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Development of a site-specific regression model for assessment of road-header cutting performance of Tabas coal mine based on rock properties

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Abstract

In underground excavation, where the road-headers are employed, a precise prediction of the road-header performance has a vital role in the economy of the project. In this paper, a new model is developed for prediction of the road-header performance using the non-linear multivariate regression analysis. This model is able to estimate the instantaneous cutting rate (ICR) of roadheader based on rock properties such as Brazilian tensile strength (BTS), rock mass cuttability index (RMCI), and alpha angle (α: is the angle between the tunnel axis and the planes of weakness). In order to construct and test the proposed model, a database including 62 cutting cases is used in the Tabas coal mine No. 1 in Iran. Various statistical performance indices were employed to evaluate the model efficiency. The results obtained indicate that the proposed non-linear regression model can be efficiently used to predict the road-header cutting performance. Furthermore, the prediction capacity of this model is better than the empirical models developed previously. Finally, it should be noted that the developed model is site-specific, and it can be used for preliminary estimation of ICR in future phases of Tabas coal mine No. 1. The outcome of this model can be helpful in adjustment of time-scheduling of the project.

Keywords: *Road-Header Machine, Instantaneous Cutting Rate, Non-Linear Multivariable Regression Analysis, Rock Properties, Tabas Coal Mine.*

1. Introduction

Road-headers are one of the most popular mechanized excavators used in mining and civil underground excavations. Road-headers were first developed in Europe for the mechanical excavation of coal in the late 1940s [1, 2]. They are partial face machines excavating only a portion of the face at once. The basic advantages of road-headers over the other underground excavation machines are their mobility, flexibility, and selective mining ability.

The successful application of road-headers is directly related to an accurate estimation of performance, which is critical for the project schedule and costs. Error in the performance estimation can result in project delays and cost over runs, as seen in many case histories. Performance prediction generally includes the assessment of instantaneous (net) cutting rate (ICR). ICR is defined as the production rate during a continuous excavation phase in m^3/h. An overview of the relevant literatures reveals that various parameters can affect the road-header performance. These parameters can be divided into three general groups: mechanical, geological-geotechnical, and technical-operational parameters [2]. A summary of these parameters is presented in Table 1.

Table 1. Main parameters influencing road-header performance [2].

Mechanical parameters	● Machine type (crawler mounted, shielded, twin boom, etc.) ● Machine weight and dimensions ● Boom force capacities (shearing, lifting, and lowering). ● Cutter-head type (transverse, axial) ● Cutter-head power and RPM, lacing design ● Bit type and dimensions, metallurgical properties of tip
Geological-geotechnical parameters	Rock Mass Properties ● RQD ● Bedding, foliation, and fault zones ● Joint sets (orientation, spacing, filling, etc.) ● Hydrogeology (water table/water ingress) ● Adverse geology (squeezing, swelling, and blocky grounds) Physical and Mechanical (Intact Rock) Properties ● Cuttability (cutter forces, SE, and optimum cutting geometry: linear cutting tests) ● Strength (UCS, BTS, elasticity modulus, cohesion, etc.) ● Texture and abrasivity (mineral/quartz content and grain size, micro-fractures, grain interlocking, etc.) ● Others (brittleness, water content, swelling, etc.)
Technical-operational parameters	Technical Parameters ● Tunnel shape and dimensions ● Inclinations, crosscuts Mining Parameters ● Support (bolting, shotcrete, steel sets, etc.) ● Muck haulage (conveyor, locomotive, LHD, etc.) ● Utility lines (power, water, and air supply) and surveying ● Ground treatment (drainage, grouting, and freezing) ● Labor availability and quality

