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Regressive and Big-Data-Based Analyses of Rock Drillability Based on Drilling Process Monitoring (DPM) Parameters

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Abstract: Accurate, rapid and effective analysis of rock drillability is very important for mining, civil and petroleum engineering. In this study, a method of rock drillability evaluation based on drilling process monitoring (DPM) parameters is proposed by using the field drilling test data. The revolutions per minute (N), thrust, torque and rate of penetration (ROP) were recorded in real time. Then, the two-dimensional regression analysis was utilized to investigate the relationships between the drilling parameters, and the three-dimensional regression analysis was used to establish models of ROP and specific energy (SE), in which the N - F - ROP , N - T - ROP and the improved SE model were obtained. In addition, the random forest (RF) and support vector machine combined with genetic algorithm (GA - SVM) were applied to predict rock drillability. Finally, a prediction model of uniaxial compressive strength (UCS) was established based on the SE and drillability index, I_d . The results show that both regression models and prediction models have good performance, which can provide important guidance and a data source for field drilling and excavation processes.

Keywords: rock drillability; DPM parameters; regression analysis; RF ; GA - SVM ; UCS prediction model



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1. Introduction

Rock drillability plays an important role in mining, civil and petroleum engineering. The traditional rock drillability analysis requires the rock mechanics parameter. This means that the procedures of site drilling, coring, sample processing and laboratory test are needed, which will be time-consuming and costly and greatly affect the engineering efficiency. Moreover, sometimes, the rock core is impossible to be obtained owing to the fracture and fragmentation of the rock mass, which results in the rock mass properties being unable to be analyzed. However, the drilling process monitoring (DPM), as a new promising technology, can compensate for the above shortcomings, and it has been widely applied in recent years. Rock drilling process refers to the rock drilling relying on the bit's thrust and rotary cutting force. The thrust is used to push the drill pipe and make it in close contact with the rock mass so as to generate enough friction. The rotary cutting force is mainly used to break the rock mass. Meanwhile, the parameters fed back in the drilling process are closely related to the rock mass properties. Therefore, how to quickly and accurately obtain the rock mass properties is very important for the parameter design of rock breaking equipment.

The scholars in United States, Japan and France have been trying to find the relationships between the rock mass quality of engineering and drilling parameters by instrument measurement since 1970 [1–3]. However, it measures the speed based on the distance, which indicates that the achievement of drilling speed has great randomness when the rock formation is not uniform or the drilling rig is vibrating [4,5]. Therefore, it is impossible to accurately obtain the rock physical properties and the related rock formation division. On this basis, Yue [6–9] developed the drilling process monitoring system (DPM), which

effectively improved the accuracy of velocity measurement and was successfully applied to stratum identification and rock strength classification. However, the DPM system cannot measure torque, so He and Li et al. [10] improved it. The new drilling process monitoring apparatus can achieve the measurement of torque. Up to now, the development of a while-drilling system has been relatively mature, which can realize the real-time measurement of thrust, torque, rate of penetration (ROP) and revolutions per minute (N), and has been successfully applied to rock property analysis and formation analysis. Rodgers et al. [11–14] used while-drilling parameters to assess field rock strength and optimize core recovery. Karasawa [15,16] et al. conducted laboratory drilling tests, and they proposed the method to estimate the unconfined compressive strength of rock. He [17] et al. performed a series of drilling tests on sandstone, limestone, marble and granite in the field to predict the cohesion, internal friction angle and uniaxial compressive strength of rock. Li [18] et al. deduced the relationships between the drilling efficiency and drilling parameters based on the method of force limit of equilibrium and energy equilibrium. Li [19] et al. analyzed the influence of working parameters, such as impact power, propulsion force, rotating speed and drill bit type, on drilling efficiency and obtained the relationships between the drilling velocity and drilling parameters. Feng [20] et al. performed a field-drilling test to obtain the optimal drilling efficiency, and they found the optimal drilling conditions and rock drillability. Moreover, the combined thermo-mechanical drilling technology and acoustic emission method were utilized to investigate the rock drillability [21–23]. However, the fractured zones were not considered in the above studies. Therefore, Kalantari et al. [24,25] established a stress limit equilibrium analysis model for a T-shaped drag bit, which considered influence factors such as bit geometry parameters, fractured zone and contact friction during drilling. On this basis, the actual drilling data were used to estimate the rock strength parameters, such as cohesion, internal friction angle and uniaxial compressive strength. The results show that the borehole test results based on this model are in good agreement with the standard test results.

Meanwhile, a large number of models have been established to evaluate rock drillability. Hughes [26] and Mellor [27] et al. proposed the theoretical models of SE based on the uniaxial compressive strength and secant modulus of rocks. An empirical formula was put forward by Poane [28] et al. to evaluate the relationships between the drilling parameters and specific energy (SE). Feng [20] et al. improved the SE model using the controllable parameters (thrust and ROP). In addition, Zhang [29] et al. proposed a new rock drillability index, I_d , to evaluate rock classification, and it was applied to classify rock types successfully as an in situ test. Yu [30] et al. compared the effect of SE and I_d on rock strength assessment. The results present that the assessment performance of I_d is superior to SE due to the smaller overall fluctuation during the modeling process. However, the most widely used model by far is the SE model proposed by Teale [31]. The ROP is also an important index to evaluate rock drilling efficiency. Kahraman [32,33] conducted rotary and percussive drilling tests and obtained the prediction equation of ROP through regression analysis. Ataei [34] et al. established an empirical formula of ROP combined with the rock mass drillability index, and the results show that the model has a better prediction effect compared with the previous model. In addition, artificial intelligence (AI) techniques have been utilized to predict rock properties. Ocak [35] et al. used the multilayer perceptron neural network (MLPNN) to predict the elastic module of intact rocks, and the prediction results show that the MLPNN has good prediction capacity. Yesiloglu-Gultekin [36] et al. employed the artificial neural network and adaptive neuro fuzzy inference system to predict the uniaxial compressive strength of granite rocks, and the study indicates that the developed models have a high prediction performance. Sarkar [37] et al. adopted the feed-forward back-propagation neural network to estimate the strength parameters of rock, and the results show that the performance of the AI techniques is better than regression analysis. He [38] et al. utilized the deep convolutional neural network to predict the cohesion, internal friction angle and uniaxial compressive strength and obtained good prediction results. Therefore, the AI technique is a promising method to analyze rock

properties. However, some explanations about the cutting actions of the drilling bits and TBM disc-cutters explained in many papers are not referred to, e.g., the explanations given by Roxborough and Phillips [39,40]. Some other researchers also used the concepts of thrust and rolling forces and the specific energy to study the mechanism of rock fragmentation by the cutters [41,42]. They used a higher order displacement discontinuity method for their analyses. The finite element method and discrete element method have also been used to analyze the drillability of the rock cutting heads.

Although many achievements have been obtained, the analysis of the relationships between the rock drillability and *DPM* parameters is still rare, and the AI algorithm is rarely used to analyze the relationships between them. Meanwhile, the relationships between the *DPM* parameters and rock properties have not been fully established. Therefore, the drilling test was conducted in this study, and the thrust (F), torque (T), rotating speed (N) and rate of penetration (ROP) were recorded in real time. Then, the two-dimensional and three-dimensional regression analyses were utilized to investigate the relationships between the rock drillability and *DPM* parameters, in which two ROP models are obtained and the SE model is improved. In addition, the random forest (RF) and support vector machine combined with genetic algorithm (GA - SVM) were used to predict the rock drillability. Finally, a model using SE and I_d for estimating the uniaxial compressive strength based on three drilling tools is established. The above efforts can achieve the accurate, rapid and effective analysis of rock drillability, and the model has very important guiding significance for field drilling and rock fragmentation.

