coating, and titanium-silica-aluminum (TiAlSi) coating when drilling in three types of hard rocks. The results showed that for any fixed drilling conditions, the wear rates of the TiAlSi drill bit in the three locations were lower than those of the tungsten carbide drill bit. It was also revealed that Diamond-DLC drill bit has lower wear rates than the WC drill bit. The mechanical properties rock also affects drill bit wear resistance [28]. Mikaeil *et al*. [29] also explained that the evaluation and prediction of cutting machine such diamond wire saw is one of the most important factors involved in planning the dimension stone quarries. They noted that cutting machine wear rate is a major criterion to evaluate its performance. Mazen *et al*. [30] mentioned that prediction of drilling performance is based on the interaction of cutter and rock. Several authors focused on the cutter-rock interface but only a few researchers tried to model the wear of the PDC bit cutters.

Mazen *et al.* [30] developed a new mathematical model to predict the PDC bit performance by considering the factors that were already not taken into account. There are different ways to figure out how fast a drill will go through rock and how fast the bit will wear down. Each method has its own limitations, which leads to different prediction mistakes.

Rock strength significantly influences both drill bit wearing and penetration rate in drilling operations [31]. Harder rocks tend to cause higher wear rates on drill bits due to the increased resistance they offer, leading to more abrasive interactions [32]. This results in quicker deterioration of the bit's cutting edges. Moreover, higher rock strength often leads to a slower penetration rate, as the bit has to exert more force to break and remove the rock. Conversely, softer rocks result in less wear on the bit but may lead to a faster penetration rate due to reduced resistance. Optimal drill bit selection and operational parameters are crucial to balance these factors and enhance drilling efficiency. A lot of different testing methods and standards can be used to figure out how fast drill tools will wear out [25]. These methods cover a wide range of sizes, from real-world drilling tests done on-site to model tests done with simple tools to microscopic and chemical studies of rocks and minerals. Depending on their size and parameters, they can take some things into account and not take others into account. So far, more attention has been paid to how machine learning can be used to solve hard engineering and rock mechanics problems. Many types of engineering, including petroleum engineering (see Table 1), have recorded the used of neural networks and deep learning to build models. Furthermore, because of the growth of high-performance computer systems, predictive models are much more accurate and complicated than they used to be [33]. Patra *et al*. used a multilayer neural network with a back propagation algorithm (BPNN) to predict the average side wear of a high-speed steel (HSS) drill bit used to drill on a mild steel work piece [34]. In a study published in Heliyon [35], Phate *et al.* investigated the prediction and optimization of tool wear rate during electric discharge machining (EDM) of an aluminum-copper-nickel alloy using an adaptive neuro-fuzzy inference system (ANFIS). The authors aimed to analyze the impact of process parameters such as input current, pulse on time, and pulse off time on tool wear rate. They employed Taguchi's L18 mixed plan for experimentation and developed a mathematical model to correlate these process parameters. ANFIS was then used to predict the tool wear rate based on these parameters. The results showed that input current had the most significant influence on tool wear rate, followed by pulse on time. The amount of aluminum in the alloy inversely affected tool wear rate, while increasing copper content increased it. Additionally, tool wear rate initially decreased with an increase in pulse on time but started to increase after reaching a median value of 25 micro-seconds [35]. The confirmation experiments conducted using optimal process parameters validated the obtained results and demonstrated ANFIS's capability to predict tool wear rate accurately. Although this study focused specifically on EDM and not drill bit wearing resistance, it demonstrates how artificial intelligence approaches like ANFIS can be utilized for predicting tool wear rates based on various process parameters [35]. This methodology could potentially be applied or adapted for predicting drill bit wearing resistance in drilling operations. While no articles directly addressed the prediction of drill bit-button performance using artificial intelligence approaches, a study published by Capik and Yilmaz used regression to develop models for figuring out how long a bit will last base on how easy it is to drill and how hard and rough the rock is [36].

Several researchers have used different databases to make predictions about aspects including blast production, blast impact, and drilling penetration rate in mining operations, as shown by a review of the relevant literature. It is widely accepted that having a large and high-quality database is crucial for successful application of soft computing models. Many studies have tried to enhance drilling operations by using regression analysis and traditional soft computing machine learning techniques. It is difficult to determine the best performing machine learning model for predicting drill tool performance due to the utilization of several databases. Additionally, recurrent neural networks like the long-short term memory network (LSTM) and deep learning approaches like the adaptive neuro-fuzzy inference system (ANFIS) have not been deployed for estimating drill bit wear rate. In addition, research on the accuracy of ANN, ANFIS, and Adam solver-based LSTM in predicting drill bit wear rate is limited. The objective of this study is to evaluate the efficacy of artificial neural networks, hybrid algorithms for ANFIS, back propagation ANFIS, and the Adam optimizer's long short-term memory (Adam-LSTM) learning algorithm in predicting drill bit wear rate, and to fill the gaps identified in the literature review. Last but not least, six evaluation indices and new performance evaluator indices are introduced and used to measure the efficiency of the proposed models. The study area includes selected quarries in Ife, Oshogbo, Osun State and

Ibadan, Oyo State, Southwest, Nigeria, as shown in Figure 1.

Table 1. Literature review of machine learning application toe field.

References	Year	Technique	Number of datasets	R^2
[37]	2011	ANN	220	0.97
[38]	2007	BNN-ANN	43	
[39]	2022	HP-ANN, ANFIS, MVR	59	ANN = 0.96 ANFIS = 0.76 MVR = 0.68
[40]	2013	ANN	103	0.85
[41]	2013	ANFIS	30	0.83
[42]	2015	FIS, LMR	185	FIS = 0.922 LMR = 0.738
[43]	2016	ANN, ANFIS	115	0.95
[44]	2020	RF, CART, CHAID	102	0.94
[45]	2020	CSO	75	0.985
[46]	2022	ANN, SVR	102	ANN = 0.87, SVR = 0.81
[47]	2022	XGBoost, RF, KNN	152	XGBoost = 0.9125, RF = 0.67, KNN = 0.87
[48]	2022	GEP	1032	0.981
[49]	2023	ANN, SVR, MVR, Ri	30	ANN = 0.94 MVR = 0.80 SVM = 0.78 Ri = 0.74

FIS: fuzzy inference system, HP: hunter point, ANN: artificial neural network, ANFIS: adaptive neuro-fuzzy inference system, LMR: linear multiple regression, CSO: cat search optimization, SVR: support vector regression, XGBoost: eXtreme gradient boosting, Ri: Ridge Regression, RF: random forest, KNN: K-Nearest Neighbors, GEP: gene expression programming