In the past years, many road-header performance prediction models have been reported in the literature using a combination of parameters. These performance prediction models can be generally classified as the theoretical and empirical models [3]. Theoretical models are based upon full-scale and small-scale linear cutting tests. These models estimate ICR using the specific energy required to excavate a unit volume of rock. The pioneering works in estimating the performance of road-headers from specific energy was carried out by McFeat-Smith and Fowell [4, 5], Fowell and Johnson [6], Farmer and Garrity [7], Poole [8], and Fowell et al. [9]. One of the most accepted theoretical methods was suggested by Rostami et al. [10] based upon full-scale cutting tests, as shown in the following equation:

$$ICR = k \cdot \frac{P}{SE_{opt}} \qquad (1)$$

where ICR is the instantaneous cutting rate in m^3/h, P is the installed cutter-head power in kW, SE_{opt} is the optimum specific energy in kWh/m^3, and k is the mechanical efficiency rate, which is between 0.45 and 0.55 for road-headers, without mentioning the type of road-header cutter head. Investigation of the literature indicated that SE obtained from full-scale linear cutting tests in optimum cutting conditions was highly correlated to mechanical properties of the rocks [11-14].

Empirical performance prediction models are mainly based on the past experience and the statistical interpretation of previously recorded case histories. Therefore, the collection of field data is very important for the development of empirical models. The accuracy and reliability of these models depend on the quality and extent of the available data. Some of the most widely used empirical models for road-headers are summarized in Table 2.

As it can be seen, the literature contains a considerable number of empirical prediction models obtained from the conventional statistical techniques. In the recent years, the soft computing techniques have been successfully employed for developing prediction models. These techniques have attracted much attention in a lot of research fields, and they are now being used as an alternative statistical tools. Recently, Yazdani-Chamzini et al. [20], Salsani et al. [21], Avunduk et al. [3], and Ebrahimabadi et al. [22] have applied the soft computing techniques (artificial neural network and fuzzy inference system) for the road-header performance prediction. The main disadvantage of the soft computing techniques is that most of them are "black box", meaning that they are not able to clearly indicate the relationship between the input and output parameters.

The current work aims to predict the road-header performance based on a transparent model. Thus a new model was developed using a non-linear multivariate regression analysis for ICR prediction. For this purpose, a database compiled from Tabas coal mine No. 1 was used, and the model was developed based on major rock properties such as Brazilian tensile strength (BTS), rock mass cuttability index (RMCI), and alpha angle (α). The method of developing the regression model and also the description of database are presented in the following sections.

Table 2. Common empirical prediction models for road-header performance.

Author	Model	Explanations
Gehring [15]	$ICR = 719 / UCS^{0.78}$	Based on performance of a road-header with a 250 kW transverse type cutter-head.
	$ICR = 1739 / UCS^{1.13}$	Based on performance of a road-header with a 230 kW axial type cutter-head.
Bilgin et al. [16]	$ICR = 0.28 \cdot P \cdot (0.974)^{RMCI}$ $RMCI = UCS \cdot \left(RQD / 100 \right)^{2/3}$	Based on in situ observation of many tunneling and mining projects.
Thuro and Plinninger [17]	$ICR = 75.7 - 14.3 \cdot \ln\left(UCS\right)$	Based on performance of a 132 kW transverse type road-header.
Copur et al. [18]	$ICR = 27.511 \cdot \exp\left(0.0023 \cdot RPI\right)$ $RPI = (P \cdot W) / UCS$	Based on performance of transverse road-headers in different power and weight classes for excavation of especially evaporitic rocks (non-abrasive).
Balci et al. [12]	$ICR = k \cdot \left[P / (0.37 \cdot UCS^{0.86}) \right]$	Based on performance of transverse road-headers in different power and weight classes and different types of rocks.
	$ICR = k \cdot \left[P / (0.41 \cdot UCS^{0.67}) \right]$	Based on performance of axial road-headers in different power and weight classes and different types of rocks.
Ebrahimabadi et al. [19]	$ICR = 30.75 \cdot RMBI^{0.23}$ $RMBI = e^{(UCS/BTS)} \cdot \left(RQD / 100 \right)^{3}$	Based on performance of a light-weight axial road-header and coal measure strata (Tabas coal mine).

ICR: instantaneous cutting rate (m^3/h).
P: installed cutter-head power (HP in Bilgin et al. model and kW in other models).
W: weight of road-header (tons).
k: energy transfer ratio (0.5 for axial and transverse road-headers).
UCS: uniaxial compressive strength (MPa).
BTS: Brazilian tensile strength (MPa).
RQD: rock quality designation (%).
RMCI: rock mass cuttability index (MPa).
RPI: road-header penetration index.
RMBI: rock mass brittleness index.