2. Methodology

2.1. Drilling Process Monitoring (DPM) Parameters

In order to analyze the relationships between *DPM* parameters and rock drillability, a new drilling-monitoring system was utilized to perform drilling test. The system, as shown in Figure 1, can record the thrust (F), torque (T), rotating speed (N) and rate of penetration (ROP) in real time at 1-s interval through the corresponding sensor. These sensors mainly include pressure sensor, rotating speed sensor, torque sensor and laser displacement sensor. Finally, the recorded data will be transformed to the data processing system, where the data can be stored and processed. Meanwhile, the system can adjust the thrust and rotating speed artificially during the process of drilling. Moreover, all sensors are easily to be mounted and have high measurement precision, so it is convenient and reliable to conduct drilling test in field.



Figure 1. Digital drilling system and in situ testing.

Among the *DPM* parameters, the thrust refers to the force required to make the drill bit in close contact with the rock mass; the rotating speed refers to the number of rotating turns of drill bit per minute and the torque refers to the moment required to rotate the drill bit, which is used to cut rock mass; the rate of penetration refers to the length of drilling per unit time.

2.2. Drilling Conditions

Different thrust and rotating speed were applied to plain concrete with a 90 mm diameter drill bit. The range of thrust is from 8.5 to 70 kN, and that of rotating speed from 40 to 400 r/min. Through uniaxial compressive test and Brazilian tensile test, the uniaxial compressive strength and tensile strength of the concrete are 14.70 ± 0.50 MPa and 1.57 ± 0.32 MPa, respectively.

2.3. DPM Data

After drilling test, the corresponding torque and rotating speed values under different thrust and rotating speed drilling conditions were obtained, and the *SE* (energy required to break unit rock) while drilling was calculated following the *SE* model proposed by Teale [31], as shown in Equation (1). The average values of *DPM* parameters and *SE* are presented in Table 1.

$$SE = \frac{F}{A} + \frac{2\pi NT}{AV}, \quad (1)$$

where *SE* is specific energy of drilling, *F* is thrust, *N* is rotating speed, *T* is torque, *V* is rate of penetration and *A* is drilling area.

Table 1. The average value of *DPM* parameters and *SE*.

<i>N</i> /r·min ^{−1}	<i>F</i> /kN	<i>ROP</i> /cm·min ^{−1}	<i>T</i> /N·m	<i>SE</i> /MJ·m ^{−3}
40	10	3.02	68.195	81.48
	11.5	3.31	72.011	78.76
	19	3.74	91.091	89.04
	28	3.69	113.987	113.48
	35	3.95	131.795	123.25
	40	4.03	144.515	132.79
	45	4.27	157.235	136.92
	50	3.61	169.955	173.99
	60	3.85	195.395	188.42
	65	4.27	208.115	181.99
115	70	4.22	220.835	195.43
	8.5	3.44	64.379	191.98
	19	4.44	91.091	211.82
	23.5	4.52	102.539	234.57
	29	4.81	116.531	251.06
	35.75	5.11	133.703	271.77
	42	6.38	149.603	244.96
	46.5	7.55	161.051	224.01
	53	7.01	177.587	265.73
	58.25	7.29	190.943	275.23
	60.5	5.87	196.667	350.07
	65	6.00	208.115	362.76

Table 1. Cont.

$N/r \cdot \min^{-1}$	F/kN	$ROP/cm \cdot \min^{-1}$	$T/N \cdot m$	$SE/MJ \cdot m^{-3}$
220	8.7	3.09	64.888	410.74
	18.25	4.784	89.183	366.12
	29	6.46	116.531	355.88
	34.85	7.71	131.4134	337.31
	40	6.68	144.515	427.54
	46.7	7.60	161.560	421.15
	51.5	7.83	173.771	440.06
	57.5	7.53	189.035	497.68
400	60	7.21	195.395	536.97
	8.5	4.36	64.399	525.06
	11.5	5.24	72.031	490.54
	18.8	6.55	90.602	492.93
	25	7.23	106.375	530.47
	30	8.09	119.095	551.47
	35.5	8.91	133.087	534.99
	42.5	13.31	150.895	435.13
	48.75	11.72	166.795	530.57
	53	10.61	177.607	584.46
	58	12.86	190.327	584.19

3. Regression Analysis

Two-dimensional and three-dimensional regression analysis were adopted to investigate the relationships between the *DPM* parameters and the influence of *DPM* parameters on rock drillability. It is worth noting that the data used for the regression analysis are the average values (Table 1) under their corresponding conditions.

3.1. Two-Dimensional Regression Analysis

The relationships between thrust, torque, *ROP* and *SE* were analyzed under different rotating speeds. There is a good positive linear relationship between thrust and torque, as shown in Figure 2, and the fitting functions are presented in Table 2. The relationship between thrust and *ROP* is powerful, and their regression curves and fitting functions are shown in Figure 3 and Table 2, respectively. Meanwhile, the relationship between torque and rotating speed was obtained, as shown in Figure 4 and Table 2, respectively.

