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НОВАЯ ЭМПИРИЧЕСКАЯ МОДЕЛЬ ДЛЯ ПРОГНОЗИРОВАНИЯ НА ОСНОВЕ ХАРАКТЕРИСТИК ГОРНОЙ МАССЫ СКОРОСТИ ПРОНИКНОВЕНИЯ КРУПНОГАБАРИТНЫХ БУРОВЫХ УСТАНОВОК В ШАХТАХ

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Аннотация: Буровые установки типа «джамбо» широко используются в подземной горной промышленности для прокладки туннелей. Скорость бурения существенно зависит от характеристик недеформированной горной породы и структурных параметров горной массы. Для оценки скорости проникновения буровых установок типа «джамбо» была использована нелинейная множественная регрессионная модель (NLMR). В этом исследовании были использованы полевые данные, включающие 737 буровых скважин. Разработана эмпирическая модель, включающая индекс буримости горной массы (RDi), для прогнозирования скорости проникновения буровых установок типа «джамбо» в подземных шахтах. Для оценки точности прогноза модели использовались показатели производительности, такие как R^2, RMSE, MAE, MAPE и VAF. Разработанная модель показала значения 0,88, 0,22, 0,17, 7,3 и 88,84 для R^2, RMSE, MAE, MAPE и VAF соответственно при применении к тренировочным данным. Учитывая как механические свойства недеформированной горной породы, так и структурные свойства горных массивов, модель продемонстрировала точные прогнозы скоростей проникновения буровых установок типа «джамбо».

Ключевые слова: скорость проникновения, буровая установка «джамбо», индекс буримости горной массы (RDi), нелинейная множественная регрессионная модель.

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A new empirical model for prediction of jumbo drills' penetration rate in underground mines based on the rock mass characteristics

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Abstract: Jumbo drills are widely used in underground mining for tunnel drivages. The drilling rate is significantly influenced by intact rock characteristics and the structural parameters of the rock mass. A non-linear multiple regression model (NLMR) was employed to assess the rate of penetration of jumbo drills. For this purpose, field data, including 737 boreholes, were utilized. This paper developed an empirical model that incorporated the Rock Mass Drillability Index (RDi) to predict the rate of penetration (ROP) of jumbo drills in underground mines. Performance indexes such as R^2, RMSE, MAE, MAPE, and VAF were evaluated to gauge the prediction accuracy of the model. The developed model exhibited values of 0.88, 0.22, 0.17, 7.3, and 88.84 for R^2, RMSE, MAE, MAPE, and VAF, respectively, when applied to the training data. By considering both intact rock mechanical properties and structural properties of rock masses, the model demonstrated accurate predictions of jumbo drill penetration rates.

Key words: Penetration rate, Jumbo drill, Rock mass drillability index (RDi), NMLR.

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Introduction

Drilling plays a vital role in the operational costs of underground mines and construction projects especially in hard rocks and poor ground conditions. Prediction of rock mass drillability along with drilling rate could lead the operation managers to select the best drill rig and to reduce the costs significantly.

Jumbo drills are powerful and complex machinery that revolutionarily have changed the drilling technology in underground operations. The performance of these machines is directly affected by three types of factors: rock mass characteristics, machines' operational parameters, and support and logistics [1]. Simultaneous variation of these factors along with high levels of geotechnical and ground condition uncertainties, make the drilling speed prediction as a big challenge for engineers. Therefore, the assessment of the drilling performance of jumbo rigs is a complicated task that requires many inputs [2].

In this paper, it is tried to develop a new prediction model for jumbo's performance based on drilling data of 737 boreholes in six different case study underground mines considering all main effective parameters, especially the rock mass characteristics.

Drilling rate prediction models, literature review

In drilling and blasting, jumbo drills are crucial for maximizing advance and production rates [3]. In tunneling using the drill and blast method, drilling constitutes a significant cost and time factor [4]. The empirical approach, relying on field data, is commonly used to study penetration rates, which depend on controllable (operational) and uncontrollable (environmental) parameters [5, 6]. Despite advancements, controlling rock parameters remains a technological challenge [7]. The performance of jumbo drills is influenced by a combination of machine parameters, operational variables, rock properties, and characteristics of the rock mass, along with structural and hydrogeological conditions [8]. Accurate prediction of the Rate of Penetration (*ROP*) is crucial for optimizing drilling efficiency, but establishing a precise prediction model remains challenging [7, 9]. The classification of surrounding rock is vital for assessing tunnel quality, reflect-