2. Mine description and database

Tabas coal mine No. 1 is the case studied here. This mine is located in a desert area approximately 85 km south of Tabas town in Yazd province in the mid-eastern part of Iran. There are five coal seams in Tabas coalfield including B_1, B_2, C_1, C_2, and D. C_1 is the most suitable seam for mechanized mining due to the least variation in thickness. In mine No. 1, the C_1 seam is extracted using the mechanized long-wall retreat mining method (Figure 1). The thickness and dip of C_1 seam vary from 1.8 to 2 m and from 11 to 26˚, respectively. Low strength sandstone and siltstone strata constitute the hanging wall of the coal seam. The footwall consists of siltstone and mudstone strata, alternately [23]. In mine No. 1, four road-header machines, DOSCO MD1100 axial (milling) type, are used to excavate entries and drifts. DOSCO MD1100 road-header, which is classified in the range of light-duty machines, is considered as an ideal machine for excavating mixed strata. The strength of rock formations to be excavated by road-headers in Tabas coal mine is low-to-medium including siltstone, mudstone, and coal. The basic specifications of this machine are summarized in Table 3.

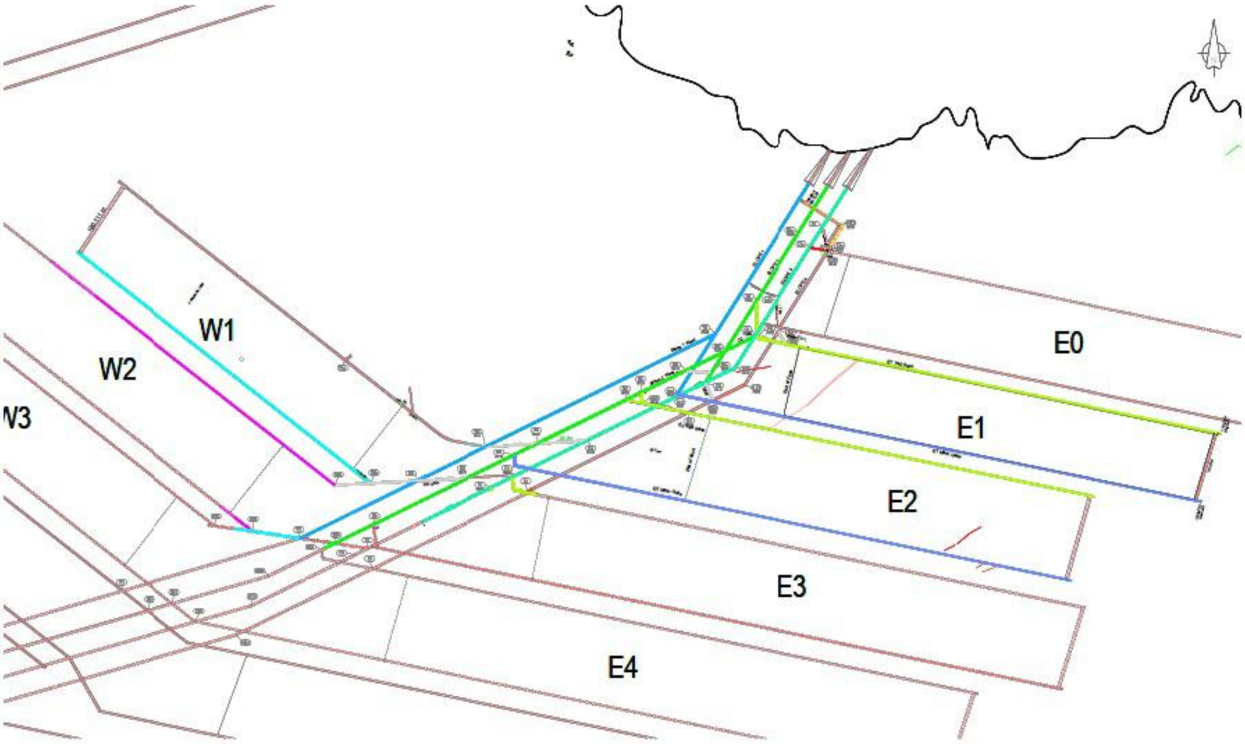

Figure 1. Layout of Tabas coal mine No. 1 [23].