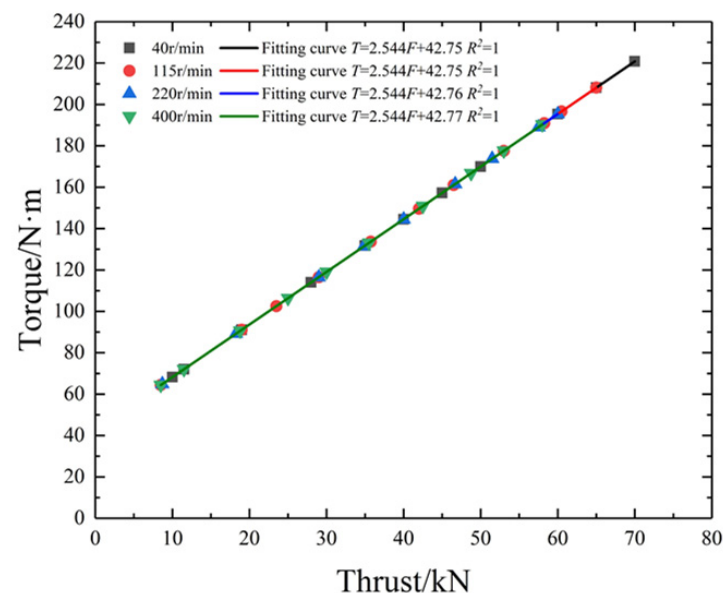
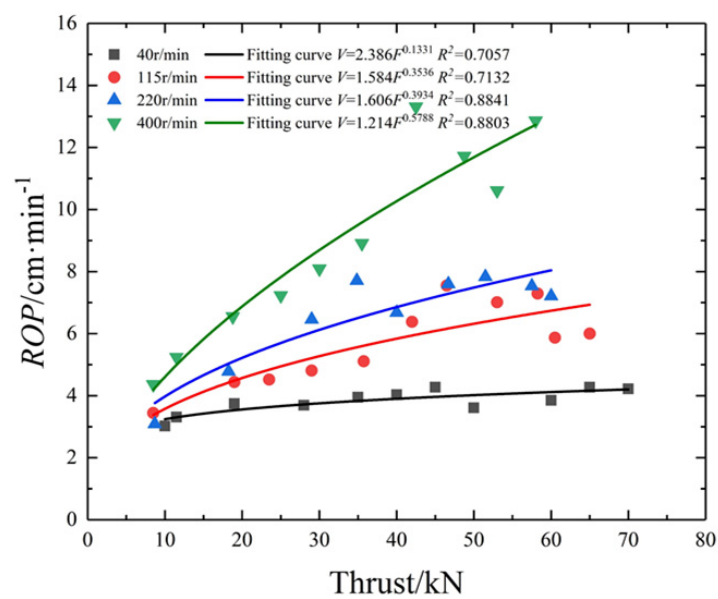
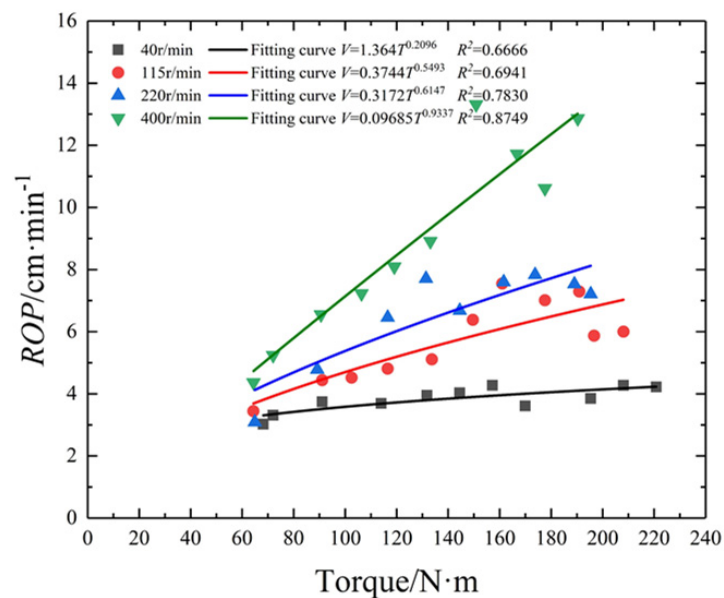


Figure 2. The relationship between thrust and torque under different rotating speed.

Table 2. Relationships between parameters of DPM.

Model Type			T-F		V-F		V-T		SE-F		SE-T	
Fitting model			$T = aF + b$	R^2	$V = aF^b$	R^2	$V = aT^b$	R^2	$SE = aF + b$	R^2	$SE = aT + b$	R^2
Rotating speed /r·min ⁻¹	40	a	2.544	1	2.386	0.7057	1.364	0.6666	2.049	0.967	0.8056	0.967
		b	42.75		0.1331		0.2096		55.2		20.75	
	115	a	2.544	1	1.584	0.7132	0.3744	0.6941	2.363	0.6803	0.9288	0.6803
		b	42.75		0.3536		0.5493		167.4		127.7	
	220	a	2.544	1	1.606	0.8447	0.3172	0.7830	2.659	0.5109	1.045	0.5109
		b	42.76		0.3934		0.6147		319.1		274.4	
	400	a	2.544	1	1.214	0.8803	0.09685	0.8749	1.108	0.1826	0.4354	0.1826
		b	42.77		0.5788		0.9337		489.3		470.6	

where a and b are fitting parameters.

**Figure 3.** The relationship between thrust and ROP under different rotating speed.**Figure 4.** The relationship between torque and ROP under different rotating speed.

Similarly, the values reflecting the relationship between SE and thrust (or torque) under different rotating speeds were obtained, as shown in Figures 5 and 6 and Table 2. There is a good linear relationship when the rotating speed is 40 r/min. However, there is no significant statistical relationship under other rotating speed conditions. This means that the single variable is unable to reflect the SE of drilling effectively.

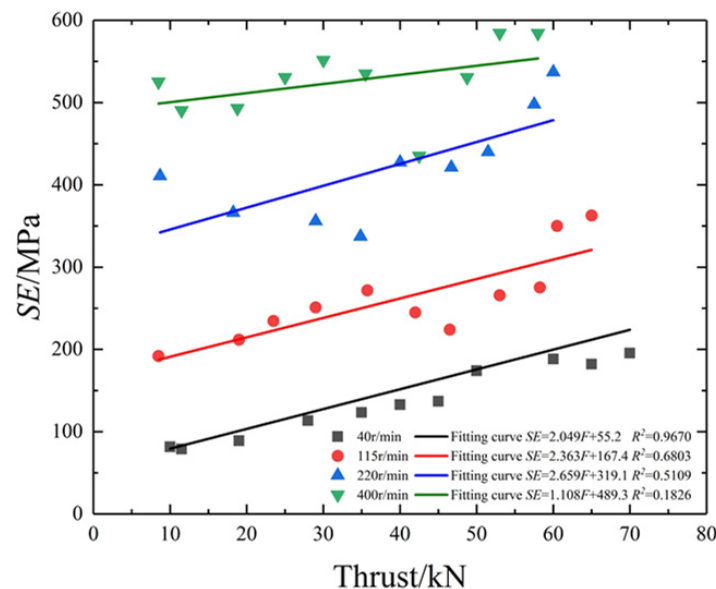


Figure 5. The relationship between thrust and SE under different rotating speed.

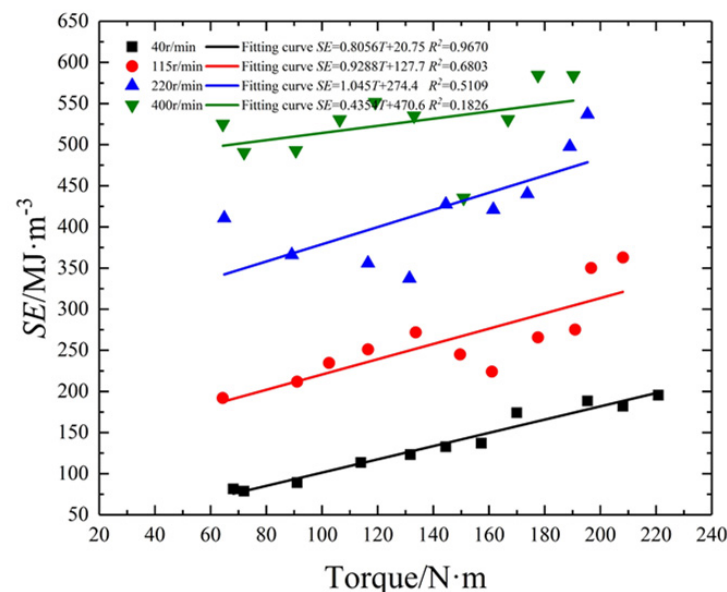


Figure 6. The relationship between torque and SE under different rotating speed.

3.2. Three-Dimensional Regression Analysis

The two-dimensional regression analysis results indicate that there is a significant statistical relationship between thrust and torque. However, for the regression analyses of ROP and SE , the fitting effects are incapable to meet the requirement of practical engineering. Therefore, the three-dimensional regression analyses were utilized to establish models based on DPM data.