ing rock strength, deformation characteristics, and tunnel stability [10]. While numerous attempts have been made to predict drilling rates in the past five decades, with a focus on both surface and underground mines, relatively few have concentrated on underground drilling. Several empirical models have been developed to predict the rate of penetration in various drilling contexts. Bauer and Calder introduced a model focusing on uniaxial compressive strength for iron ore [11], later updated by Bauer and Crosby [12]. In the 1980s, Rabia and Howarth expanded this model based on uniaxial compressive strength [13, 14]. Workman and Szumanski proposed a new model incorporating drilling parameters like weight on bit and RPM [15]. In 2007, Tutmez classified the sawability of building stones using uniaxial compressive strength, tensile strength, Schmidt hammer value, point load strength, impact strength, Los Angeles abrasion loss, and P-wave velocity [16]. Ersoy determined performance of drilling equipment based on intact rock properties [17]. Thuro determined rock mass excavatability in drilling based on mechanical and petrographic rock properties. Kahraman presented regression-based models for rotary and percussive drilling, introducing a drillability index [18]. In 2003, He developed models for percussive drills based on Schmidt hammer value and point load strength [19], and for jumbo drills based on volumetric joint count [20]. Then he developed models for percussive drills based on indirect tests [21]. Hoseinie et al. introduced a new classification system known as the Rock Penetrability Index, utilized for estimating the penetrability and drillability of rocks. This index incorporates various parameters of the rock material. He introduced a system for estimating rock penetrability and drillability, utilizing parameters like compressive strength, abrasivity, Mohs hardness, texture, grain size, and Young's modulus [22]. Ataei et al. demonstrated the predictive capability of Rock Drillability Index (RDi) for surface drilling [23]. Munoz, Su, and Capik et al. conducted related research [24—26]. Shi developed a ROP prediction model that rock mechanical properties and bit type and properties are input parameters to predict ROP [27]. Hung developed an empirical model for predicting penetration rates in very hard rocks, emphasizing the influence of Brazilian tensile strength [28]. Navarro explored the significance of experimental models in predicting penetration rates and analyzing jumbo drill parameters [29]. Wang utilized measure-while-drilling (MWD) data and machine learning to classify tunnel surrounding rock accurately [30]. In this paper, the most famous and important studies that have been presented until now have been reviewed. The rotary drilling in surface mining has been studied very well and empirical models developed significantly. However, in underground drilling the general study has been done rarely and a few studies have been published on the penetration rate of jumbo drills. In the developed models, the characteristics of the rock mass have not been incorporated, and mainly single parameters have been used to predict the penetration rate. Resulting in these models being associated with uncertainty. The research literature acknowledges that numerous parameters impact penetration rates, yet accounting for all of them is complex, time-consuming, and costly. Therefore, there is a strong need for a comprehensive model that covers all parameters that influence the penetration rate. Hence, this study opts for a more efficient approach by utilizing the Rock Mass Drillability Index (RDi) as a representative of rock mass properties. This index has a simple method for surveying the data and also takes into account the rock mass parameters affecting the drilling rate. RDi encompasses both intact rock properties and structural parameters of the rock mass, ma-

Table 1

Rock mass drillability index (RDi) classification [2]

Классификация массивов горных пород по показателю буримости RDi [2]

Texture	Porous	Fragmental	Granitoid	Porphyritic	Dense
Grain size, mm	–	>5	2 – 5	0.05 – 1 & 2 – 5	0.05 – 1
Rating	15	10	7	4	1
Mohs Hardness	1 – 3	3 – 4.5	4.5 – 6	6 – 7	>7
Description	very soft – soft	comparatively soft	comparatively hard	hard	very hard
Rating	18	13	9	4	1
UCS (MPa)	1 – 25	25 – 50	50 – 100	100 – 200	>200
Description	very low strength	low strength	average strength	high strength	very high strength
Rating	22	16	11	6	2
Joints Spacing[a], m	>2	1 – 2	0.5 – 1	0.15 – 0.5	0 – 0.15
Rating	18	13	9	5	1
Joint aperture & filling[b], mm	closed joint 0 – 2	>20	12 – 20	9 – 12	2 – 9
Rating	15	10	7	4	1
The angle between the joint & borehole axis, °	70 – 90	55 – 70	35 – 55	20 – 35	0 – 20
Rating	12	8	6	3	1

For investigation of parameters as to the joints system, in case of more than one set of joints, specification of the dominant joint set is classified. In the case of the joint sets with the same importance, for each set of joint one RDi is obtained and the mean of RDi rates is the standard of judgment.

For marginal values, the rate related to the lower class is appropriated.

[a] The rock masses which have rule-abiding cleavage and sheets, because of the drilling easiness, a rate of 12 is assumed for spacing.

[b] For the joints filled with soil and very fine powders, the rate of seven is assumed for the fillers.

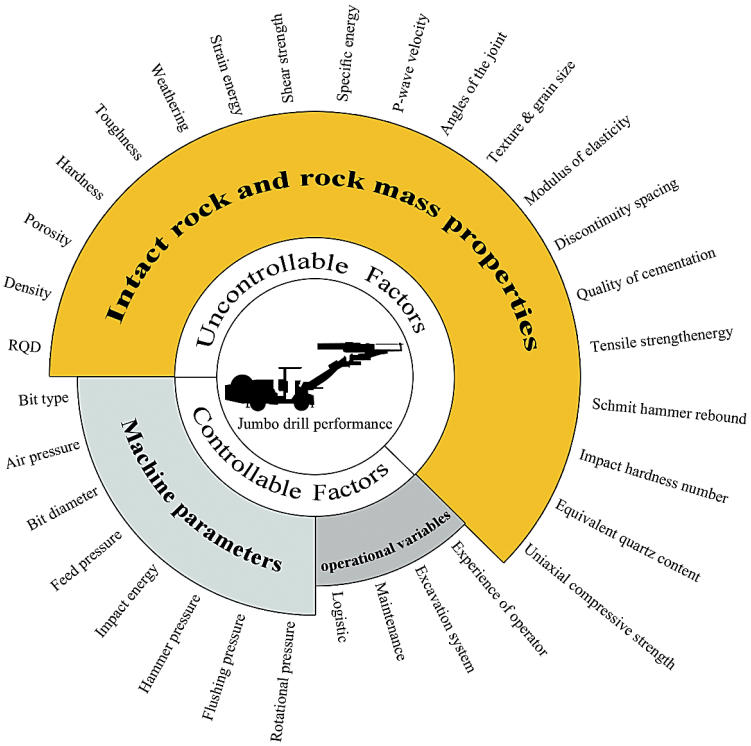

Fig. 1. The most important factors influencing drilling performance (resulting from literature review)
Рис. 1. Наиболее значимые факторы, оказывающие воздействие на эффективность бурения (на основе обзора литературных источников)

king it a suitable representative for overall rock mass characteristics. This classification system is represented in Table 1 and its qualitative prediction is presented in Table 2. For detailed methodology, the readers can refer to Hoseinie et al. [2]. according to present literature review the effective parameters on the underground drilling could be figured out as shown Fig. 1.