Table 3. Main specifications of DOSCO MD1100 road-header.

General	
Total weight	34 tons
Length of machine	8.16 m
Width of machine	2.5 m
Height of machine	1.86 m
Width over apron	3 m
Machine ground pressure	0.14 MPa
Cutting profile	
Cutting height max.	4.378 m
Cutting width max.	6.16 m
Undercut below floor level	188 mm
Conveying system	
Type of conveyor	Centre strand scraper
Width of conveyor	600 mm
Velocity of conveyor	1.18 m/s
Negotiable gradients	
Max. incline/decline	16 degrees
Max. cross gradient	8 degrees
Speeds	
Speed of cutter-head	2.54 m/s
Tracking speed	0.038 to 0.12 m/s
Electrical system	
Cutter motor	82 kW (axial)
Total installed power	157 kW

For the purpose of this work, the database compiled by Ebrahimabadi et al. [24] was used. Ebrahimabadi [25] has performed a comprehensive study on the entries and drifts of mine No. 1 to establish a database for evaluating the performance of road-header machines. He gathered detailed data including machine performance and geo-mechanical parameters for 62 cutting cases in tunnels and entries. Table 4 presents a summary of the original database. The database contains intact rock properties including uniaxial compressive strength (UCS), Brazilian tensile strength (BTS), and also rock mass properties including the rock mass cuttability index (RMCI) and the alpha angle (α) [the angle between tunnel axis and the planes of weakness] together with the actual measured instantaneous cutting rate (ICR). ICR was calculated based on the cutting volume and cutting duration recorded for each cutting case under highly controlled conditions. In each cutting case, UCS and BTS were measured in the laboratory according to the ASTM standards [26, 27]. RMCI and α were computed using Eqs. (2) and (3), respectively [16, 28]. In these equations, α_f and α_s are dip and strike of encountered planes of weakness in rock mass, respectively, and α_t is the direction of the tunnel axis, all in degrees.

$$RMCI = UCS \cdot \left({RQD}/{100} \right)^{2/3} \tag{2}$$

$$\alpha = \arcsin\left(\sin\alpha_f \cdot \sin\left(\alpha_t - \alpha_s \right) \right) \tag{3}$$

As it can be seen in Eq. (2), calculating RMCI requires the rock quality designation (RQD) index. Generally, RQD is determined based on drill cores, and in this work, its value ranged from 18 to 28 [24].

Table 4. Summary of original database.

Type of data	Parameter (unit)	Min.	Mean	Max.	Std. dev.
Inputs	UCS (MPa)	14.10	19.61	28.20	5.48
	BTS (MPa)	3.60	4.08	5.30	0.30
	RMCI	4.62	6.65	11.64	1.93
	α (deg.)	39.00	47.13	54.00	4.84
Output	ICR (m^3/hr)	14.60	28.75	46.20	10.24
Total number of data points is 62.					

3. Development of non-linear regression model

As it can be seen in Table 4, the Tabas database contains four input parameters but to develop the predictive model of ICR, only three parameters (i.e. BTS, RMCI, and α) were considered as the predictor variables. UCS was excluded from the input parameters because it was considered in the RMCI calculation indirectly (Eq. 2).

At first, a series of simple regression analyses were carried out in order to identify the relationship between the predictor variables and the dependent variable. It should be mentioned that all the statistical analyses were done using the SPSS software [29]. The relationship between ICR and the predictor variables was analyzed using the linear, logarithmic, power, exponential, and quadratic functions. A summary of the results obtained can be seen in Table 5.

The statistically significant and strong correlations were then selected, and the regression equation was established among the index parameters with the ICR (Table 6). As it can be seen in Table 6, the strongest relationship between BTS and RMCI with ICR was quadratic, whereas this relationship for sin (α) was exponential. Figure 2 shows the plots of ICR versus BTS, RMCI, and sin (α).

Table 5. Determination coefficient (R^2) obtained from simple regression between ICR and predictor variables.

