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Research article

A combination model of multiple regression and rock engineering systems (MR-RES) to identify main parameters' effect value on tunnel face advance

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Abstract

To accurately predict the advance of a tunnel excavated by the drilling and blasting method, various parameters related to the rock and the operational conditions of the project should be taken into account. In this paper, a comprehensive model was developed to investigate the effects of different parameters on the advancement of such a tunnel. To achieve this goal, we conducted a systematic study at the tailrace tunnel of the Azad Dam in Iran. Rock properties, including the rock mass rating (RMR) and tunneling quality index (Q), as well as operational conditions such as blasting specific charge (q) and tunnel face area (A), were measured to establish comprehensive datasets for prediction. A total of 86 tunneling data points were collected and considered in this study. A novel model was developed, combining multiple regression (MR) and rock engineering systems (RES), to estimate tunnel face advance. The RES coding method was improved by incorporating a multiple regression model. The proposed coding method creatively assesses the influencing parameters, providing the advantage of accommodating uncertainties in the RES analysis. It achieves this by modeling the relationship between the explanatory (independent) variables and response (dependent) variables, thereby quantifying the interaction matrix. To evaluate the accuracy of the proposed models for both MR and RES datasets, we used the coefficient of determination (R2), a significant statistical criterion. A comparison of the values predicted by the models demonstrated that RES offers a more suitable performance than MLR for predicting tunnel advance. Sensitivity analysis of the MR-RES models reveals that the effective parameters on tunnel advance, in descending order of influence, are RMR (35.62%), Q (28.6%), q (20.35%), and A (15.42%). This hybrid method can be developed in other fields of engineering without human judgment and considering the statistical background of the data.

1. INTRODUCTION

Tunneling by drill-and-blast remains the most typical method in subsurface construction worldwide (Girmscheid and Schexnayder, 2002). This method involves the controlled use of explosives to break rock (Rana et al., 2020) and is adaptable to a wide range of rock conditions (Satici and Hindistan, 2006). However, drill and blast are often the only viable methods in situations such as short tunnels, large cross-sections, cavern construction, cross-overs, cross passages, shafts, penstocks, etc. (Spathis and Gupta, 2012). To enhance the performance of this method in tunnel construction, it is vital to optimize each rock property and working condition involved in the construction process. The realistic assessment of the time and cost required to complete a tunnel is intrinsically tied to accurately predicting the tunnel advance rate (Farrokh, 2020).

Due to the significant uncertainty in the rock mass, estimating the tunnel advance rate is one of the most complex and critical tasks frequently encountered in tunnel excavation (Yagiz and Karahan, 2011). On the other hand, assessing tunnel advance rates is central to planning schedules and determining project costs in rock formations (Armaghani et al., 2019). Therefore, accurate progress estimations can be instrumental in reducing both costs and risk management challenges in tunneling projects. Developing predictive models has been a primary task and has been progressing for many years (Tarkoy, 1975; Ozdemir, 1977; Bruland, 1999; Okubo et al., 2003). Thankfully, with the accumulation of well-documented data and advancements in prediction methods, more understandable and applicable estimation equations and models are being created.

A review of existing literature reveals that many models focus exclusively on tunneling with tunnel boring machines (TBM). Predicting TBM performance remains a pivotal research subject for tunnel engineers, as this problem has not yet been fully solved (Gokceoglu, 2022). Farrokh (2020) surveyed various models used in estimating advance rates for hard rock TBMs. Several prediction methods have been explored by researchers, including statistical multiple regression analysis (Alber, 2000; Gong and Zhao, 2009; Hassanpour et al., 2009; Hassanpour et al., 2010; Delisio et al., 2013; Salimi et al., 2016), artificial neural networks (Zhao et al., 2007; Yagiz et al., 2009; Armaghani et al., 2019; Koopialipoor et al., 2020; Nagrecha et al., 2020; Zhou et al., 2020), metaheuristic algorithms (Zhou et al., 2021), support vector machines (Mokhtari and Mooney, 2020), and neuro-fuzzy methods (Grima et al., 2000) to estimate TBM performance. However, these methods, derived from survey data from various tunnels and specific ranges of rock types, cannot be generalized for all ground conditions. Despite this, it is evident from the literature that drill-and-blast tunnel advance rates have been studied far less than those of mechanized tunnels, likely due to the challenges in assessing the interplay between input parameters, which renders the advance rate difficult to predict.