Methodology

The geo-mechanical properties of rock masses play a crucial role in assessing rock drilling performance and predicting associated factors like time, costs, and efficiency. Regression analyses, particularly multiple regression, prove valuable in understanding the intricate relationships between dependent and independent variables. The main goal of this paper is to generate an empirical model that can predict the penetration rate of jumbo drills in underground mines with minimal information about the condition of rock masses in the face. For this purpose, six parameters related to drilling parameters and properties of rock masses were considered. Initially, simple regression analyses involving linear, logarith-

Table 2

Qualitative prediction of the penetration rate of drilling in the rock mass using RDi [2]
Характеристический прогноз скорости проходки скважин с помощью RDi [2]

RDi	7 – 20	20 – 40	40 – 60	60 – 80	80 – 100
Prediction of drilling rate	Slow	Slow – medium	Medium	Medium – fast	Fast

Table 3

Technical specifications of jumbo drills

Технические характеристики самоходных бурильных установок

Parameter	Unit	Minemaster 2.3-1B	Ht81
Overall dimension (mm)	mm	1990×3000×12 500	2100×1850×11 050
Hole depth	mm	4080	3300 – 3900
Hole diameter	mm	42 – 76	42 – 102
Total length feeder	mm	3700 – 4305	3700 – 4305
Electric motor power	KW	75	65
Rated voltage	V	380	380
Traveling speed	km/h	15	14
Power diesel engine	KW	95	70
Engine	–	DUETZ	Yanmar
Percussion power	KN	14	18
Drilling speed	m/min	1.5 – 3.5	0.8 – 2
Boom rotation	degree	±180	±180
Weight	kg	20 600	12 500
Drifter	model	Montabert HC 109	Montabert HC 109

mic, power, and exponential functions were conducted to explore the connection between individual independent variables and ROP. However, it became evident that ROP is influenced by multiple parameters, and a more accurate prediction necessitated multiple regression analyses. To avoid redundancy in the multiple regression analyses, correlations between each pair of independent variables were considered in the second step. Subsequently, non-linear multiple regression (NLMR) models were developed, exploring different relationships statistically. In the third step, the relationships between each independent variable and ROP led to the creation of various NLMR models, which were statistically investigated. The dataset was divided randomly, with 80% allocated for training and 20% for testing. NLMR model was developed and performance evaluated using determination coefficient values. Real data from six underground lead and zinc mines extracted using the sublevel stopping mining method were used to develop the model. The presented steps are shown in Fig. 2. Data from four different jumbo drill brands, including minemaster 2.3-1B, Jiusheng Ht81, Atlas Copco 282 Boomer, and böhler were used. The technical specifications of the minemaster 2.3-1B and Ht81 jumbo drills are listed in Table 3.

Data collection from case study mines

The database in this paper was collected from some underground mines located in the Irankouh mining district and the Sormeh mining district in Iran. Irankouh, situated 20 km southeast of Isfahan, and Sormeh, located 55 km southwest of Fars province, have five and two underground mines, respectively. The main minerals extracted from these mines are lead and zinc, and the main lithology of the surrounding rock in these mines is dolomite. The mining method employed in all of these mines is sublevel stoping, the tunnel faces area is about 16 – 24 m^2 and contains approximately 30~35 blasting holes per face. The used drill bits have 51 and 64-mm diameters and are made of carbide with a diamond content of 7%, a spherical shape.

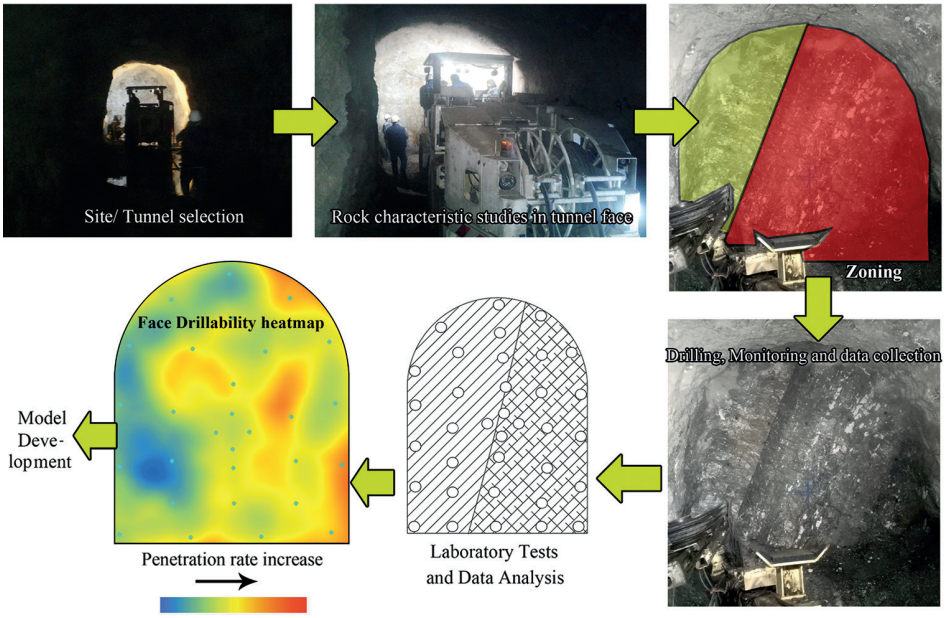

Fig. 2. Data collection and field study steps from tunnel faces and jumbo drill machines