The rotating speed, thrust and torque were selected to establish regression models of ROP . We defined them as N - F - ROP and N - T - ROP models. The three parameters correspond to the X-axis, Y-axis and Z-axis variables, respectively. Through regression analyses, the N - F -

ROP and N-T-ROP models were obtained, and their corresponding three-dimensional fitting curves and formulas are shown in Figures 7 and 8, and Equations (2) and (3), respectively.

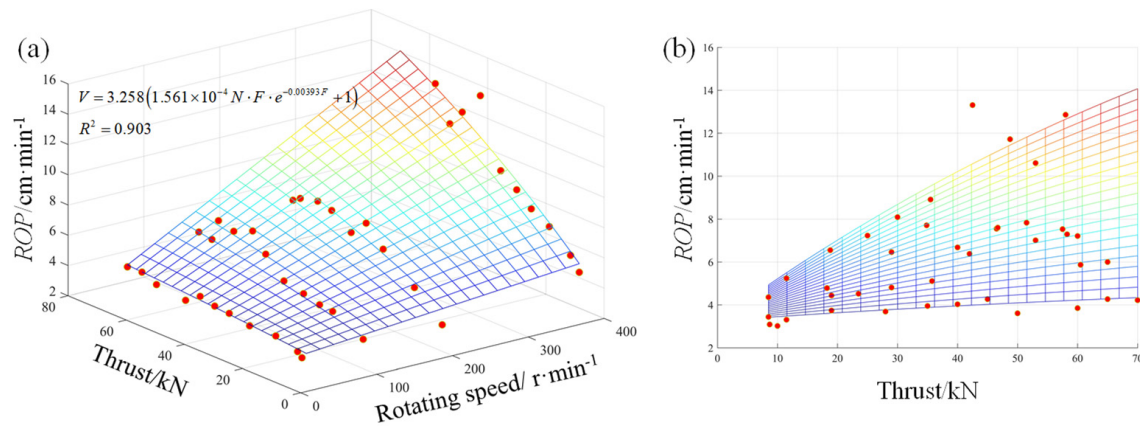


Figure 7. Regressed model of N-F-ROP, where (a) is three-dimensional surface view and (b) is the view of Y-Z direction.

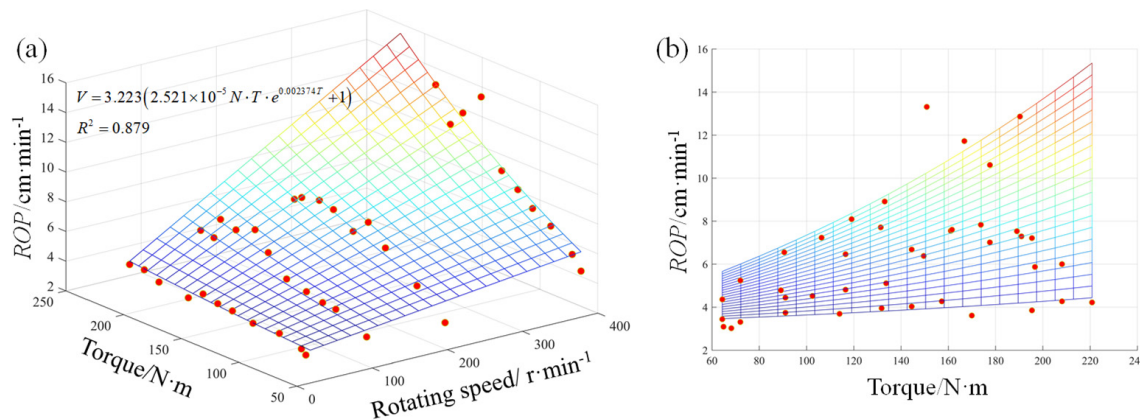


Figure 8. Regressed model of N-T-ROP, where (a) is three-dimensional surface view and (b) is the view of Y-Z direction.

Moreover, because there is a good linear relationship between thrust and torque, we improved the SE model proposed by Teale. The thrust, rotating speed, ROP and drilling area (A) were taken as independent variables to establish the regression model of SE. The results show that the above parameters have a significant statistical relationship, as presented in Figure 9 and Equation (4).

$$V = 3.258(1.561 \times 10^{-4} N \cdot F \cdot e^{-0.00393F} + 1) \quad (2)$$

$$V = 3.223(2.521 \times 10^{-5} N \cdot T \cdot e^{0.002374T} + 1) \quad (3)$$

$$SE = 0.2973 \frac{F}{A} + 236.4 \frac{N}{V \cdot A} + 94.87 \frac{F}{A} \cdot \frac{N}{V \cdot A} \quad (4)$$

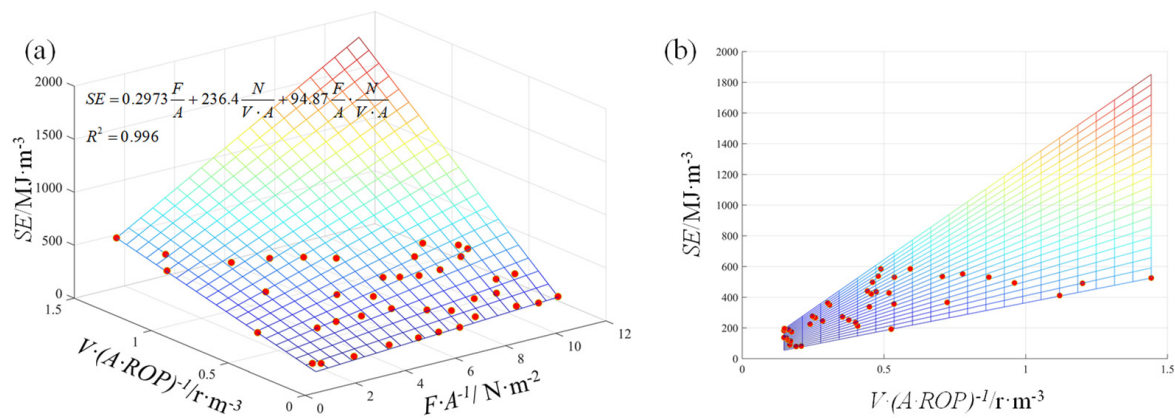


Figure 9. Regressed model of SE , where (a) is three-dimensional surface view and (b) is the view of Y - Z direction.

3.3. Regression Model Evaluation

The determination coefficient (R^2) and root mean square error ($RMSE$) were utilized to evaluate regression performance of two-dimensional and three-dimensional regression models, and the corresponding calculation formulas are shown in Equations (5) and (6), respectively. The ultimately calculation results are shown in Table 3.

$$R^2 = \frac{\sum_{i=1}^n (y_{p(i)} - \bar{y}_t)^2}{\sum_{i=1}^n (y_{t(i)} - \bar{y}_t)^2} \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_{p(i)} - y_{t(i)})^2} \quad (6)$$

where $y_{t(i)}$, $y_{p(i)}$, $\bar{y}_t$ and n are the test value, predicted value, mean of all test values and the total number of values, respectively.

Table 3. The R^2 and $RMSE$ values of regression models.