	BTS (MPa)	RMCI (MPa)	sin (α)
Linear	0.508	0.899	0.380
Logarithmic	0.517	0.911	0.374
Quadratic	0.527	0.914	0.403
Power	0.476	0.851	0.453
Exponential	0.466	0.829	0.457

Table 6. Predictive models for assessing ICR.

	Prediction model	R^2
ICR *vs.* BTS	$ICR = -8.590BTS^2 + 96.893BTS - 222.850$	0.527
ICR *vs.* RMCI	$ICR = -0.466RMCI^2 + 11.774RMCI - 27.197$	0.914
ICR *vs.* sin (α)	$ICR = 1.173\exp\left(4.291 \cdot \sin(\alpha)\right)$	0.457

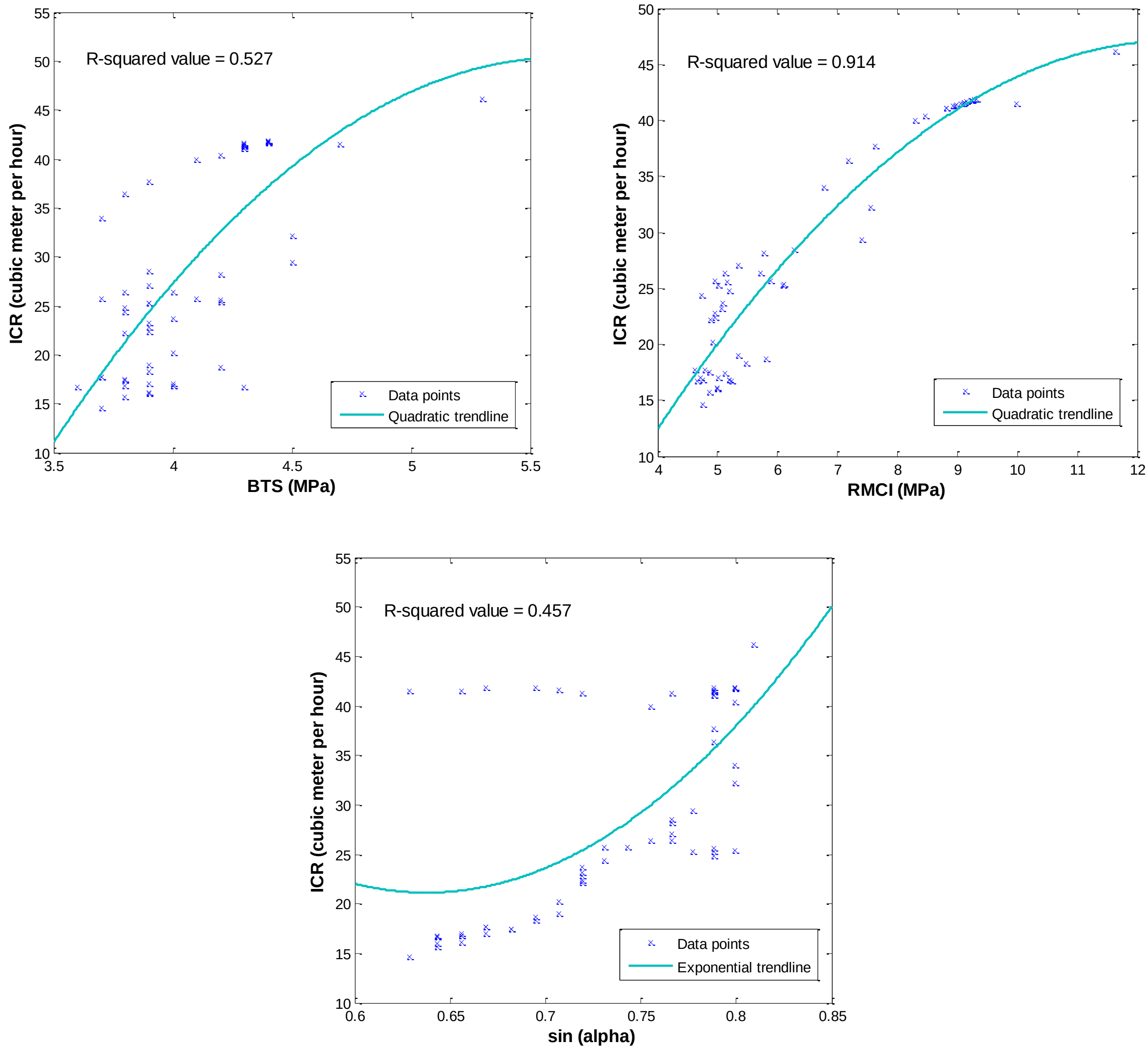

Figure 2. Relationships between ICR *vs.* BTS, RMCI, and sin (α).