Рис. 2. Данные и этапы полевых исследований для забоев и самоходных бурильных установок

The database covers tunnel details, rock mass characteristics, and drilling parameters. Tunnel information, such as depth and water presence, was collected before drilling. Data on discontinuity properties like joint spacing, joint aperture and filling and the angle between the joint and borehole axis were gathered prior to jumbo drill operations. Selected rock samples underwent lab analysis for physical and mechanical properties. Information from 737 boreholes across 26 faces was collected. Careful sample preparation was emphasized to ensure quality results. Uniaxial compressive strength, density, porosity, grain size, texture, and Mohs hardness were determined in accordance with ISRM standards [31].

After surveying the discontinuities, each face is divided into different areas or zones (Fig. 2). These zones, which have varying amounts of rock mass drillability index based on the characteristics of the face, are marked for borehole drilling. Information related to the drilling in each specific area is then recorded.

Drilling parameters are collected during the drilling of the borehole at the tunnel face. The collected parameters are penetration velocity, feed pressure, rotation pressure, and hammer pressure. Each parameter during drilling is recorded for each hole from the control panel of the machine. The collected parameters are described in Table 4. The geological sketch record card of the tunnel face is shown in Table 5.

With the above method, 737 boreholes, which is equivalent to more than 2400 m of drilling, were collected in seven mines of the Irankoh and Sarmeh mining complex. More details are shown in Table 6. Table 7 summarizes the ranges of input data, including 737 boreholes, and their statistical descriptions.

Relationship between RDi and penetration rate

The obtained Rock mass drillability index parameters from tunnels were rated as in Table 6. The rock mass drillability classification was determined by summing up

Table 4

Description of parameter symbols and values used in the model
Описание символов и значений параметров, входящих в модель

Symbol	Parameter	Description
P_F	Feed pressure	The hydraulic pressure inside the cylinders required to keep the bit in contact with the bottom of the hole
P_R	Rotation pressure	The pressure of the bit against the rock to maintain the required rotation
P_P	Hammer pressure	The measurement of the impact pressure of the bit against the rock mass
D_h	Borehole Diameter	Borehole Diameter
RDi	Rock mass drillability index	Rock mass drillability index
ROP	The rate of penetration	The result of dividing the drilling time by the length of the borehole

Table 5

The geological sketch record card of the tunnel face
Карточка учета геологической структуры массива в области забоя выработки

ROP (m/min)	Drilling time(s)	RDi	Rock mass drillability index (RDi)													Machine parameters			Borehole		
			Rating	Ap. (mm)	Rating	Ang. (deg)	Rating	JS (cm)	Rating	Hardness	Rating	UCS (MPa)	Rating	Texture	Zone no.	P_P (bar)	P_R (bar)	P_F (bar)	Length (m)	Diameter (mm)	Hole no.
2.4	80	33	15	0–2	1	0–20	1	0–15	9	4.5–6	6	100–200	1	dense	1	130	80	62	3.2	51	1
2.67	72	38	15	0–2	6	35–55	1	0–15	9	4.5–6	6	100–200	1	dense	2	130	85	63	3.2	51	2
2.31	83	33	15	0–2	1	0–20	1	0–15	9	4.5–6	6	100–200	1	dense	1	125	70	62	3.2	51	3
2.95	65	38	15	0–2	6	35–55	1	0–15	9	4.5–6	6	100–200	1	dense	2	125	80	70	3.2	51	4
2.49	77	38	15	0–2	6	35–55	1	0–15	9	4.5–6	6	100–200	1	dense	2	130	85	70	3.2	51	5
2.43	79	33	15	0–2	1	0–20	1	0–15	9	4.5–6	6	100–200	1	dense	1	125	80	70	3.2	51	6

Table 6

Rock mass classification sample statistics

Выборочная статистика классификаций массивов горных пород

Rock mass drillability index (RDi)	Mine name	Number of studied boreholes	Total studied boreholes
20 – 40	Tappe Sorkh	18	307
	Romarmar	129	
	Ghoushfil	20	
	Middle Sormeh	140	
40 – 60	Romarmar	70	370
	Middle Sormeh	184	
	Kolah Darvazeh	48	
	Ghoushfil	68	
60 – 80	West Sormeh	60	60
Total studied boreholes for model development			737

the rates as described in Table 7. Fig. 3 illustrates the probability distribution of RDi values across 26 faces, with over 55% falling within the range of 36 to 44. This categorizes the rock mass into three drillability classes: slow-medium, medium, and medium-fast, with more than 50% in the medium class. Using ArcGIS Pro software, RDi values for each zone were calculated, and penetration rate values for boreholes in each zone were input to generate a heatmap diagram (Fig. 2).