Due to the complexity of geological and geotechnical conditions along tunnel routes, predicting the advance rate is difficult. Robbins (1992) identified geologically related conditions and tunnel diameter as the most significant factors influencing the tunnel's advance rate. The literature states that rock properties are one of the most crucial parameters for tunneling performance estimation. Yagiz (2008) demonstrated that rock mass properties strongly affect TBM performance. Moreover, he pointed out that one of the most important parameters for predicting the TBM penetration rate is the engineering properties of the rock mass. Therefore, the primary issue for tunnels excavated in rock involves understanding the rock mass and engineering geological characteristics. Utilizing a rock mass classification system can be considerably beneficial in this scenario. Among the most commonly used classification systems, Rock Mass Rating (RMR) and Rock Mass Quality Index (Q) have been more frequently employed in tunneling performance prediction (Hamidi et al., 2010).

When designing a rock structure, it is essential to consider individual parameters such as intact rock, fractures, excavation, and their collective interaction. At this juncture, it is vital to identify the relevant physical variables and linking mechanisms and then consider their combined operation. We must also ensure that all pertinent factors and their interactions are accounted for. Due to the limitations of empirical and computational methods, a method that can consider all the relevant parameters simultaneously in the modeling to accurately predict the tunnel's advance rate is necessary. In such cases, Rock Engineering Systems (RES) can serve as one of the most potent innovative methods capable of simultaneously analyzing the relationships between effective parameters in the model (Hudson and Harrison, 2000). Considering how such interactions can be characterized when connecting rock mechanics principles to rock engineering applications is prudent.

Many researchers have applied the RES model to various engineering problems, especially in the field of rock mechanics (Mazzoccola and Hudson, 1996; Yang and Zhang, 1998; Latham and Lu, 1999; Zhang et al., 2004; Rozos et al., 2008; Shin et al., 2009; Younessi and Rasouli, 2010; Rozos et al., 2011; Faramarzi et al., 2013; Frough and Torabi, 2013; Huang et al., 2013; Naghadehi et al., 2013; Andriani and Parise, 2017; Hasanipanah et al., 2013; Rahmati et al., 2014; Mohammadi and Azad, 2021). Further information regarding the application of RES in other fields can be found in the existing literature. However, this research demonstrates that rock engineering systems consider the influence of all the various factors in rock engineering problems. Consequently, a RES description of the overall interactive mechanisms in tunneling operations appears to be a promising foundation for an approach to predicting tunnel advance. Therefore, further research might be essential, and the method could be updated for more confident usage.

This paper addresses the RES analysis of face advance in tunnels excavated by the drill-and-blast method. The study aims to develop a predictive model for tunnel face advance using data collected from the tailrace tunnel of the Azad dam in Iran. The database encompasses information on the properties of the rock, explosives, and tunnel. Consequently, a novel model was developed, combining multiple regression (MR) and rock engineering systems (RES). In the MR-RES model, efforts were made to reduce uncertainty in the assignment of codes through the statistical analysis of the data. Subsequently, the results obtained are compared with those derived from multiple linear regression models applied to the same data. Lastly, a sensitivity analysis was conducted to identify the parameters with the least and most impact on tunnel advance.

Within the MR-RES model, an innovative approach is employed to mitigate uncertainty in code assignments through rigorous statistical analysis of the dataset. The outcomes derived from this model are then juxtaposed with those obtained from multiple linear regression models applied to the same dataset. Additionally, the study concludes with a sensitivity analysis, shedding light on the parameters exerting the least and most significant influence on tunnel advance. In summary, the paper offers a distinctive contribution by combining MR and RES methodologies, enhancing the reliability of predictive models, and conducting a thorough sensitivity analysis to discern the varying impacts of parameters on tunnel face advance.