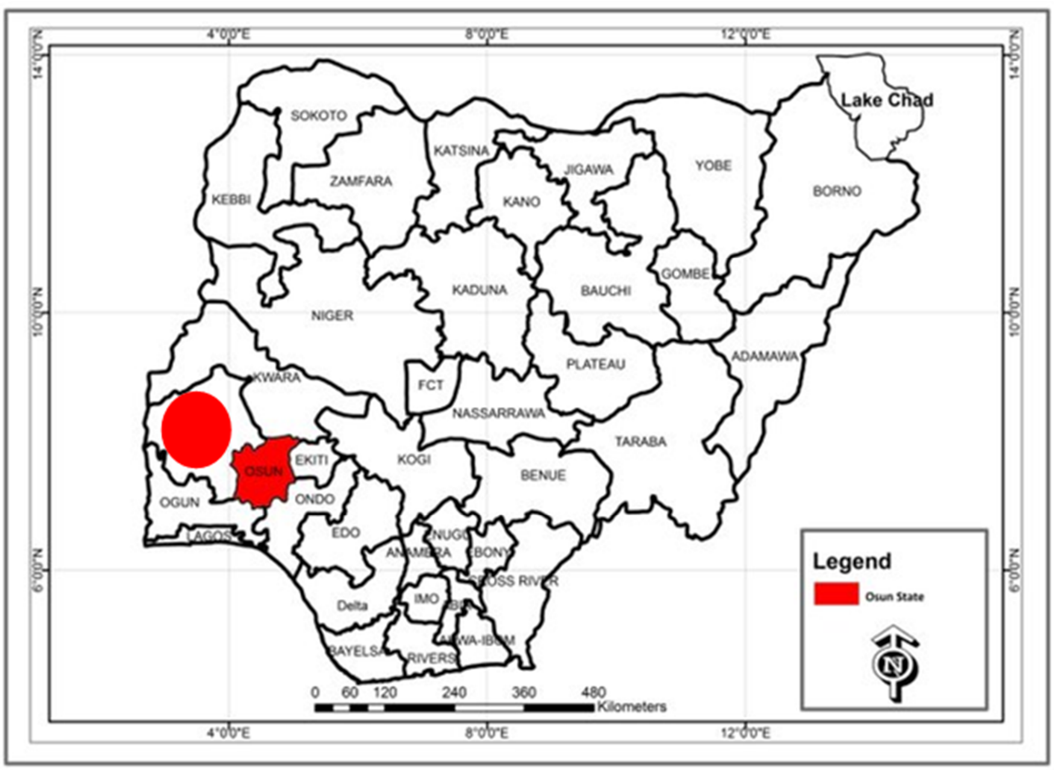


Figure 1. Map of Nigeria showing case study area at southwest region.

2. Data Collection and Model Methodology

In this paper, the granite quarries in Ile-Ife, Osogbo Osun State and Ibadan, Oyo State, all these locations fall within the Southwest basement complex of Nigeria, served as a case study. In addition, the number of outcrops in this region varied from isolated boulders to large exfoliated domes and inserlberg. Seventy-five drilling instances were monitored in preparation for production blasting. During drilling operations at the quarries, the drill bit diameter and the length of the gauge bit cones and centre buttons were periodically monitored. For the monitored drilled formations, we also calculated the rock uniaxial compressive strength (UCS), porosity (POR), equivalent quartz content (EQC), grain size (AGS), circularity factor (CF), and rock abrasive index (AB-I), as detailed in Section 2.1.

2.1 Rock parameters

Three different locations with the following granite rock types which medium feldspar granite, coarse muscovite granite, and biotite hornblende granite were considered in this study. Twenty-five samples were collected using purposive sampling techniques according to Etikan and Bala [50] from the three locations.

2.1.1 Determination of average grain size and angular factor

In order to calculate the mean grain size of the samples, an observation window or reference region was established, as per ISRM [51]. Samples were captured under a microscope and the grain size was determined according to standard method suggested by ISRM. In order to calculate the circularity shape factor, Equation (1) was used which was proposed by Erosy and Waller [15].

$$cicularityfactor = \frac{4\Pi(Area)}{(Perimeter)^2} \qquad (1)$$

2.1.2 Determination of porosity of rock samples

Porosity was determined using saturation and calliper technique as suggested by ISRM [45]. The pore volume and porosity were obtained using Equations 2 and 3.

$$\text{Vp} = \frac{(\text{Msat} - \text{Ms})}{\rho\text{w}} \qquad (2)$$

where ρ_w is the density of the saturated fluid (water), Ms is the grain mass, and M_{sats} is the saturated mass.

$$\text{Porosity (n)} = \frac{100\ \text{Vp}}{\text{Vb}} \qquad (3)$$

Vp is the pore volume (cm^3) and V bis the bulk volume (cm^3).

2.1.3 Determination of equivalent quartz content of rock samples

The equivalent quartz content (EQC) of the samples were determined in accordance with the Thuro [52] method; this was calculated by multiplying percentage of the mineral present in the rock sample with Rosiwal abrasiveness value using Equation (4).

$$\text{EQC} = \sum_{i=0}^{n} A_i R_i \ (\%) \qquad (4)$$

where A is the mineral amount (%), R is the *Rosiwal* abrasiveness (%), and n is number of minerals.

2.1.4 Determination of uniaxial compressive strength of selected rocks

The uniaxial compressive strength of the rock samples was determined using 1100 kN compression machine. The test procedure was in accordance with ISRM [51]. The uniaxial compressive strength was determined using Equation (5).

$$\sigma = \frac{F}{A} = \frac{F}{W.D} \qquad (5)$$

where:

σ represents the uniaxal compressive strength measured in MPa, F is the applied peak load in kN, W denotes the sample width in mm, and D represents the sample height in mm.

2.1.5 Rock abrasive index

The abrasiveness index of the rock samples collected from three different locations was determined. Rock abrasive index was computed using Equation (6) proposed by Thuro [52].

$$\text{RAI} = \sigma \times \text{EQC} \qquad (6)$$

where σ is compressive strength (MPa), and EQC is the equivalent quartz content (%).

Each rock property database has numerous data points spread out across many rows and columns. Therefore, we use the database to construct the descriptive statistics shown in Table 2 and Figure 2. Mean, standard deviation, skewness, kurtosis, minimum and maximum skewness, and kurtosis are some of the descriptive statistical measures utilized in the current study (Equations 7 and 8). The skewness of a distribution is a statistical indicator of its disproportionality. It is a statistical method for determining the extent to which a distribution favors the left or right.

$$\text{Skewness} = \frac{1}{N} \times \frac{\sum_{i=1}^{n}\overline{(X_i - X)}^3}{S^3} \quad (7)$$

$$\text{Kurtosis} = \frac{1}{N} \times \frac{\sum_{i=1}^{n}\overline{(X_i - X)}^4}{S^4} \quad (8)$$

The distribution has a fat left tail, negative skewness, and Kurtosis [53] if the number of negative returns is much larger than the number of positive returns. The distribution is platykurtic if and only if the excess kurtosis is negative [53].

Table 2. Descriptive statistics of both training and testing database.