Regression Model	Rotating Speed /r·min ⁻¹	R^2					$RMSE$				
		F - T	F - V	T - V	F - SE	T - SE	F - T	F - V (kN)	T - V (N·m)	F - SE (MJ·m ⁻³)	T - SE (MJ·m ⁻³)
Two-dimensional	40	1	0.7057	0.6666	0.9670	0.9670	0.005	0.207	0.2198	7.547	40.841
	115	1	0.7132	0.6941	0.6803	0.6803	0.005	0.675	0.6970	28.640	98.618
	220	1	0.8447	0.7830	0.5109	0.5109	0.00496	0.591	0.7047	43.047	43.983
	400	1	0.8803	0.8749	0.1826	0.1826	0.00498	1.032	1.0551	38.552	18.222
Three-dimensional		N - F - V	N - T - V	$SE=f(F, N, V, A)$			N - F - V (cm·min ⁻¹)	N - T - V (cm·min ⁻¹)	$SE=f(F, N, V, A)$ (MJ·m ⁻³)		
		0.903	0.879	0.996			0.794	0.890	10.11		

4. Analyses Using Machine Learning Methods

The RF and GA-SVM were used to analyze the relationships between the SE and DPM parameters. These two methods belong to the category of machine learning, and it has been successfully applied in many fields [43–46].

4.1. Random Forest

RF is an ensemble algorithm based on a decision tree, and it was developed by Breiman [47]. The RF model takes the bootstrap method to select a training set in the way of sampling with the replacement method. Then, the selected training sets are utilized to establish the classification or regression model based on a pre-designed number of decision trees (n_{tree}) and node value (m_{try}). Finally, the test sets are taken to evaluate the model. In

the prediction process, the classification model uses the method of classification voting to get the final result, while the prediction model adopts the method of regression mean.

A total of 11041 sets of real-time DPM data were used for training and testing in the RF model. Because there is a good linear relationship between torque and thrust, and the drilling area (A) is a constant, the rotating speed, thrust and ROP were taken as the input variables, and the output variable was SE . It should be noted that the average speed was used for the training and testing process in the RF model instead of the real-time speed under different thrust conditions due to the real-time speed possibly being a negative value caused by the slight rebound of the drill pipe during drilling. Of the DPM data, 70% were selected randomly to be the training set, and the remaining 30% of the data were taken as the test set. The $ntree$ and $mtry$ were set to 150 and 2, respectively. The optimized prediction model was obtained by training, and the ultimate result was obtained through prediction. The architecture of RF is shown in Figure 10.

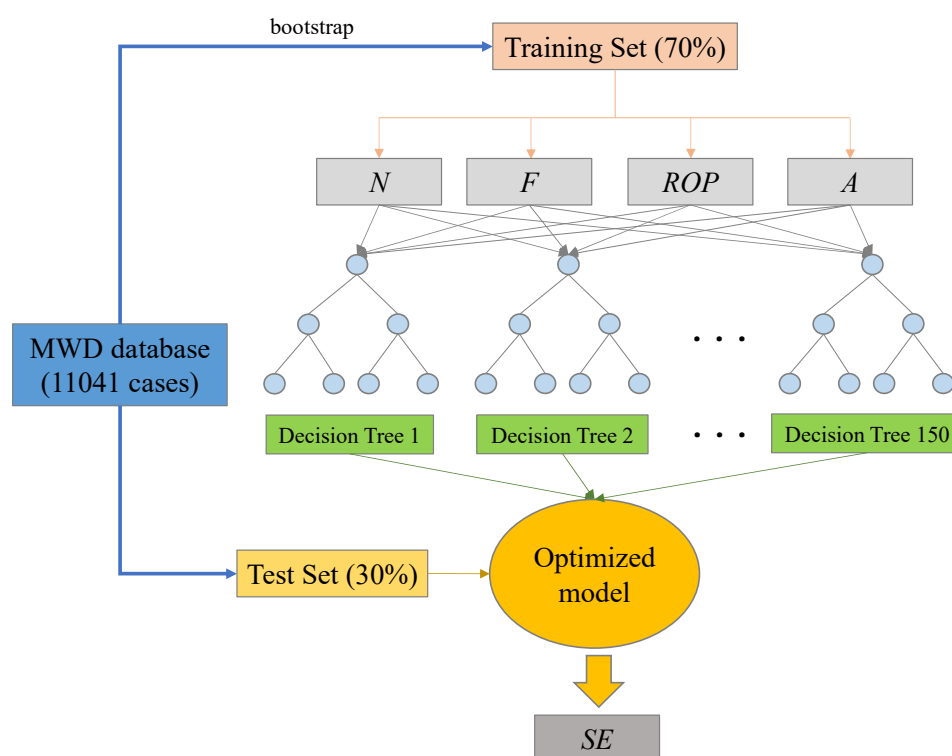


Figure 10. The architecture of random forest.

In order to evaluate the prediction accuracy of the established RF model, the R^2 and RMSE were calculated, as shown in Table 4. Meanwhile, the comparison of the original value and predicted value is shown in Figure 11. From the predicted results, we can find the R^2 and RMSE of the training set and test set are 0.9455 and 0.9591, 42.1341 and 48.7496, respectively, which indicates that the established RF model has a good prediction performance.

Table 4. The R^2 and RMSE of prediction models.

Prediction Models	Trian Set		Test Set	
	R^2	RMSE (MJ·m ⁻³)	R^2	RMSE (MJ·m ⁻³)
GA-SVM	99.99%	0.2578	99.98%	2.5208
RF	94.55%	42.1341	95.91%	48.7496

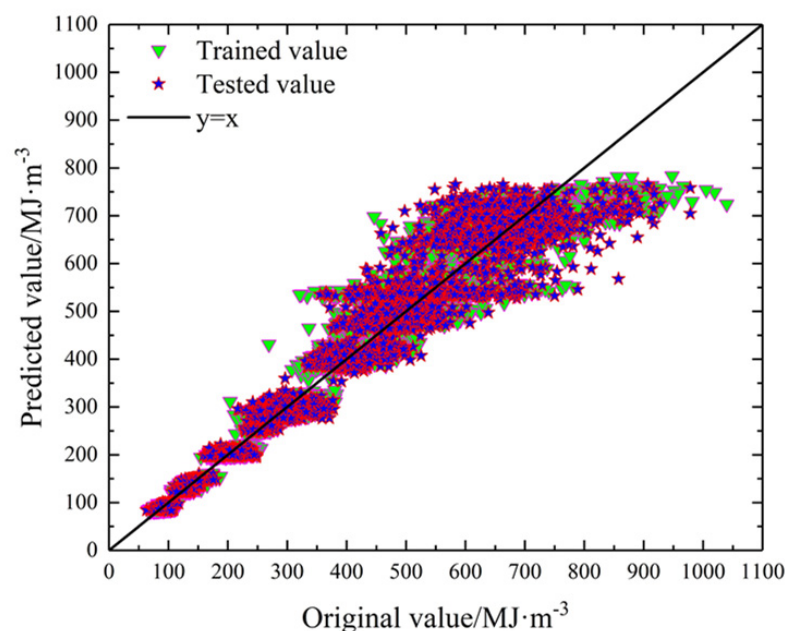


Figure 11. The comparison of original value and predicted value of RF model.