The relationship between RDi and ROP was assessed using correlation diagrams for two borehole diameters (51 mm and 64 mm) as shown in Fig. 4. The analysis revealed a linear increase in penetration rate with higher RDi values in the rock mass. This linear relationship was chosen based on the highest correlation coefficients among linear, logarithmic, power, and exponential functions. The variability in penetration rate for each RDi value is attributed to differences in machine operating

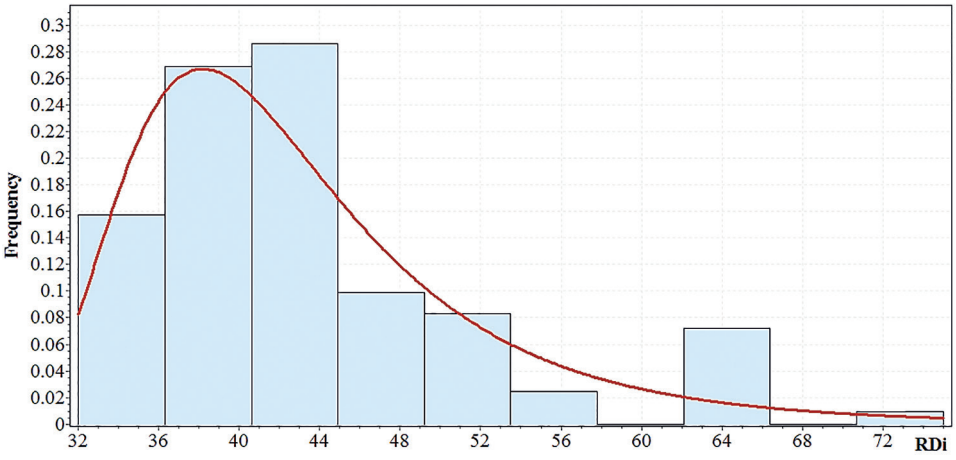

Fig. 3. Distribution of RDi values for all mines

Рис. 3. Распределение значений RDi для всех изученных рудников

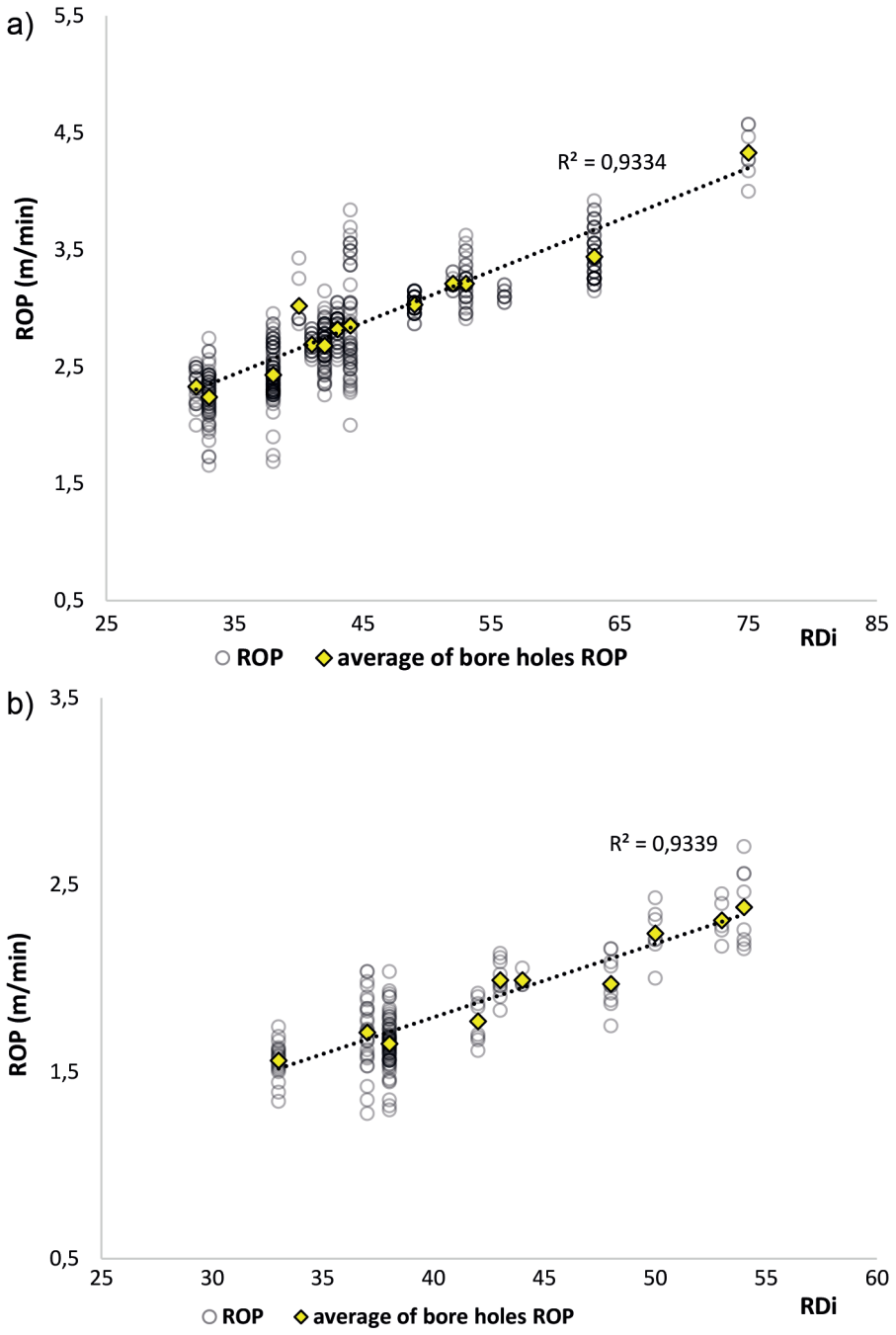

Fig. 4. Relationship between RDi and all available datasets penetration rate and the average of many numbers of blasting holes 51 mm (a), 64 mm (b)