	AB-I	UCS	POR	CF	EQC	AGS	WR
			Training data				
Mean	5646.820	99.474	1.066	0.713	56.283	0.648	0.024
StDev	1367.560	12.272	0.229	0.072	9.747	0.387	0.007
N	60.000	60.000	60.000	60.000	60.000	60.000	60.000
Variance	1870219.736	150.608	0.053	0.005	95.009	0.149	0.000
Min	4092.800	90.390	0.770	0.620	45.150	0.100	0.013
Max	7265.700	119.740	1.430	0.861	67.260	1.040	0.037
Skewness	-0.134	1.029	0.436	0.015	-0.158	-0.413	0.316
Kurtosis	-1.784	-0.893	-1.599	-1.300	-1.823	-1.523	-1.172
			Testing data				
Mean	6894.095	109.469	0.879	0.669	63.351	0.458	0.024
StDev	467.838	12.848	0.044	0.039	3.273	0.279	0.010
N	60.000	60.000	60.000	60.000	60.000	60.000	60.000
Variance	218872.623	165.069	0.002	0.002	10.712	0.078	0.000
Min	6336.600	93.790	0.770	0.621	60.670	0.110	0.013
Max	7263.170	119.740	0.940	0.702	67.280	0.690	0.040
Skewness	-0.455	-0.456	-0.885	-0.456	0.454	-0.454	0.134
Kurtosis	-2.094	-2.091	1.791	-2.084	-2.093	-2.086	-1.479

Table 1 presents the training and testing database including the result of various abrasive index, uniaxial compressive strength (UCS in MPa), Porosity (POR in %), circuarity factor (CF), equivalent quartz content (EQC in %), average grain size (AGS in mm), and wear rate (WR in mm/m) in the range of 4092.8-7265.7, 119.74-90.39, 1.43-0.77, 0.86-0.62, 67.26-45.15, 1.04-0.1, 0.037-0.013, respectively. In Table 1, skewness and kurtosis results revealed that the data distribution is Platykurtic with high negative returns (see Figure 2).

2.2. Model development

Figure 3 presents the pair wise plot for the dataset used in this work. The aim of building a pair wise plot was to determine the influential attributes of the proposed model input variables on LSF. The input and output variables (Table 1) were standardized between -1 and 1 using Equation (9) [38] to achieve the dimensional consistency of the parameters and also eliminate model over-fitting.

$$Yi = \frac{2(Xi - Xmin)}{(Xmax - Xmin)} - 1 \quad (9)$$

where Xmin is the minimum input value in the input dataset, Xmax is the maximum input value in the input dataset, Di is the input value to be normalized, and Yi is the normalized input value result [9]. The data preparation process for the model development is present in Figure 4.

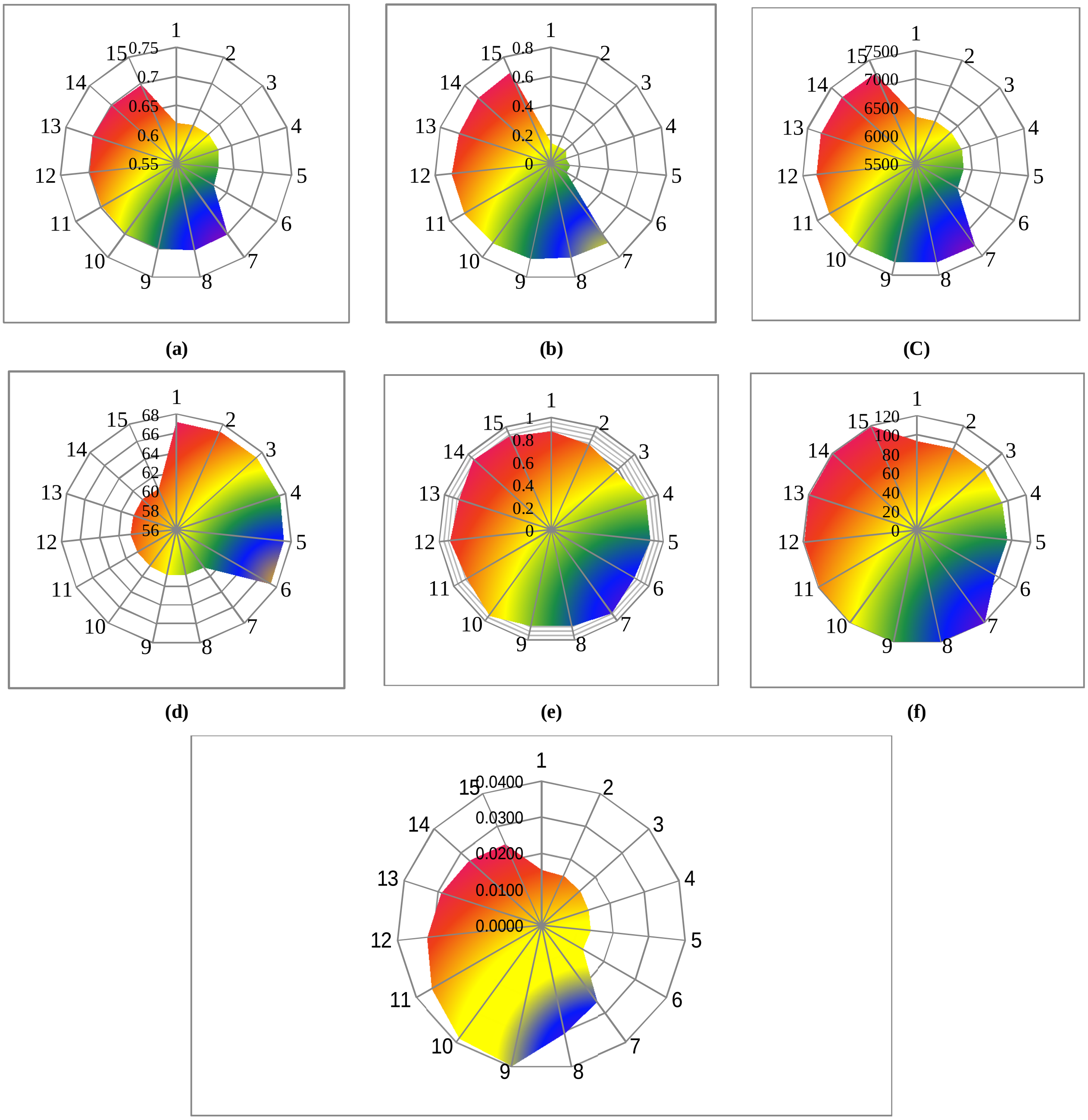


Figure 2. Illustration of the frequency distribution of parameters: a. CF, b. AGS, c. AB-I, d. EQC, e. POR, f. UCS, g. WR.