These results obtained reveal that all the predictor variables have a significant effect on ICR, and should be considered as the input parameters for developing the ICR predictive equation. On the other hand, based on these results, the relationship between ICR and the predictive variables was non-linear. Thus it was necessary to employ the non-linear multivariable regression analysis for the precise prediction of ICR. Considering the results obtained from simple regression analysis, the following equation may be suggested for the ICR prediction:

$$ICR = w_1 \cdot BTS^2 + w_2 \cdot BTS + w_3 \cdot RMCI^2 + w_4 \cdot RMCI + w_5 \cdot \exp(w_6 \cdot \sin\alpha) + w_7 \quad (4)$$

where w_i is the corresponding regression coefficient.

To develop the above equation, all datasets (62) were randomly divided into two categories, namely training and testing datasets. The training datasets were used to develop the regression models and the testing datasets for evaluating the performance of the models. In this work, based on recommendations in the literature, 80% of the whole datasets (50) were used for training, and the remaining 20% (12) for testing the models. The SPSS software was applied to find the optimal values of regression coefficients based on the training datasets. The aim was to find the regression coefficient so that the developed model had the minimum prediction error. The regression coefficients for the suggested equation were obtained as below:

$$ICR = -9.254BTS^2 + 68.667BTS + 0.396RMCI^2 - 0.081RMCI + 1196\exp(0.035\sin\alpha) - 1342 \quad (5)$$

4. Performance of proposed model

In this section, the performance of the developed prediction model was evaluated using the testing datasets (12 cutting cases). In order to evaluate the model performance, the predicted ICR values were compared with the actual ones. Table 7 shows this comparison between the predicted ICR using the proposed regression model with the actual ICR values.

In this work, the adequacy of the prediction model was also evaluated in terms of the coefficient of determination (R^2), variance account for (VAF), and Root Mean Square Error (RMSE). A value for R^2 close to one shows a good fit of the prediction model, and a value close to zero presents a poor fit. Figure 3 shows the relationship between the measured and predicted values, with good coefficient of determination, obtained from the prediction model. As it could be seen, the determination coefficient was 0.956. Furthermore, a prediction model is accepted as excellent when RMSE is equal to zero and VAF is 100%. The statistical values for VAF and RMSE, obtained from the proposed regression model, were 95.281% and 2.110, respectively. The values for R^2, VAF, and RMSE indicated the acceptable performance of the proposed model. Therefore, the output of this model can be considered as a preliminary estimation of ICR.

Table 7. Measured and predicted ICR values by proposed regression model for testing datasets.

No.	UCS (MPa)	BTS (MPa)	RMCI (MPa)	α (deg.)	Measured ICR (m^3/h)	Predicted ICR (m^3/h)				
						Proposed model	Gehring	Bilgin et al.	Balci et al.	Ebrahimabadi et al.
1	14.8	3.8	4.89	46	22.2	20.86	82.78	51.81	31.48	23.95
2	16	3.9	5.47	44	18.3	21.91	75.80	51.03	29.88	26.02
3	15.5	4	5.12	50	26.4	23.08	78.56	51.50	30.52	23.84
4	14.4	3.8	4.76	41	16.8	17.67	85.38	51.99	32.06	23.37
5	15.1	3.9	4.99	40	16	17.73	80.92	51.68	31.06	23.82
6	14.5	3.7	4.62	42	17.7	17.80	84.71	52.18	31.91	23.20
7	17.2	3.9	6.27	50	28.5	28.60	69.85	49.97	28.46	29.83
8	15.3	3.9	5.06	46	23.2	21.24	79.73	51.59	30.79	24.10
9	16.2	4.2	5.16	52	25.6	22.75	74.74	51.44	29.63	22.87
10	25.6	4.2	8.46	53	40.4	40.74	44.56	47.16	21.81	39.72
11	27.6	4.3	9.12	45	41.6	40.34	40.93	46.35	20.73	42.79
12	28.1	4.4	9.29	42	41.9	38.71	40.11	46.15	20.49	42.47