2. THEORY AND METHOD

2.1. Rock Engineering System (Res)

The Rock Engineering Systems (RES) methodology serves as a valuable analytical tool for characterizing influential factors and interaction mechanisms in rock engineering problems (Hudson, 1992). Interaction matrices enable a systematic approach to examining these interactions within the RES method. Such a matrix is a square matrix used to characterize the principal parameters and interaction mechanisms in RES.

In the provided interaction matrix for a rock engineering system, all parameters influencing the system are arranged along the leading diagonal, known as the diagonal terms. The impact of each parameter on others is recorded at the corresponding off-diagonal positions, referred to as the off-diagonal terms. Fig. 1 illustrates a 2×2 interaction matrix, where 'A' occupies the top left entry, and 'B' is located in the bottom right entry. The upper right and bottom left elements represent the effects of 'A' on 'B' and 'B' on 'A', respectively. Importantly, the influence of 'A' on 'B' may differ from that of 'B' on 'A', resulting in an asymmetric matrix. Therefore, organizing the parameter interactions in a clockwise manner in the matrix is essential for accurate representation.

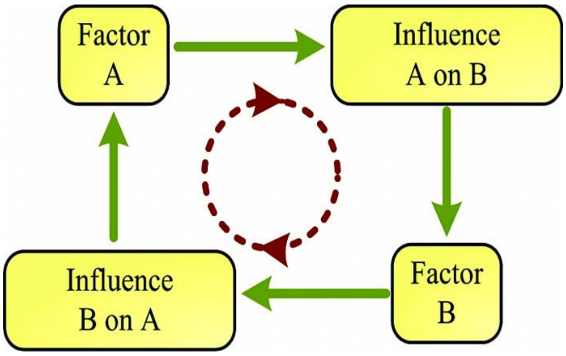

Fig. 1. A general view of the interaction matrix featuring factors 'A' and 'B' in a RES (Hudson, 1992).

The off-diagonal terms in the matrix are assigned numerical values, determining the extent to which one parameter influences others. This process is known as coding the matrix. Hudson proposed various methods for coding the interaction matrix to elucidate rock engineering systems, as depicted in Fig. 2 (Hudson, 2013). This figure illustrates five fundamental matrix coding methods in RES; namely binary, expert semi-quantitative, relation between P_j and P_i, partial differential equation, and explicit numerical analysis of the mechanism.

The Expert Semi-Quantitative (ESQ) method is often favored in most studies due to its simplicity. It involves assigning a unique code to each interaction, representing a parameter's influence on another within the matrix. Generally, codes range from 0 to 4, with 0 denoting no interaction and 4 signifying the maximum level of interaction. The main weakness of this coding method is the significant variability in the values assigned to the classes. Consequently, it fails to elucidate all the mechanisms of the parameters and their interrelationships. Additionally, the values in this coding method are not always constant; in most cases, it is impractical to designate an exact digit code for the precise particular interaction. This variability could arise from uncertainties in value assignments or even the underlying physics of the problem at hand. Therefore, it is imperative to employ coding methods that meticulously address uncertainties in code assignments are meticulously addressed.

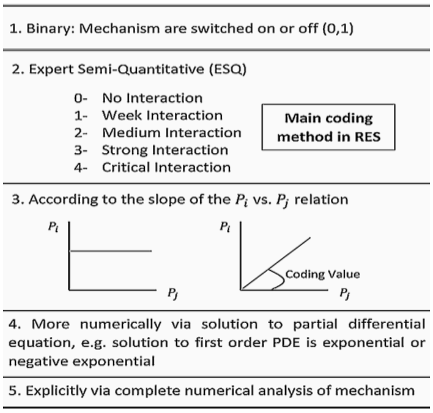

Fig. 2. Five basic matrix coding methods in RES (Hudson, 2013).