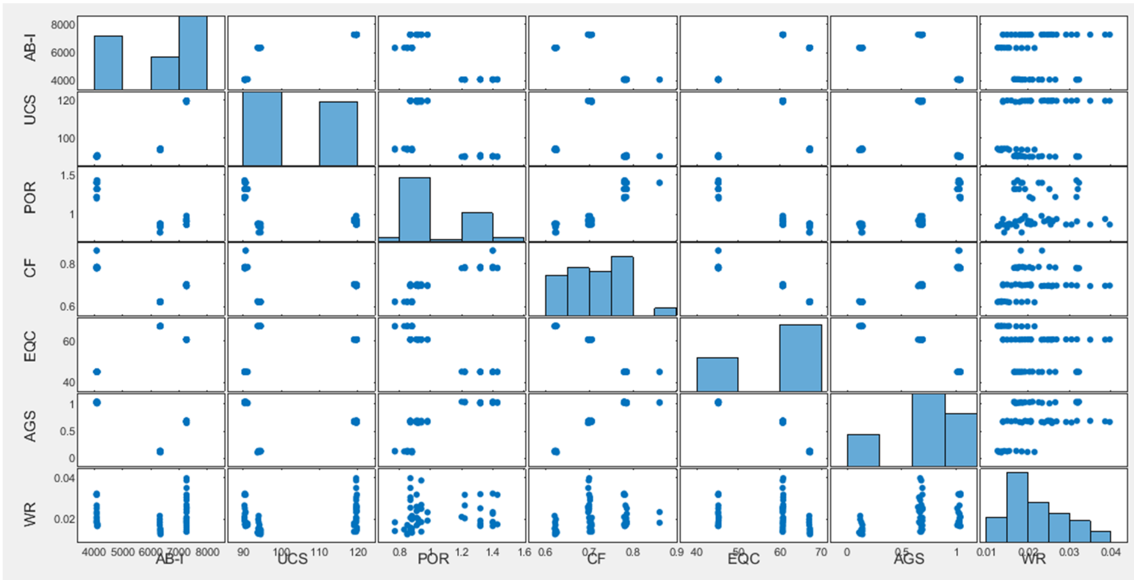


Figure 3. Pairwise plot of the dataset used in this study.

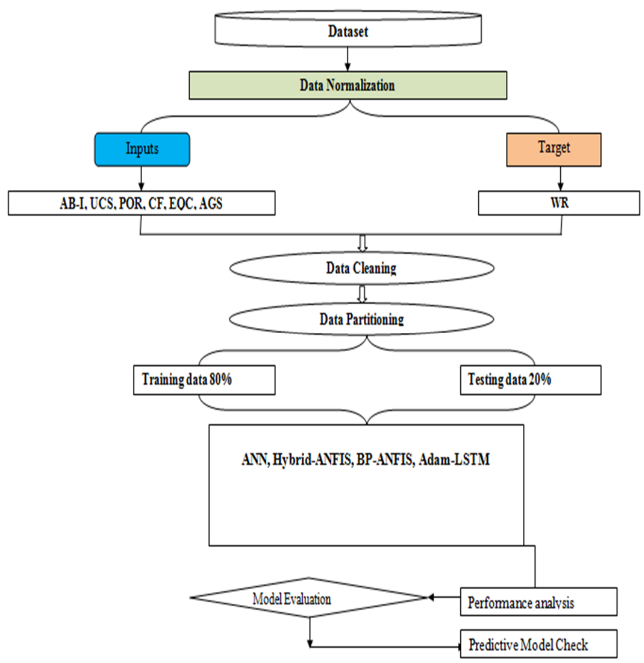


Figure 4. Shows the proposed model development flow sheet.

2.2.1. Artificial Neural Nework (ANN)

In order to attempt to represent the relationship between the historical set of model inputs and their corresponding outputs, artificial neural network (ANN) algorithms learn from the data samples supplied to the system and adopt this data to alter their weights. The hidden layer, input layer, and output layer make up the neural system. Weighted joints link each of the three levels. Using Equation (10), we can determine the output of each neuron layer. Every neuron communicates with its neighbours in the layer above it. In contrast, interlayer connections do not exist [54].

$$Q = \sum_{i=1}^{n} X_i \times w_i + b \tag{10}$$

The activation of the neuron layer output was done using activation functions expressed in Equation (11).

$$f(Q) = f(\sum_{i-1}^{n} X_i \times w_i + b \tag{11}$$

There have been multiple successful implementations of ANN as a modelling tool over the years. The artificial neural network (ANN) approach-based model was created by Bhatawdekar *et al.* [55] to predict blast-induced fly-rock distance based on eight input factors. In estimating the number of boulders produced by blasts in limestone quarries, Dhekne *et al.* [56] used 300 recorded blasting data points to create an ANN model. The mean size of blasts was estimated by Amoako *et al*. using ANN and support vector machines [37]. In order to predict the rate at which a drill bit will wear out, this research utilized an ANN approach with four different neuron possibilities. The suggested model made use of seventy-five datasets, with eighty percent of the data utilized for training and twenty percent used for testing. Table 3 displays the results of this study's use of two different methods to create eight ANN-based models. Both the correlation coefficient and the mean square error index were used to assess the quality of the models. Figure 5 depicts the optimal model architecture and training performance. With an R-value of 0.76 and an MSE of 0.000025 for the training dataset and an R-value of 0.74 and an MSE of 0.000026 for the testing dataset, respectively, Table 3 demonstrates that the Levenberg-Marquardt model with 12 hidden layers yielded the best prediction result in the error assessment.

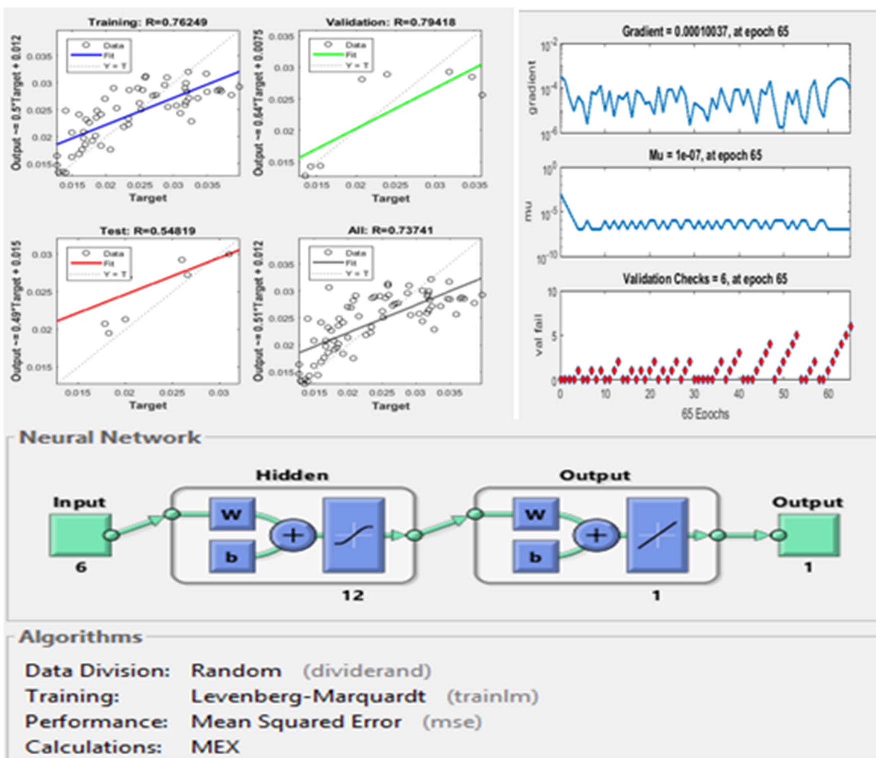


Figure 5. Model training parameters and architecture.