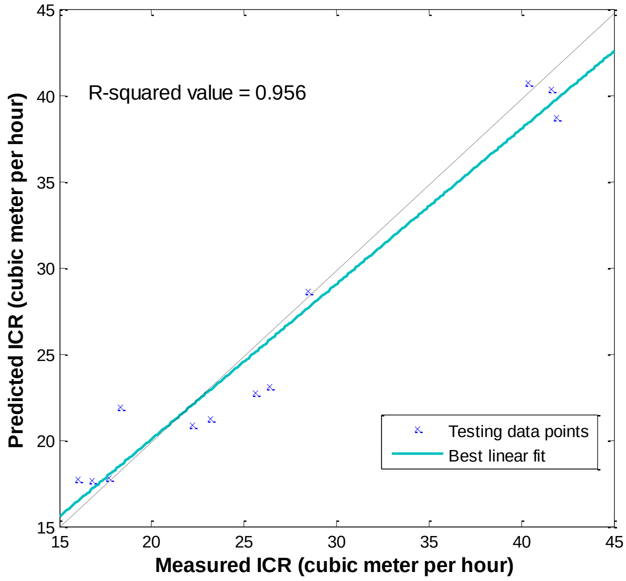

Figure 3. Relationship between measured and predicted ICR by proposed non-linear regression model.

To indicate the prediction error of the proposed model, the model was compared with the previously developed empirical models, i.e. the Gehring, Bilgin et al., Balci et al., and Ebrahimabadi et al. models (see Table 2). It should be mentioned that all of these empirical models were developed for axial road-headers. The predicted ICR values for testing datasets by these models are presented in Table 7. The values of RMSE for these models, based on the testing datasets, are presented in Figure 4. As it can be seen, the prediction error of the proposed regression model is lower than the previously developed empirical models. Thus the non-linear multivariate regression analysis is a useful and powerful means for predicting ICR of DOSCO MD1100 road-headers in Tabas coal mine.
Finally, to show the strength of developed model, it was compared with one of the most efficient non-linear models, i.e. power form regression. The equation of this model is expressed as follows:

$$ICR = w_1 \cdot BTS^{w_2} \cdot RMCI^{w_3} \cdot (\sin\alpha)^{w_4} \qquad (6)$$

where w_1, w_2, w_3, and w_4 are the regression coefficients, which can be determined by the non-linear regression analysis using the SPSS software. Based on the training datasets, the coefficients were determined as below:

$$ICR = 15.985 \cdot BTS^{-1.321} \cdot RMCI^{1.386} \cdot (\sin\alpha)^{0.600} \qquad (7)$$

Based on the testing datasets, the R^2, VAF, and RMSE performance indices were obtained as 0.905, 90.393%, and 2.993, respectively. Although these values indicated that the model efficiency was acceptable, its efficiency was lower than the proposed model (Eq. 5).
Based on what mentioned above, Eq. (5) is a useful tool for estimating the cutting performance of the road-header machine in Tabas coal mine, which exhibits a reliable ICR prediction.

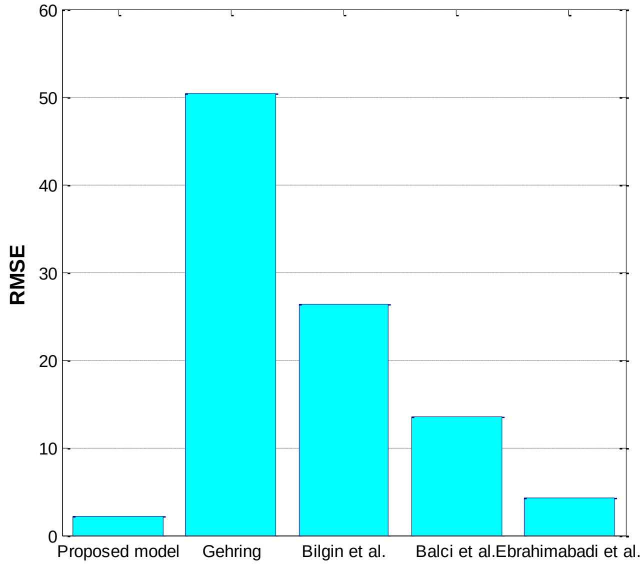

Figure 4. RMSE values for various models.