Рис. 4. Соотношение RDi и скоростей проходки согласно всех доступных данных для средних размеров шпуров 51 мм (а), 64 мм (б)

Table 7

Statistical analysis of measured data in field and laboratory
Статистический анализ данных измерений, полученных в полевых и лабораторных условиях

RDi	Index	P_F	P_R	P_P	ROP
20 – 40	Mean	80.55	70.17	125.71	2.10
	Standard deviation	15.98	9.94	7.00	0.42
	Minimum	50	49	105	1.28
	Maximum	105	105	140	3.43
40 – 60	Mean	85.52	78.31	124.63	2.73
	Standard deviation	16.67	12.80	7.23	0.45
	Minimum	33	55	100	1.34
	Maximum	110	115	145	3.84
60 – 80	Mean	87.79	82.51	133.63	3.78
	Standard deviation	11.76	9.15	11.04	0.53
	Minimum	70	72	119	3.05
	Maximum	101	110	147	4.58

parameters. To clarify the correlation between these two factors, the data related to each RDi class was clustered. Each solid point in Fig. 4 represents the average of multiple blasting holes, ranging from 32 to 75, with one point representing each group.

Fig. 4 demonstrates that as the RDi increases, the penetration rate of jumbo drills also increases. However, this relationship applies specifically to drilling with 51 mm and 64 mm diameters. For smaller or larger boreholes, distinct curves for each stan-

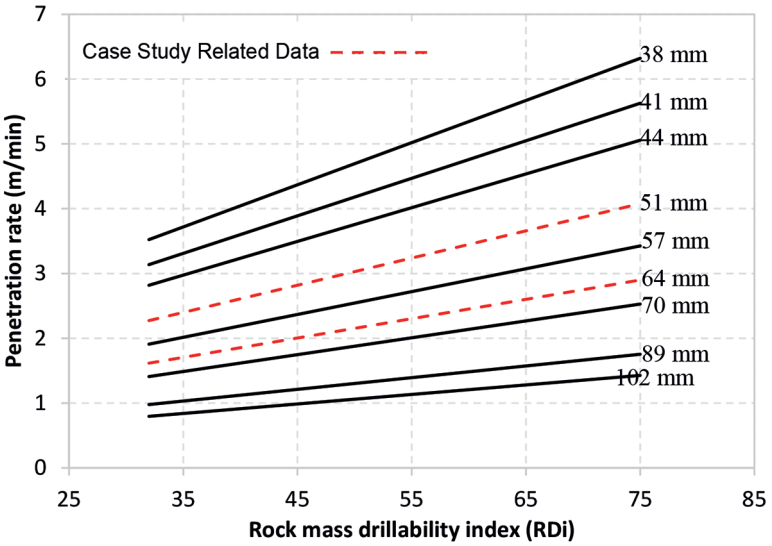

Fig. 5. Relationship between RDi and jumbo drills penetration rate in different hole diameters
Рис. 5. Соотношение RDi и скоростей проходки самоходных бурильных установок при разных диаметрах скважин

dard diameter are required. Jimeno et al. provided coefficients for predicting drilling rates in specific rock types with various borehole diameters [32]. By knowing the penetration rate for one diameter, this method allows predictions for other diameters. In this study, mathematical relationships between drilling rate and RDi for different diameters were calculated using the equations provided by Jimeno and the curve in Fig. 4 (For detailed methodology, the readers can refer to Jimeno et al. 1995 [32]). These relationships are presented in Fig. 5. As seen in Fig. 5, in rocks with poor drillability, the penetration rate with different diameters are closer to each other. The higher hardness and the dense structure of these rocks are the reasons for this phenomenon.

A penetration rate model for Jumbo drills

Multiple regression techniques are valuable for establishing relationships between multiple input variables and a dependent variable. They are particularly useful when dealing with complex relationships. Nonlinear multiple regression (NLMR) is employed when the relationship between variables is nonlinear, allowing for predictions with arbitrary relationships.

Previously, many researchers proposed multiple regression techniques for solving geotechnical problems, as well as for predicting TBM performance and rotary drilling. However, there has been no attempt to predict the jumbo drill penetration rate using an NLMR model. Since there are nonlinear relationships, such as power between inputs and output, in this paper, an NLMR technique was employed. In this regard, the NLMR equation was described using regression functions, and the process was conducted using an iterative estimation algorithm.

Initially, simple regression analyses were conducted, employing linear, logarithmic, power, and exponential functions to explore the relationship between each independent variable and the rate of penetration. The determination coefficients from these analyses are summarized in Table 8. These analyses revealed that the rate of penetration cannot be accurately predicted by a single variable, as it is influenced by numerous parameters. Consequently, more precise predictions were achieved through multiple regression analyses. Correlation analyses were also performed between each pair of independent variables, as shown in Table 9. These analyses indicated that there was no significant redundancy among the independent variables, and therefore, none of them were excluded during the model development process.