Fig. 3 illustrates the general concept of interaction matrix coding. In this matrix, the sum of each row is termed the cause (C) (Eq. 1), while the sum of each column is identified as the effect (E) (Eq. 2). In other words, each parameter's influence on the system and vice versa is denominated as C and E, respectively.

$$\mathrm{C}_{pi} = \sum_{j=1}^{n} I_{ij} \tag{1}$$

$$\mathrm{E}_{pj} = \sum_{i=1}^{n} I_{ij} \tag{2}$$

The coordinate values for each parameter can be plotted in a cause-and-effect space, creating a C–E plot. The interactive intensity of each parameter is represented by the sum of the C and E values (C+E), serving as a gauge for the parameter's significance within the system. The (C+E) value, expressed as a percentage, can be utilized as the parameter's weighting factor (αi), defined as (Jiao and Hudson, 1995):

$$\alpha_i = \frac{(\mathrm{C}_i + \mathrm{E}_i)}{(\sum_i \mathrm{C}_i + \sum_i \mathrm{E}_i)} \times 100 \tag{3}$$

Where C_i signifies the cause of the i^{th} parameter, E_i represents the effect of the i^{th} parameter.

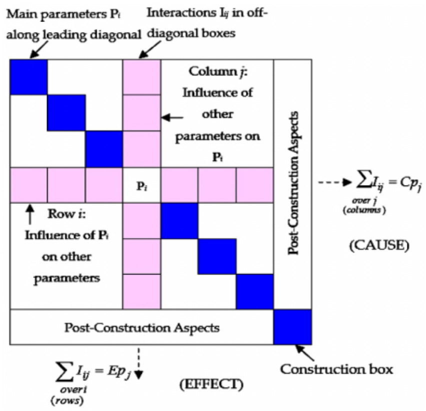

Fig. 3. General perspective on the coding of the interaction matrix in a RES (Hudson, 1992).

Each point's location on the cause-and-effect diagram indicates the interaction state of the corresponding parameter. A higher numerical value (C+E) for a given parameter suggests a more substantial interaction with the entire system. Conversely, depending on its sign, a larger differential value of (C−E) denotes a dominant influence of the parameter over the system. A negative (C−E) value highlights the system's dominance over the parameter. Fig. 4 displays the extended C−E diagram encompassing N-influencing parameters.

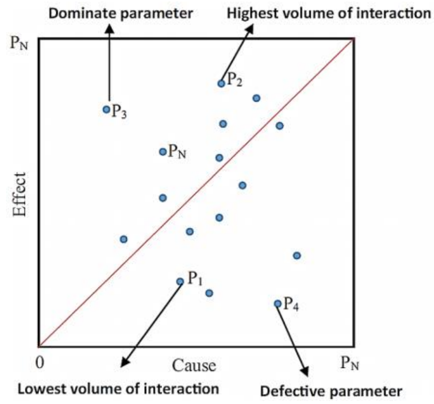

Fig. 4. The cause-effect diagram incorporating N influencing factors (Hudson, 1992).

2.2. Multiple regressions (MR)

The regression analysis is a set of statistical methods that can be utilized to identify the relationships between a response (dependent) variable and several explanatory (independent) variables. Multiple regression is a statistical technique used to analyze the relationship between a single dependent variable and several independent variables. It works by considering the values of the available multiple independent variables to predict the value of one dependent variable. Consequently, it increases reliability by avoiding dependence on just one variable and using more than one independent variable to support the event (Montgomery et al., 2021).

The multiple linear regression (MLR) statistical technique is a method to establish a linear relationship between a dependent variable and several independent variables. Multiple nonlinear regression is a statistical technique used to model the relationship between a dependent variable and two or more independent variables when the relationship is not linear. The standard term used in statistical modeling for the scenario where there are multiple independent variables and a nonlinear relationship is Multiple Nonlinear Regression (MNLR) or simply Nonlinear Regression. In Nonlinear Regression, the relationship between the dependent variable and the independent variables is modeled as a nonlinear function. This is in contrast to Multiple Linear Regression (MLR), where the relationship is modeled as a linear function. In Nonlinear Regression, the functional form of the relationship is not a straight line, allowing for more complex modeling of various relationships in the data. Multiple non-linear regression (MNLR) is used to model complex phenomena that linear models cannot handle. In this approach, both non-linear and linear relationships, such as exponential, logarithmic, and power relationships, can be employed. However, these methods have been used to establish mathematical formulas to solve many engineering applications (Moore et al., 1993; Gessler et al., 2000).