4.2. GA-SVM

The support vector machine (SVM) algorithm was invented by Cortes and Vapnik [48]. It is one of the machine learning methods based on statistical learning theory. The SVM model mainly includes the input layer, kernel function layer and output layer. Among them, the key function layer mainly includes radial basis function (RBF), polynomial and linear functions, which are the key factors to affect the prediction performance. In this paper, the genetic algorithm (GA) is combined with SVM to optimize the parameters. The GA [49] is a new method to find the optimal solution through the natural evolution process simulation, and the steps of GA mainly include population initialization, individual evaluation, selection operation, crossover operation, mutation operation and termination condition judgment. The SVM combined with GA can better optimize the parameter selection and improve the prediction accuracy.

Similar to the analysis of RF, the rotating speed, thrust and ROP are taken as the input variables, and SE as the output variable. Of the DPM data, 70% were randomly selected for model training, and the remaining 30% of the data were used for the model verification, as shown in Figure 12. In GA, the maximum evolutionary generation (*ga_option.maxgen*), maximum population (*ga_option.sizepop*), crossover validation (*ga_option.v*) and crossover probability (*ga_option.ggap*) were set as 100, 20, 10 and 0.9, respectively. By optimizing the parameters, the optimal penalty coefficient (*c*) and kernel radius (*g*) were 6.5961 and 27.2206, respectively. Then, the above parameters were used to establish the prediction model. Finally, the test sets were used to verify the model. The prediction results show the established model has good performance.

The R^2 and RMSE were used to evaluate the prediction accuracy of GA-SVM. By calculation, the corresponding evaluation results and comparison picture are shown in Table 4 and Figure 13, respectively. The results show that the prediction performance of the GA-SVM model is superior to the RF model. It also shows that it is feasible to use the thrust, rotating speed and ROP to evaluate the SE when the drilling area is a constant.

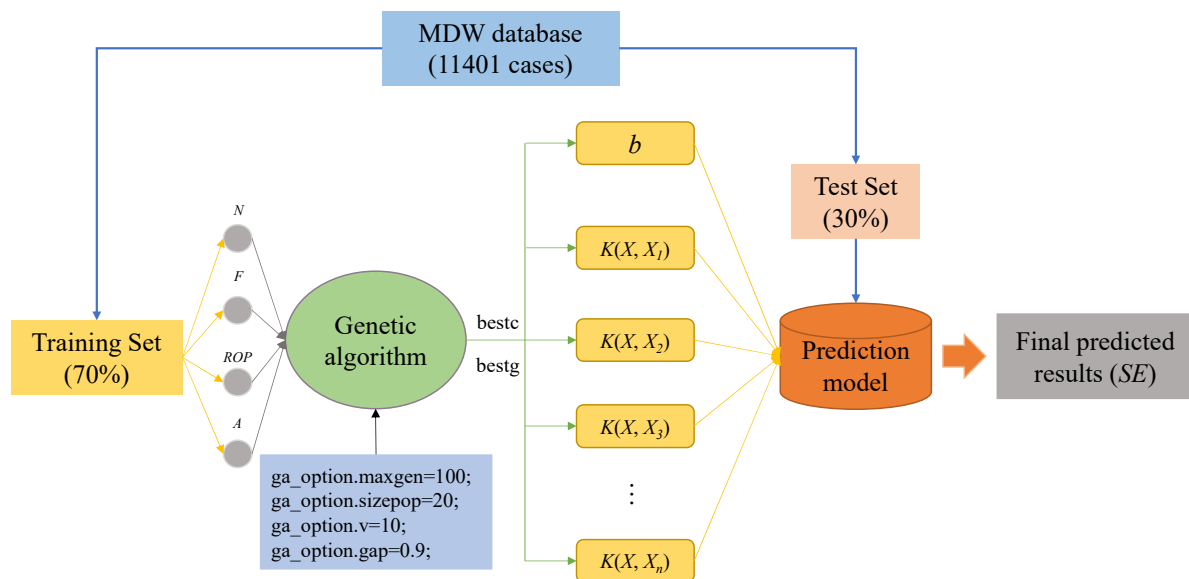


Figure 12. The architecture of GA-SVM.

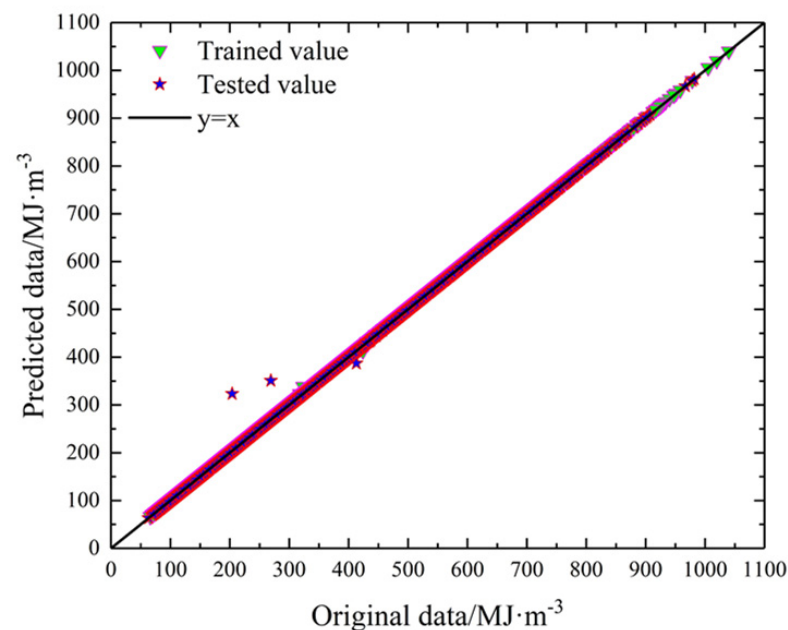


Figure 13. The comparison of original value and predicted value of GA-SVM model.

5. Relationships between Rock Properties and DPM Parameters

The rock properties and in situ stress conditions obviously affect rock cutting and drilling [50–53]. The fast and accurate prediction of the rock properties is the key to evaluating rock drillability and cuttability. Therefore, in order to find the relationships between the rock properties with DPM parameters, the SE and drillability index, I_d , were utilized to establish the rock strength prediction model. The SE can be obtained according to the improved model based on Teale's model. The drillability index, I_d , was proposed by Zhang [29], and it can be calculated based on Equation (7). Both SE and I_d can be calculated by DPM parameters.

The data used to establish the prediction models are present in Table 5. According to these data, the SE and I_d were obtained. Then, the prediction models of uniaxial

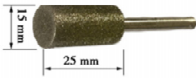
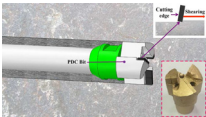
compression strength of rock based on SE and I_d were established, which include the univariate model and two-variable model.

$$I_d = \gamma \pi_1^\alpha \pi_2^\beta \quad (7)$$

$$\pi_1 = \frac{DF}{T}, \pi_2 = \frac{V}{D\omega}, \omega = 2\pi N \quad (8)$$

where D is drill bit diameter, F is thrust force, T is torque, V is rate of penetration, ω is angular velocity, N is rotating speed and α , β , γ are fitting parameters. In this study, α , β , γ are determined to be 0.5, 0.6 and 1, respectively.

Table 5. Data source, quantity and bit types of UCS prediction model.