5. Conclusions

The performance prediction of the road-headers is one of the main subjects in determining the economics of the underground excavation projects. The poor prediction of machine performance can lead to project delays and over-costs. This work was performed to evaluate the application of the non-linear multivariate regression analysis for estimating the cutting performance of the road-header machine (ICR) based on the rock properties. In fact, in this work, a new non-linear regression model (Eq. 5) was developed to predict ICR for DOSCO MD1100 road-headers in Tabas coal mine No. 1. This model was constructed using the SPSS software. In addition, the following main conclusions may be drawn from this work:

- Based on the results obtained from the simple regression analysis, all the predictor variables (i.e. BTS, RMCI, and sin (α)) had significant effects on ICR, and the relationship between these variables and ICR is non-linear. Therefore, the non-linear multivariable regression analysis was used for developing the model.

- Based on the results obtained, the proposed regression model could be used effectively for prediction of the road-header performance. The values for R^2, VAF, and RMSE for the proposed model were 0.956, 95.281%, and 2.110, respectively.
- The comparison of this model with the previously developed models indicates that the non-linear regression model gives more reliable predictions than the other empirical models.
- The outcome of the proposed model can be considered site-specific and used as a preliminary estimation of ICR for DOSCO MD1100 in the future phases of Tabas coal mine No. 1. Adjustment of the time-scheduling of the project can be more accurate based on this model. Furthermore, this model gives a preliminary view to the researchers so similar models can be developed in other sites by modifications based on the geotechnical and machine conditions.

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توسعه یک مدل رگرسیون مکان ویژه برای ارزیابی کارایی برش رودهدر در معدن زغال‌سنگ طبس بر اساس خصوصیات سنگ

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چکیده:

در حفاری زیرزمینی، جایی که رودهدرها به کار گرفته می‌شوند، پیش‌بینی دقیق کارایی رودهدر نقش حیاتی در اقتصاد پروژه دارد. در این پژوهش، با استفاده از آنالیز رگرسیون چند متغیره غیرخطی مدلی جدید برای پیش‌بینی کارایی رودهدر توسعه داده می‌شود. این مدل قادر به تخمین نرخ برش آنی (ICR) رودهدر بر اساس خصوصیات سنگ مانند مقاومت کششی برزیلی (BTS)، شاخص برش‌پذیری توده سنگ (RMCI) و زاویه آلفا (α: زاویه بین محور تونل و صفحات ناپیوستگی) است. به منظور ساخت و آزمایش مدل پیشنهادی، پایگاه داده‌ای مشتمل بر ۶۲ مورد برش از معدن شماره یک زغال‌سنگ طبس استفاده شد. برای ارزیابی کارایی مدل، شاخص‌های آماری گوناگونی به کار گرفته شدند. نتایج به دست آمده نشان داد که مدل رگرسیون غیرخطی پیشنهاد شده می‌تواند به طور مؤثری برای پیش‌بینی کارایی برش رودهدر استفاده شود. علاوه بر این، ظرفیت پیش‌بینی این مدل بهتر از مدل‌های تجربی گذشته است. در آخر باید ذکر شود که مدل توسعه داده شده مکان ویژه است و می‌توان از آن برای تخمین اولیه ICR در فازهای بعدی معدن شماره یک زغال‌سنگ طبس استفاده کرد. خروجی به دست آمده از این مدل می‌تواند برای اصلاح برنامه‌ریزی زمانی پروژه مفید واقع شود.

کلمات کلیدی: ماشین رودهدر، نرخ برش آنی، آنالیز رگرسیون چند متغیره غیرخطی، خصوصیات سنگ، معدن زغال‌سنگ طبس.