3. CASE STUDY AND DATA SOURCE

The case study of this paper centers on the Azad pumped storage power plant project, from which excavation data were collected to create a robust database for tunnel face advance analysis. This project is situated in the western region of Iran, 40 km west of Kurdistan province, Northwest Iran (Fig. 5).

From the geological standpoint, this region lies within the Sanandaj-Sirjan metamorphic zone, one of the geological divisions of Iran. The bedrock is composed of low-grade metamorphic sandstone, schist, and phyllite. Furthermore, limestone outcrops can be found in highland regions of the study area. Stratigraphically speaking, the region is covered by units dating from the Upper Cretaceous to the Quaternary periods.

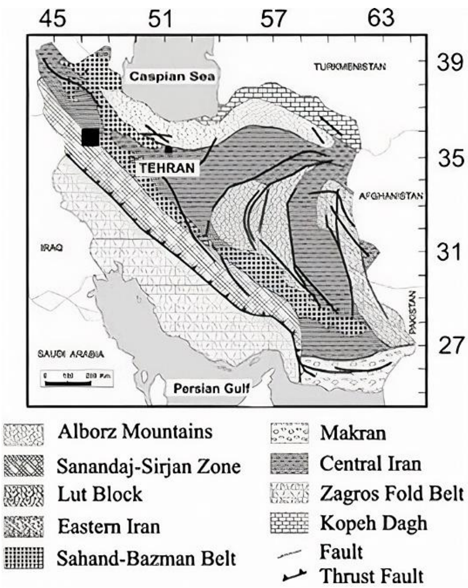

Fig. 5. Location map of the Azad pumped storage power plant project.

This project is designed to store hydraulic potential using a pumping system under low-load conditions of the power supply network and then generate electricity using a turbine and generator during the peak load conditions of the network. It encompasses a set of underground excavations, including the upstream reservoir, pressure shaft, penstock, access, and tailrace tunnels, powerhouse and transformer caverns, and the lower dam reservoir (Fig. 6). The tailrace tunnel, also known as Payab, facilitates the transfer of water from the Azad dam. This tunnel was constructed using the drilling and blasting method, spanning 660 meters with a 40 square meter cross-sectional area. The drilling process necessitated blast holes with diameters of 51 mm and a depth of 3.5 meters. Dynamite served as the primary explosive material, utilized in both the drilling and initiation phases.

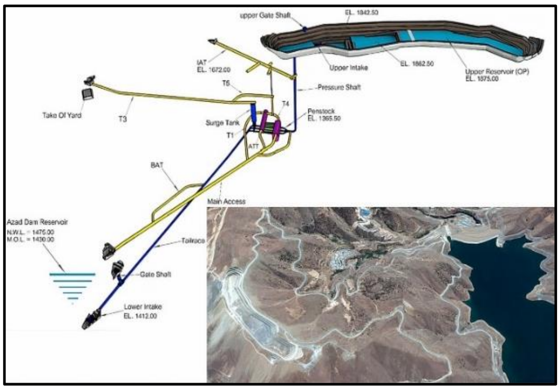

Fig. 6. Layout of the Azad pumped storage power plant project.

For this study, extensive fieldwork was conducted in the tailrace tunnel of the Azad pumped storage power plant project to gather sufficient data. The research employed the Rock Mass Rating (RMR) system to guide predictions of tunnel face advancement based on a comprehensive dataset compiled from 86 unique tunneling records. Data was collected with the contractor's professional team after each run of blasting to find the main effective parameters and use them in other blasting patterns. Numerous factors can influence the face advancement of a tunnel excavated by drilling and blasting operations. Pertinent data highlighted rock properties such as the RMR and tunneling quality index (Q), in addition to operational conditions such as the blasting specific charge (q) and tunnel face area (A), as pivotal in forming a robust dataset for predictions. Both RMR and Q are integral in clearly delineating the properties of the rock mass. Meanwhile, parameter A represents the transverse cross-section of the tunnel. Table 1 details the extremities of these four parameters alongside the observed tunnel face advancements (P_t).