Table 3. Different model ANN structure and performance with wear rate database.

State		**Mod 1**	**Mod 2**	**Mod 3**	**Mod 4**
	Number of Neurons	4	6	8	12
			Levenberg-Marquardt-ANN		
Training	R-value	0.2	0.75	0.66	0.76
	MSE	0.000057	0.000025	0.000035	0.000025
Test	R-value	0.25	0.69	0.64	0.74
	MSE	0.0000343	0.0000299	0.000035	0.000026
			BR-ANN		
		Mod 5	Mod 6	Mod 7	Mod 8
State	Number of Neurons	4	6	8	12
Training	R-value	0.22	0.39	0.44	0.65
	MSE	0.000054	0.000053	0.000055	0.000057
Test	R-value	0.106	0.108	0.105	0.11
	MSE	0.0000657	0.000057	0.000057	0.000057

2.2.2. ANFIS modelling technique

According to [57], the modelling techniques of an Adaptive Neuro-Fuzzy Inference System (ANFIS) use fuzzy logic (FL) and artificial neural network (ANN) techniques to determine the optimal distribution of membership function parameters extracted from a data set according to given error criterion, thereby mapping the possible connections between the input and output data. The ANFIS method is distinguished by its hybrid nature, adopting the Tagaki-Sugeno-Kang (TSK) fuzzy interference system to estimate the optimal relationship between membership functions [58], and by its use of fuzzy "if-then" rules from the Tagakagi and Sugeno fuzzy systems. Hadi and Wang [59] point out that there are two different fuzzy interference systems strategies that may be utilized to create models during training. One of them, the Mamdani approach, necessitates the adoption of fuzzy rules to connect fuzzy sets to the target output dataset. The second strategy, of the Sugeno type, does not factor in the output membership function or distribution at any point in the learning process; rather, it obtains the output function by multiplying the input membership function by a constant and summing the resulting results. Typical ANFIS design is depicted in Figure 6; it takes in two inputs (N and M) and produces a single output (f) using two fuzzy If-then rules. Circles and squares stand for the static node and an adaptive node, respectively. Symbolized by (12) and (13) [26], this is an inference system of the first order of the Sugeno type.

Rule 1: If n is $A1$ and m is $B1$, then $f1 = p1n + q1m + r1$ (12)

Rule 2: If n is $A2$ and m is $B2$, then $f2 = p2n + q2m + r2$ (13)

where n and m are the inputs, f is the output, and $A1$, $B1$, $A2$, and $B2$ are fuzzy sets, $p1$, $p2$, $q1$, $q2$, $r1$, and $r2$ are the coefficients of the output function that are determined during the training.

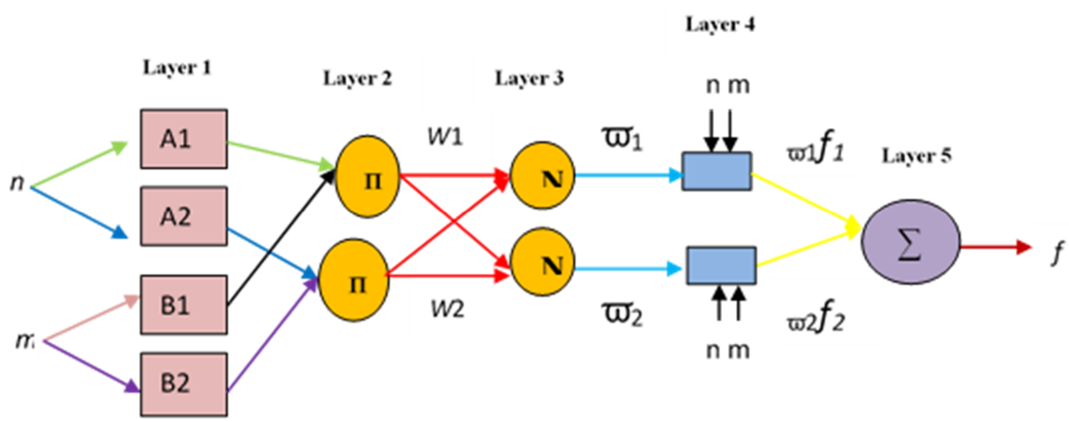


Figure 6. Adaptive Neuro-fuzzy inference system (ANFIS) working structure.

Combining hybrid and backward propagation optimization techniques, the Adaptive Neuro-Fuzzy Inference System (ANFIS) was used to generate a model of a 6:1 structure. First, we utilized the MATLAB-based ANFIS tool to design the ANFIS network by specifying all of the model parameters. The two optimizations' experimental results were then evaluated and compared to those generated by ANN and LSTM models. The training interface during model creation is depicted in Figure 7. Parameters and guidelines for ANFIS training are shown in Table 4.

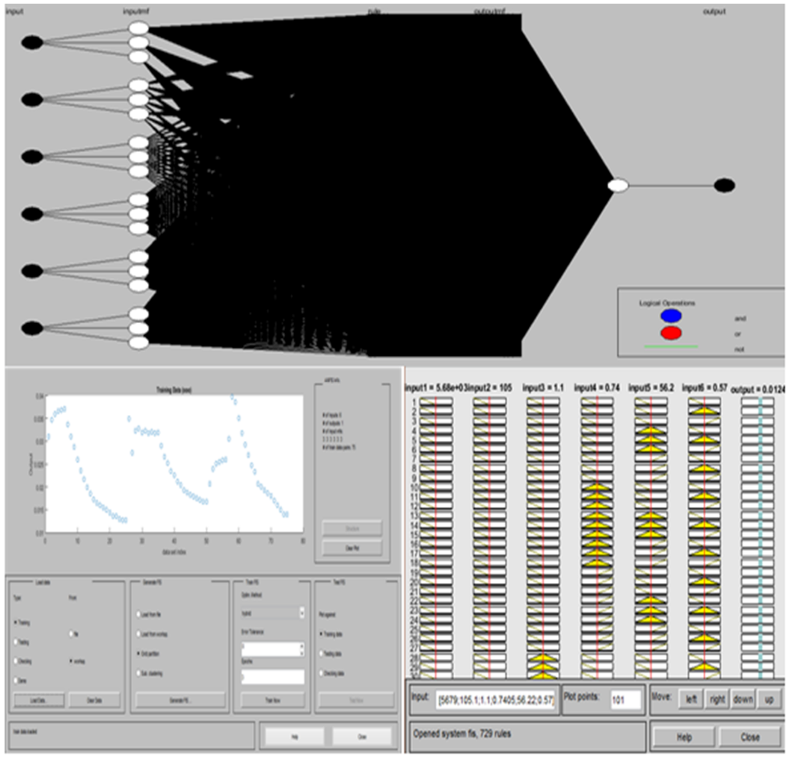


Figure 7. ANFIS training structure and learning rue interface.