80% of the whole database was randomly chosen as the testing dataset, and 20% of the database was chosen as the validation data. Based on these datasets, different NLMR models were developed and their performance was evaluated using determination coefficient values. To validate each model, several statistical indices were used, including the root mean square error

Table 8

Correlation analysis of the rate of penetration and individual parameters
Корреляционный анализ зависимости скорости проходки скважин от индивидуальных параметров

Parameter	Linear	Logarithmic	Power	Exponential
P_F	0.13	0.19	0.25	0.18
P_R	0.45	0.49	0.53	0.46
P_P	0.27	0.28	0.34	0.31
RDi	0.72	0.72	0.70	0.68

Table 9

Correlation analysis between the parameters
Корреляционный анализ параметров

Parameter	P_F	P_R	P_P	RDi	D_h	ROP
P_F	1	0.21	0.34	0.08	0.04	0.22
P_R		1	0.38	0.43	–0.02	0.5
P_P			1	0.21	–0.03	0.41
RDi				1	–0.19	0.7
D_h					1	–0.6
ROP						1

(RMSE), the variance accounted for (*VAF*), mean absolute error (*MAE*), mean absolute percentage error (*MAPE*), and the F-test. *VAF* can be used to evaluate the variance proportion of the variables, while *RMSE*, *MAE*, and *MAPE* are frequently used to compare the prediction errors of different models – the lower the *RMSE*, *MAE*, and *MAPE*, the better the model performs. These statistical indices are expressed as follows (Eqs. (1) to (4)):

$$RMSE = \sqrt{\frac{\sum_{i}^{n}\left(T_i - O_i\right)^2}{n}} \quad (1)$$

$$MAE = \frac{\sum_{i=1}^{n}\left|T_i - O_i\right|}{n} \quad (2)$$

$$MAPE = \frac{100}{n} \times \sum_{i=1}^{n}\left|\frac{T_i - O_i}{T_i}\right| \quad (3)$$

$$VAF = \left[1 - \frac{\mathrm{var}\left(T_i - O_i\right)}{\mathrm{var}\left(T_i\right)}\right] \times 100 \quad (4)$$

where var denotes the variance, T_i and O_i are the measured and predicted values, n is the sample size.

The NLMR model was constructed using the statistical software package SPSS version 27. The same 590 datasets were used to build the NLMR equation, and the remaining 147 datasets were used to check the model's performance capacity. The proposed NLMR equation, comprising five predictors, is shown in Eq. (5):

$$ROP = 5.3 \times \frac{P_F^{0.08} \times P_R^{0.23} \times P_P^{0.54} \times RDi^{0.63}}{D_h^{1.76}} \quad (5)$$

where *ROP* is the penetration rate in m/min, P_F is the feed pressure in the bar, P_R is the rotation pressure in the bar, P_P is the Hammer pressure in the bar, *RDi* is the rock mass drillability index and D_h is the bit diameter in mm.

The results of multiple regression analyses and performance indices of developed non-linear multiple regression models are shown in Table 10. The cross-correlation

Table 10

The results of multiple regression analyses and performance indices of developed non-linear multiple regression models
Результаты многократного регрессионного анализа и показатели работоспособности разработанных моделей множественной нелинейной регрессии

Model type	Training set					Testing set				
	R^2	RMSE	MAE	MAPE	VAF	R^2	RMSE	MAE	MAPE	VAF
NLMR	0.88	0.22	0.17	7.30	88.84	0.88	0.23	0.17	7.22	87.99

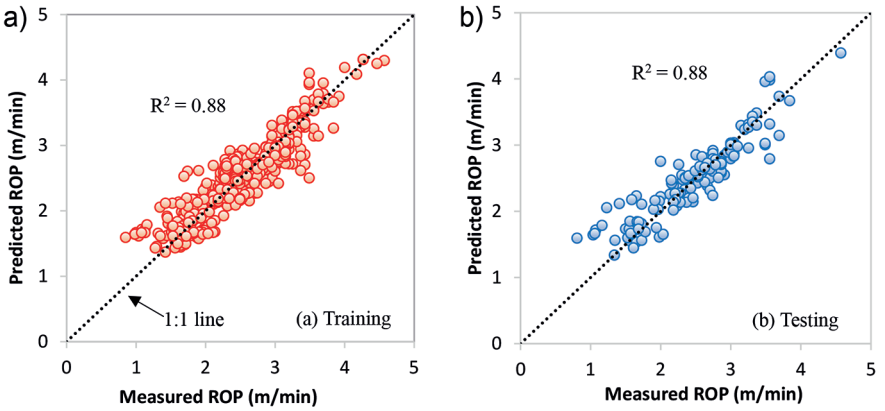

Fig. 6. Correlation of predicted ROP versus the measured ROP of the non-linear multiple regression (NLMR) models: training set (a); testing set (b)

Рис. 6. Соотношение замеренных и прогнозных значений скоростей проходки скважин по моделям множественной нелинейной регрессии: тренировочный набор (а); проверочный набор (б)

graph of the nonlinear multiple regression model is presented in Fig. 6.