References	Bit Types	Bit Geometry Parameter	Data Size
Wang [54]	Standard diamond solid bit 	Radius is 7.5 mm	34
He [55]	Impregnated diamond bit 	External diameter is 70mm, and external diameter is 60 mm	17
Wang [56,57]	PDC bit 	Cutting edge L_1 , L_2 and L_3 are 18, 18 and 27 mm, respectively, and radius is 30 mm	42

5.1. Univariate Model of UCS

According to the calculated SE and I_d , the relationship between them and uniaxial compressive strength of rock under different cutting tools is established, respectively. When the standard diamond solid bit was used, the relationship between SE (or I_d) and UCS is present in Figure 14a, and the corresponding regression model is shown in Table 6. Similarly, the relationship between SE (or I_d) and UCS is present in Figure 14b,c, in which the impregnated diamond bit and PDC bit were performed to drilling. Their regression models are also shown in Table 6. Finally, all the data under the three types of bits were used to establish the relationship between the SE (or I_d) and UCS of rock. The regression model and fitting curve are shown in Table 6 and Figure 14d, respectively.

Table 6. Established UCS model based on SE and I_d separately under different bits.

Bit Types	UCS Prediction Model	
	SE -UCS	I_d -UCS
Standard diamond solid bit	$SE = 0.5129UCS$	$I_d = 0.01519UCS^{-0.305}$
Impregnated diamond bit	$SE = 0.08552UCS$	$I_d = 0.0122UCS^{0.2208}$
PDC bit	$SE = 0.002172UCS$	$I_d = 0.03025UCS^{0.1704}$
Combine the above three bits	$SE = 0.4227UCS$	$I_d = 0.03247UCS^{-0.05269}$

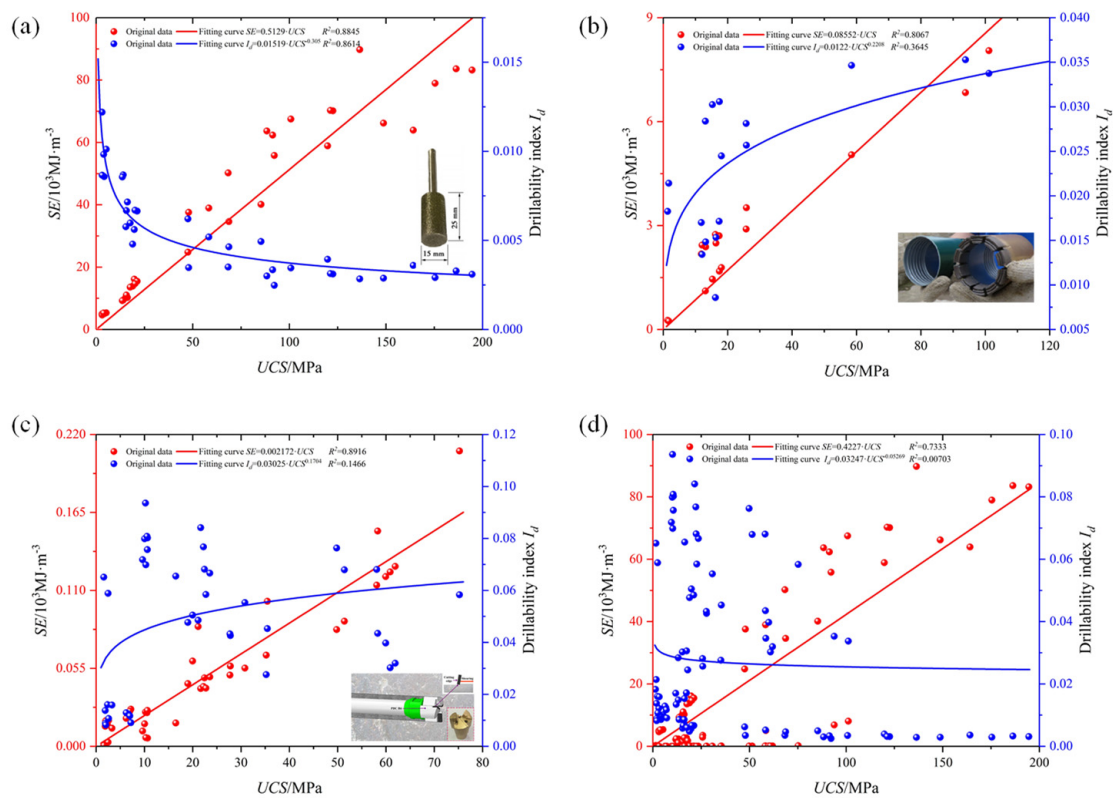


Figure 14. The relationship between SE (or I_d) and UCS for different bits of (a) standard diamond solid bit, (b) impregnated diamond bit, (c) PDC bit and (d) combine the above three bits.

From these univariate prediction models, we can find that there is a good relationship between SE (or I_d) and UCS for the standard diamond solid bit. The result indicates SE is positively correlated with the UCS , while the I_d is negatively correlated with UCS , which is consistent with Yu's [30] study. However, compared to the regression model for the standard diamond solid bit, the relationship between I_d and UCS presents an opposite law for the impregnated diamond bit and PDC bit, and the relationship between UCS and SE is obviously better than that between UCS and I_d .

5.2. Two-Variate Model of UCS

The univariate models of UCS indicate that the performances of the UCS models based on SE (or I_d) under different bits are not very good, especially for the model based on I_d . Therefore, the UCS prediction model was established by combining the SE and I_d . Similar to the univariate modeling, the UCS prediction models under different bits were established, respectively. The UCS prediction models under standard diamond solid bit, impregnated diamond bit and PDC bit are shown in Figure 15a–c, respectively, and the corresponding fitting equations are shown in Equations (9)–(11). Finally, all the data were combined to produce an UCS prediction model, and the regression curve and fitting equation are shown in Figure 15d and Equation (12). The results show that the performances of the established models combining SE and I_d are significantly superior to that of the univariate model.

$$UCS = 0.02973 \left(19.96 \cdot SE \cdot e^{0.6472 I_d^{-0.1}} + 1 \right) \quad (9)$$

$$UCS = 0.006402 \left(1.081 \times 10^4 \cdot SE \cdot e^{-1.285 I_d^{-0.1}} + 1 \right) \quad (10)$$

$$UCS = 1.844 \left(967.5 \cdot SE \cdot e^{-1.07 I_d^{-0.1}} + 1 \right) \quad (11)$$

$$UCS = 16.93 \left(0.08349 \cdot SE \cdot e^{0.06913 I_d^{-0.1}} + 1 \right) \quad (12)$$