Table 4. ANFIS Training parameters and node structure.

Number of nodes	1503
Number of linear parameters	729
Number of nonlinear parameters	54
Total number of parameters	783
Number of training data pairs	75
Number of checking data pairs	6
Number of fuzzy rules	729

2.2.3. Long Short–Term Memory (LSTM) for prediction of bit wear rate

The use of recurrent neural networks (RNNs) has become commonplace in studies that focus on sequential data types [60]. According to Ghatak and Ghatak explanation, RNNs are made up of sigma cells or “tanh” cells that are unable to learn the pertinent information of input data when the input gap is significant [61]. To complement the problem of long-term dependencies in RNN, the long short-term memory (LSTM) accompanied with gate functions, as shown in Figure 8, were introduced into the cell structure. Since its inception, the LSTM has been responsible for nearly all of the impressive achievements based on RNNs. Recently, the used of deep learning as tool for solving engineering has shifted its attention to the LSTM. Wang developed an earthquake prediction model based on spatio-temporal data mining using LSTM with two-dimensional input approach [62]. In the process of developing LSTM model for learning bit wear relation with rock properties, an input gate was built using Equation (14) for decision-making regarding the position of each data parameters “x_t” and the storage decision in the cell state.

$$P_t = \sigma(W_i h_{t-1} + W_i h_t + b_i) \tag{14}$$

where P_t is the input gate, and W_i and b_i represent the input weight and bias of the input gate, respectively.

The model output memory block h_t (see Figure 8) was constructed using the output gate o_t, with an interlinked tanh layer, as expressed in Equations (15) and (16).

$$o_t = \sigma(W_o h_{t-1} + W_o x_t + b_o) \tag{15}$$

$$h_t = o_t * \tanh(c_t) \tag{16}$$

where $h_t$and h_t indicates the input weight and bias of the output gate.

Updating the time series after each state, a new data point feed to the network at each time instant t; the sequences forget gate response is computed using Equation 17.

$$f_t = \sigma(W_f h_{t-1} + W_f h_t + b_f) \tag{17}$$

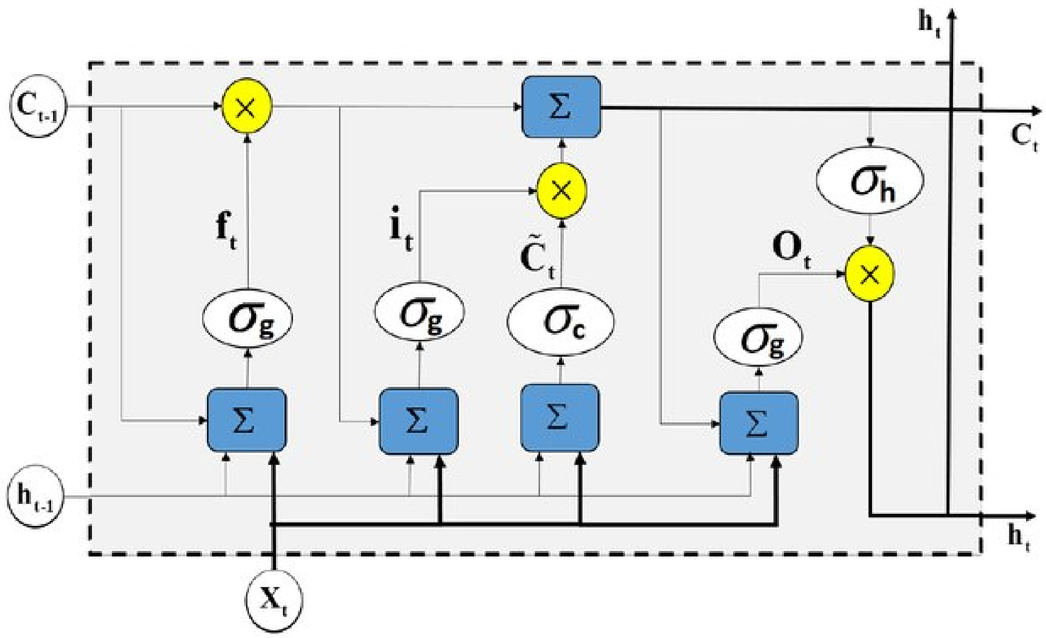


Figure 8. A typical architecture of a long short-term memory (LSTM) cell [63].

where W_f and W_f represent the input weight and bias of the forget gate, respectively, f_t denotes the forget gate, and h_{t-1} represents the output block memory.

In order to create the LSTM model suggested currently, the authors relied on train data to test a data ratio of 80:20. According to [64-65], adaptive optimization algorithms like Adam and RMSprop outperform stochastic gradient descent (SGD) in terms of optimal performance in a number of real-world applications. For the LSTM model training procedure, we decided on the Adam optimizer-solving technique.

3. Results and Discussion

3.1. Development of bit wear rate prediction model

In the present research work, ANN, ANFIS-hybrid, ANFIS-BP, and Adam-LSTM approaches have been developed, trained, tested, analyzed, and designated by MD1, MD2, MD3, and MD4. The performance of these models has been measured (R^2), as shown in Figures 9 and 10.