Sensitivity analysis

To recognize the most sensitive factors affecting penetration rate, the cosine amplitude method (CAM) was utilized. To apply this method, all the data pairs are expressed in a common *X*-space which is used to construct a data array *X*, defined as Eq. (6).

$$X = \{X_1, X_2, X_3, \dots, X_n\} \qquad (6)$$

Each of the elements, X_i, in the data array *X* is a vector of lengths of *n*, that is:

$$X_i = \{X_{i1}, X_{i2}, X_{i3}, \dots, X_{in}\} \qquad (7)$$

Thus, each of the data pairs can be thought of as a point in *n*-dimensional space, in which each point requires *n* coordinates for a full description. Each element of the relation, r_{ij}, results in a pairwise comparison of two data pairs. The strength of the relation between the data pairs, x_i and x_j, is given by the membership value expressing the strength:

$$R_{ij} = \frac{\sum_{k=1}^{n}\left(x_{ik} \times x_{jk}\right)}{\sqrt{\sum_{k=1}^{n} x_{ik}^2 \times \sum_{k=1}^{n} x_{jk}^2}} \qquad (8)$$

where *i*, *j*, and *k* represent respectively the counters of the number of input indicators in each data series, the indicators or factors related to each data series, and the number of data series or samples. The closer R_{ij} is to one, the greater the impact of the input indicator on the target index. If there is no effect, the value of R_{ij} will be zero.

The strengths of relations (r_{ij} values) between the *ROP* and input parameters are shown in Fig. 7 and Table 11. Considering that the values of R_{ij} are high for all pa-

Table 11

Strengths value (R_{ij}) between the penetration rate and each input parameters
Значения прочности корреляции (R_{ij}) между скоростью проходки скважин и входными параметрами

Parameter	Feed pressure	Rotation pressure	Hammer pressure	Borehole Diameter	RDi
R_{ij}	0.959	0.975	0.972	0.950	0.984

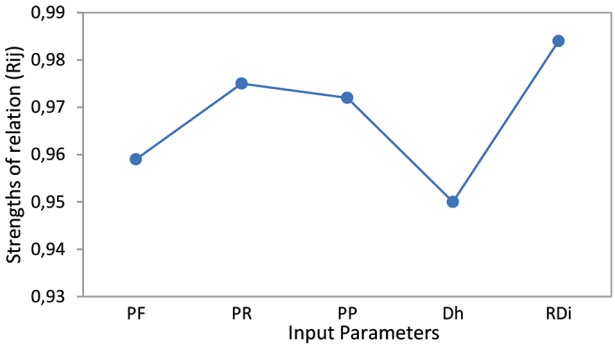

Fig. 7. Strengths of relation (R_{ij}) between the penetration rate and each input parameters
Рис. 7. Значения прочности корреляции (R_{ij}) между скоростью проходки скважин и входными параметрами

rameters affecting the penetration rate, and based on the graph presented in Fig. 7, it can be concluded that all of the considered parameters are significantly involved in the rate of penetration. As is shown, the most effective parameter on the *ROP* is the rock mass drillability index. In other words, the characteristics of the rock mass have a great influence on the drilling speed.

Conclusions

The rate of penetration depends on a number of parameters including rock mass properties (intact rock properties and structural parameters), machine specifications, and operational parameters. In this paper, the nonlinear multiple regression model was used to predict the penetration rate of jumbo drills. This method was applied as the first attempt at the prediction of *ROP* in underground mines. To prepare a suitable database, the effective parameters on *ROP* including rock mass properties and machine specifications for 737 boreholes in the underground mines were collected and these parameters were used as model inputs to predict *ROP*. For this purpose, the RDi factors as joint spacing, joint aperture, and filling and joint inclination were collected along with drilling rate from 737 boreholes and then several representative rock blocks were collected from each face to obtain physicomechanical properties and as rock texture, UCS, and Mohs hardness. Also, data of the RDi for each zone were correlated with the net drilling rate. Some of the important results are as follows:

- Linear relationships between RDi and penetration rate were obtained with high correlation coefficients (R^2 = 0.93 for 51 mm and 64 mm).
- Several simple regression analyses were performed and the correlations between different variables and the penetration rate were determined. The results of this step of the studies indicated that determination coefficients of simple regression analyses are rather low.
- Then several NLMR models were employed and the performance indexes of these models, such as R^2, *VAF*, *RMSE*, *MAE*, and *MAPE* evaluated. In constructing the NLMR technique, datasets were divided randomly into training (80%) and testing (20%) datasets and a new penetration rate model based on the RDi and machine specifications, has been presented.
- The application of the developed model is intended for use in the mass of dry and semi-dry rock formations. However, challenges may arise when dealing with saturated rock conditions and mines experiencing an above-normal water volume. Problems may also arise in not so much jointed rock masses, particularly those lack-

ing cohesion, such as homogeneous rock masses. Furthermore, it's important to note that the model has been specifically designed for underground drilling conditions. In scenarios involving drilling in open pits or holes with larger diameters, the model may not be suitable for accurately predicting the infiltration rate.

• Since the model includes intact and mass properties of rocks, it provides a good estimation of rock mass penetration in underground mines. Thus, the proposed mo del is feasible and reliable in the prediction of the jumbo drill's penetration rate. This predicted value could be successfully applied for scheduling the future of underground mines. However, this prediction is limited to the geological conditions and operations of the case studies in this paper. The results of this study can be successfully used to estimate jumbo drill penetration in projects with similar geological conditions. In addition, the samples collected in this study only covered three classes in the rock mass drilabillity index. Thus, the sample types and numbers should be further expanded in the future to improve the application range of the model.

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