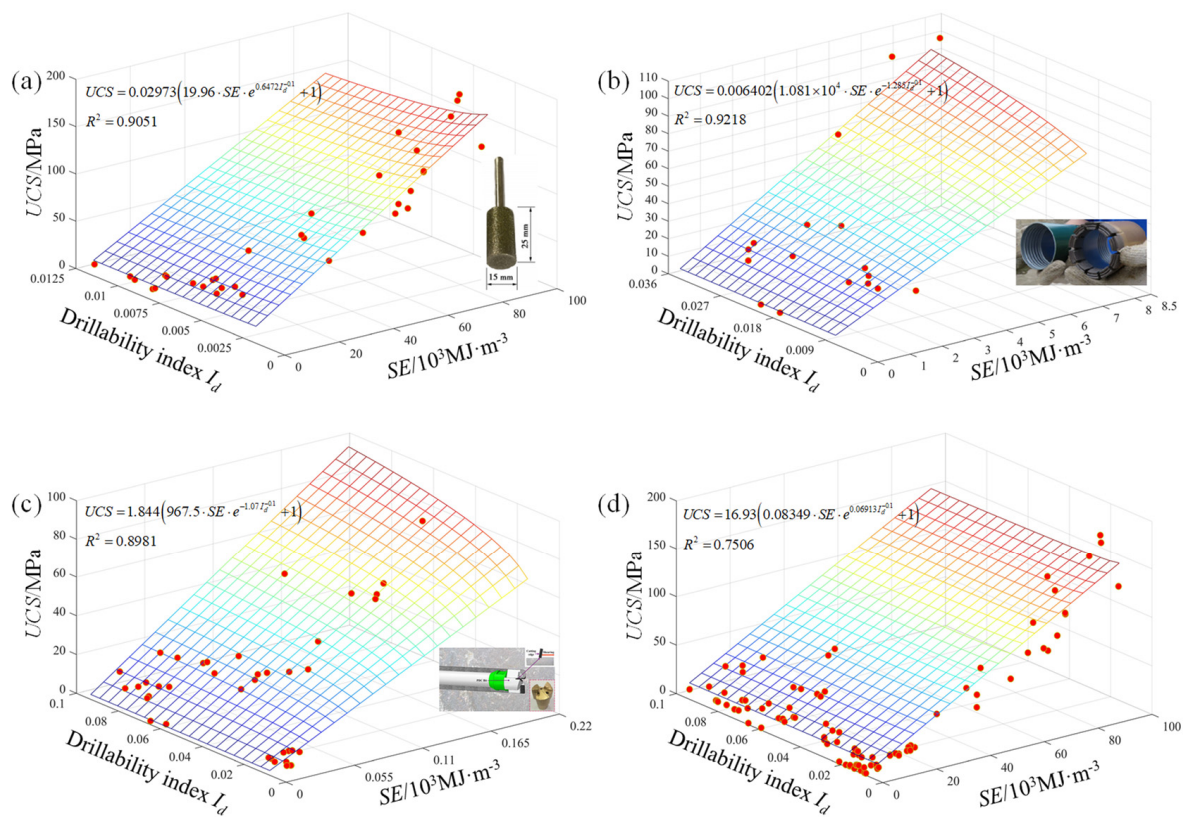


Figure 15. Established UCS models combine SE and I_d for different bits of (a) standard diamond solid bit, (b) impregnated diamond bit, (c) PDC bit and (d) combine the above three bits.

5.3. Evaluation of UCS Prediction Models

The determination coefficient (R^2) and root mean square error (RMSE) were used to evaluate the performance of univariate and two-variate models of UCS, and it can be calculated by Equations (5) and (6), respectively. The corresponding evaluation indexes obtained through calculation are shown in Table 7. The results show that the performance of the established UCS prediction model based on SE and I_d is better than that based on a single variable.

Table 7. The R^2 and RMSE of UCS models.

UCS Models		Standard Diamond Solid Bit		Impregnated Diamond Bit		PDC Bit		Combine the Above Three Bits	
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
Univariate model	SE-UCS	0.8845	9.6273 (10^3 MJ·m $^{-3}$)	0.8067	0.8927 (10^3 MJ·m $^{-3}$)	0.8916	0.0151 (10^3 MJ·m $^{-3}$)	0.7333	12.7979 (10^3 MJ·m $^{-3}$)
	I_d -UCS	0.8614	0.0041	0.3645	0.0064	0.1466	0.0240	0.0070	0.0260
Two-variate model	SE- I_d -UCS	0.9051	18.3554 (MPa)	0.9218	7.9442 (MPa)	0.8981	6.5318 (MPa)	0.7506	22.8337 (MPa)

By substituting the drilling experiment data into the established UCS prediction model, it can be obtained that the prediction UCS of concrete material is 17.49 MPa. Compared to the tested UCS of concrete (14.7 MPa), the prediction accuracy is 81.02%.

6. Discussion

In order to investigate the relationships between the DPM parameters and rock drillability, the essential parameters, such as thrust, rotating speed, etc., needed to be collected during drilling. Therefore, the feasibility for evaluating rock drillability with DPM parameters is discussed in this chapter.

6.1. The Key DPM Parameters

According to the formula of SE and I_d , the thrust, rotating speed, torque and ROP are essential during drilling. They can be divided into two categories that are controllable and uncontrollable, respectively. Among these parameters, the thrust and rotating speed belong to the former, while the torque and ROP belong to the latter. In the process of drilling, the drilling performance can be improved by reasonably controlling the thrust and rotating speed. However, the torque and ROP , as the characterization parameters while drilling, change with the thrust and rotating speed, and they are also very sensitive to the mechanical properties of the rock mass. Therefore, it is very important to accurately measure the thrust, rotating speed, torque and ROP for the real-time analysis of rock drillability.

6.2. UCS Prediction Model

The established UCS prediction model by combining SE and I_d under three kinds of different drilling tools (standard diamond solid bit, impregnated diamond bit and PDC bit) has better prediction performance, and its performance is better than the univariate model established by SE or I_d separately. It can well reflect the relationships between the UCS of rock and DPM parameters. By substituting the drilling experimental data into the model, the prediction accuracy is 81.02%, which can meet the requirement of field application. However, the amount of data to establish the model is not very large, and the types of bits are not very comprehensive, so it is impossible to accurately predict the rocks with low UCS . Therefore, more DPM data in different rock layers and more kinds of drill bits should be considered in future study.

7. Conclusions

In order to investigate the relationships between the DPM parameters and rock drillability, drilling tests were performed. The rotating speed, thrust, torque and ROP were recorded in real time. Then, these DPM parameters were utilized to carry out regression analyses, and the RF and $GA-SVM$ algorithms were applied to predict the SE for reflecting the rock drillability. Finally, the UCS prediction model using three types of drilling bits was established by combining the SE and I_d . Based on the above analyses, the following conclusions can be drawn:

(a) There is a good linear relationship between thrust and torque at a constant rotating speed condition, and the relationships between thrust and ROP , and torque and ROP are powerful, but their statistical relationship is not very significant. The relationships of the SE with thrust and torque are linear at a lower rotating speed, while there is no significant statistical relationship at medium and high rotating speeds.

(b) The established $N-F-ROP$ and $N-T-ROP$ regression models have better performance than the two-dimensional regression models. Meanwhile, the SE model of Teale has been improved based on the good relationship between thrust and torque. The new model has good performance to predict the SE . However, the improved SE model is not applicable to all the fields completely, and the general formula needs to be further studied.

(c) The prediction performance of the $GA-SVM$ model is superior to the RF model, and it can reach more than 99%. Therefore, machine learning based on $GA-SVM$ is a promising method to analyze the relationships between the DPM parameters and rock drillability. Moreover, it is feasible to evaluate the SE of drilling based on thrust, rotating speed, ROP and drilling area (A).

(d) The UCS prediction model was established by combining SE and I_d . It can reflect the relationships between the UCS and DPM parameters well for three types of bits (standard diamond solid bit, impregnated diamond bit and PDC bit).

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