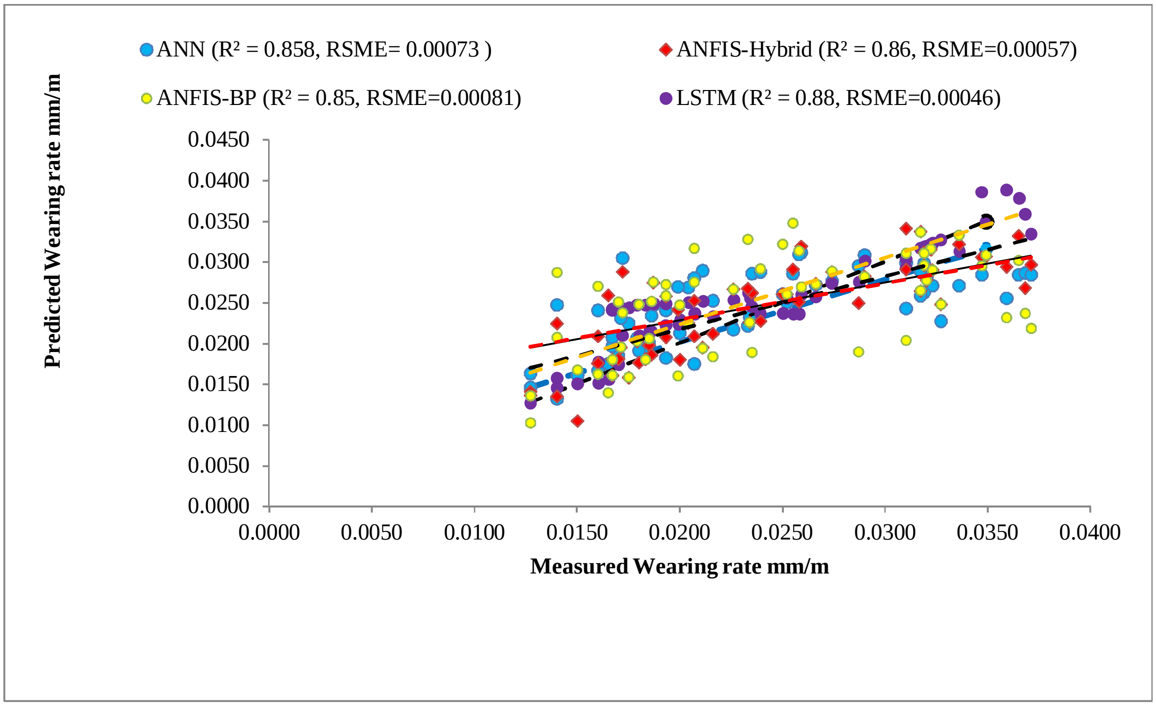


Figure 9. Relationship between predicted and measured drill bit wear rate (training dataset).

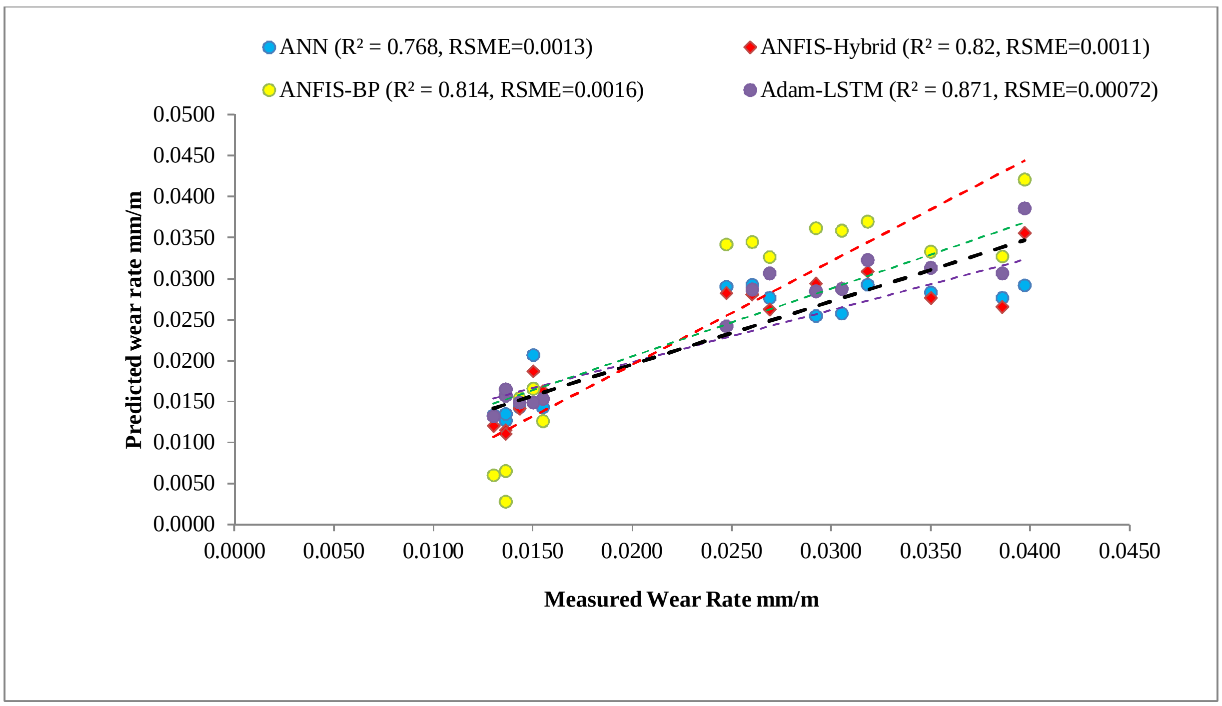


Figure 10. Relationship between predicted and measured drill bit wear rate (test dataset).

Figures 9 and 10 demonstrate that the prediction evaluation for model MD4 has gained higher performance (testing = 0.87, training = 0.88) than other proposed conventional soft computing models that is ANN, hybrid-ANFIS, and BP-ANFIS.

3.2. Model error analysis result

The performance of the proposed models was evaluated using five prediction error evaluation indices errors: root mean square error (RMSE), value account for (VAF), performance index (PI), average absolute error (AAE), and Evaluation

Ratio Index (ERI). The mathematical formulation of the performance indicators is as follows:

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{N}(\alpha-\theta)^2}{G}} \quad (18)$$

$$\text{VAF}=\left[1-\frac{Var(\alpha-\theta)}{var(\theta)}\right]\times 100 \quad (19)$$

$$PI = R^2 + \left({VAF}/{100}\right) - RMSE \quad (20)$$

$$\text{AAE}=\frac{1}{G}\sum_{i=1}^{N}\frac{|\alpha-\theta|}{\theta} \quad (21)$$

$$ERI = VAF + (R^2/100) - AAE \quad (22)$$

where α is measured, θ is predicted, and G is the number of data sample.

Table 5. Error analysis results.

Models/Performance	R^2 train	R^2 test	AAE train	AAE test	RSME train	RSME test	VAF train	VAF test
MD1	0.858	0.77	0.17679	0.13190	0.00073	0.00130	0.743	0.921
MD2	0.86	0.82	0.12913	0.11171	0.00057	0.00108	0.760	0.946
MD3	0.85	0.814	0.17242	0.26574	0.00081	0.00159	0.696	0.878
MD4	0.88	0.871	0.11443	0.09289	0.00046	0.00072	0.827	0.975
	PI-train	**PI-Test**	**ER-train**	**ERI-test**				
MD1	0.865	0.778	0.575	0.797				
MD2	0.867	0.828	0.640	0.842				
MD3	0.856	0.821	0.532	0.621				
MD4	0.888	0.880	0.721	0.891				
ANN (MD1), ANFIS-Hybrid (MD2), ANFIS-BR (MD3), LSTM-Adam (MD4)								

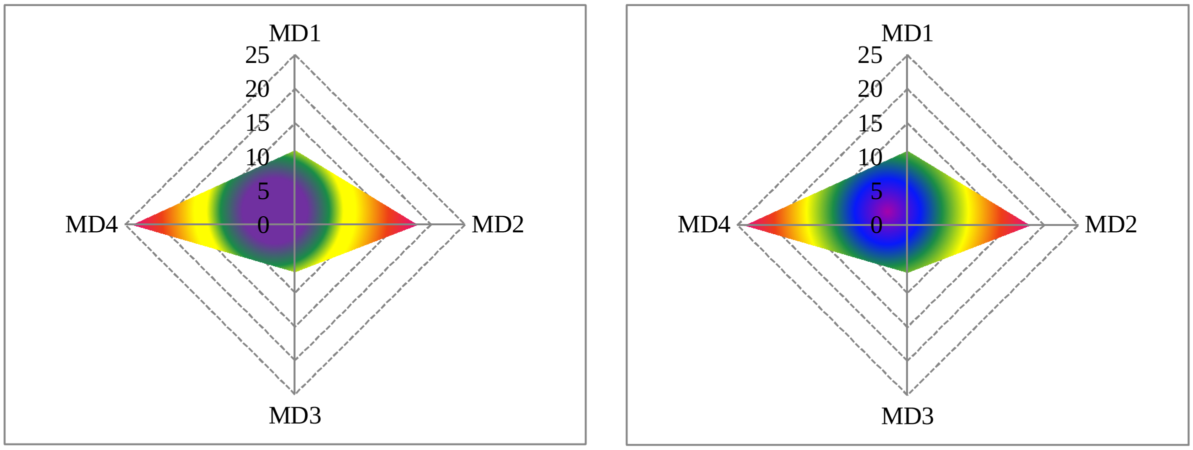
The results of the error study for models MD1, MD2, MD3, and MD4 are shown in Table 5. During the testing process, it was seen that the MD4 model predicted the drill bit wear rate (WR) with the least amount of error, with an AAE of 0.0929 mm/m and an RSME of 0.000719 mm/m. Also, a comparison of hybrid-ANFIS and back-propagation ANFIS models shows that hybrid algorithm-based ANFIS model MD2 performs better than back-propagation algorithm-based ANFIS model MD3, which has the highest testing performance (AAE = 0.1117 mm/m, RSME = 0.00108 mm/m, VAF = 0.95, PI = 0.83, ER = 0.84, R^2 = 0.82). Also, the performance and accuracy of the deep learning-based models, ANN (model MD1) and Adam-LSTM (model MD4) were compared. Comparing the performance of models MD1 and MD4 show that the Adam-LSTM model is better at both training (R^2 = 0.88) and testing (R^2 = 0.871) at predicting the rate of drill bit wear when drilling into the granite rock. Based on a review of how well the models work and how accurate they are; it has been found that the adaptive moment estimation-based LSTM model MD4 is the best model for figuring out how quickly drilling bits wear out while drilling.

4. Model Performance Score Analysis

For a better understanding and analysis, the data have been turned into a picture. In this part, we talked about the score analysis and present the results. Statistical analysis was used in the score analysis to compare how well the soft computing models work. In this study, the model for choosing the best value for each performance indicator was given a score of n, where n is the amount of performance indicators that were observed. The higher and lower values of the performance indicators in the score analysis show which training and testing cases for the models were better and which ones were worse. The final model score was found by adding up the performance indicator scores from both the training and testing stages. The results of the score analysis for the training and testing performances of the soft computing models MD1, MD2, MD3, and MD4 are shown in Table 6 and Figure 11 (a-b).

Table 6. Score analysis result.

Models/ Performance	R^2 train	R^2 test	AAE Train	AAE Test	RSME Train	RSME Test	VAF Train	VAF Test	PI-train	PI-Test	ER-train	ER-test	Train Score	Test Score
MD1	2	1	1	2	2	2	2	2	2	1	2	2	11	10
MD2	3	3	3	3	3	3	3	3	3	3	3	3	18	18
MD3	1	2	2	1	1	1	1	1	1	2	1	1	7	8
MD4	4	4	4	4	4	4	4	4	4	4	4	4	24	24



(a) **(b)**

Figure 11. Visualization of score analysis result. a. training, b. testing.

5. Conclusions

This research work was conducted for the determination of best performing model for estimating drill bit wear when boring into the rock at quarries. This was achieved by creating four soft computing models based on deep and hybrid learning techniques. Three different types of granite quarries contributed 75 data points used to build, train, and evaluate soft computing models. The novel error estimation index, together with four additional convective performance estimators, was used to assess the models' accuracy. The results of the performance comparison revealed that all three methods—the ANN model (MD1), the hybrid algorithm-based ANFIS (MD2), and the LSTM (MD4)—are very good at estimating the drill bit wear rate during blast hole drilling. The Adam-LSTM model MD4 had shown to have superior performance and accuracy compared to the other models. Finally, Adam-LSTM, an optimal performance model introduced here forecast the wear rate of a drill bit. Drilling and mining experts can use this work to better predict the pace at which drill bits will wear while creating blast holes. It is also submitted that the Adam-LSTM model can be utilized to address a variety of deviation problems associated with drilling. Potential future work in this area could include incorporating gradient-based optimization, black hole optimization, and the Hunger games search strategy into the RNN framework. Finally, to the best of the author's knowledge, this is the first time that a unified database has been utilized for predicting the rate at which a drill bit will wear out.

Conflicts of Interest

The authors declare no conflict of interest.

Ethical Statement

Authors state that the research work was conducted according to ethical standards.

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بهبود عملکرد و کارایی دکمه مته حفاری در حین حفاری: کاربرد مدل LSTM در معادن جنوب غربی نیجریه

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چکیده:

اپراتورها و مدیران معدن در تعیین دقیق میزان خرابی سرمته و همچنین میزان مصرف آن با یکدیگر درگیر هستند. بنابراین، این مطالعه قرار است بهترین مدل را برای پیش‌بینی میزان سایش دکمه سرمته در حین حفاری سنگ پیدا کند. همچنین، سرعت فرسودگی دکمه‌های سرمته در حین حفاری سنگ در ایله-ایفه، اوسوگبو، ایالت اوسون، و ایبادان، ایالت اویو، جنوب غربی، نیجریه مورد بررسی قرار گرفت. شبکه عصبی مصنوعی (ANN)، سیستم استنتاج عصبی فازی تطبیقی (ANFIS) و رویکردهای یادگیری ماشین مبتنی بر حافظه بلند مدت کوتاه مدت (LSTM) مبتنی بر تخمین لحظه‌ای تطبیقی برای ایجاد مدل‌هایی برای تخمین نرخ سایش بیت بر اساس ضریب دایره‌ای استفاده شد. اندازه دانه سنگ، محتوای کوارتز معادل، مقاومت فشاری تک محوری، تخلخل و خواص سایشی سنگ و عملکرد مدل‌ها با استفاده از یک شاخص تخمین خطای جدید و چهار برآوردگر عملکرد همرفتی دیگر اندازه گیری شد. تجزیه و تحلیل عملکرد نشان می‌دهد که مدل LSTM مبتنی بر الگوریتم برآورد گشتاور تطبیقی بهتر و دقیق‌تر از مدل‌های دیگر عمل می‌کند. بنابراین، مدل‌های LSTM ارائه شده را می‌توان برای بهبود عملیات حفاری در موقعیت‌های واقعی استفاده کرد.

کلمات کلیدی: حفاری، نرخ سایش بیت، گرانیت، شاخص دایره‌ای، حافظه کوتاه مدت بلند مدت.