Table 1. The parameters used for predicting tunnel face advance

Parameter	Unit	Min	Max
Rock mass rating (RMR)	-	32	57
Tunnelling Quality Index (Q)	-	0.72	3.5
blasting specific charge (q)	kg/m³	0.505	4.007
Tunnel face area (A)	m²	36.7	54.53
Tunneling penetration (P_t)	m	1	4.65

The significance of parameters in the modeling was investigated based on correlations between the independent variables and the actual measurements of tunnel face advance, with the latter serving as a dependent variable. The coefficient of determination (R^2) and the root mean square error (RMSE) were used as indicators of correlation strength for each model (see Table 2). In Table 2, a second-order polynomial equation was selected to correlate main parameters with actual measurements. These four independent variables were chosen for further statistical analysis and model development at each stage.

Table 2. The statistical relationship between the four independent variables with tunnel face advance.

Independent variables	Regression equation	R^2	RMSE
RMR	$P_t = -0.0054RMR^2 + 0.5741RMR - 11.709$	0.6047	0.4639
Q	$P_t = 0.1598Q^2 - 1.3139Q + 4.4917$	0.3341	0.6021
q	$P_t = -0.1853q2 + 0.0064q + 3.7636$	0.4129	0.5654
A	$P_t = 0.0095A^2 - 0.859A + 22.127$	0.0854	0.7057

4. TUNNEL FACE ADVANCED PREDICTION

Based on the database collected from 86 tunneling datasets, multiple linear regression (MLR) and RES were utilized to estimate the tunnel face advance.

4.1. MLR Analysis

MLR is one of the most established methods for fitting a linear equation between one or more independent parameters about a single dependent parameter. This method has been extensively developed to address problems in rock and tunnel engineering domains.

Typically, the MLR model can be expressed as follows:

$$Y = P_0 + P_1X_1 + \ldots + P_nX_n \qquad (4)$$

Where X_i (i=1,…,n) and Y define independent and dependent parameters, respectively. In addition, Pi (i=0,1,…,n) represents regression coefficients. Taking the established datasets into account, Eq. (5) was derived to the tunnel face advance (P_t) using SPSS V16 software:

$$Pt=2.84+ 0.051RMR - 0.39Q - 0.48q - 0.02A \qquad (5)$$

Where P_t represent penetration per each blasting run, RMR represent rock mass rating, Q represent tunneling quality index, q represent blasting specific charge kg/m³, and A represent tunneling area (m²).

The calculated value of the Durbin-Watson test is 1.38, which is an acceptable range of results.

In this equation, it initially appears that the parameter 'q' has a direct relation with 'P_t' but it's essential to note that the unit of this parameter is kg/m³. Even a small amount of penetration can result in a high 'q' It's important to recognize that 'q' is related to the volume of excavation rock and the total charge of holes.

According to Fig. 7, a relation between tunnel face advance's predicted and measured values can be plotted and developed.

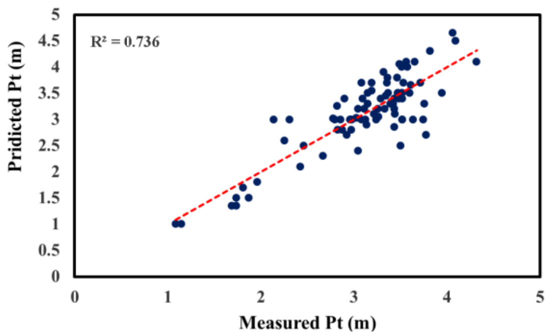

Fig. 7. A correlation between the predicted and measured values of tunnel face advance (P_t).

In the following Multiple Linear Regression (MLR) analysis was conducted to investigate the effect of each parameter on tunnel face advance (P_t). As stated earlier, this research utilizes RMR, Q, q, and A as independent variables. Fig. 8 displays the results of the sensitivity analysis for these variable parameters in tunnel face advance. As indicated in the figure, RMR is the most effective factor in the tunnel face advance prediction at the studied site. In this figure, with the percentage increase of the parameters, the value of the dependent variable also increases with different percentages. This figure shows the amount of penetration rate (P_t) changes based on the changes of the main parameters RMR, Q, q, and A. It was shown that RMR, Q, q and A have effect, respectively.

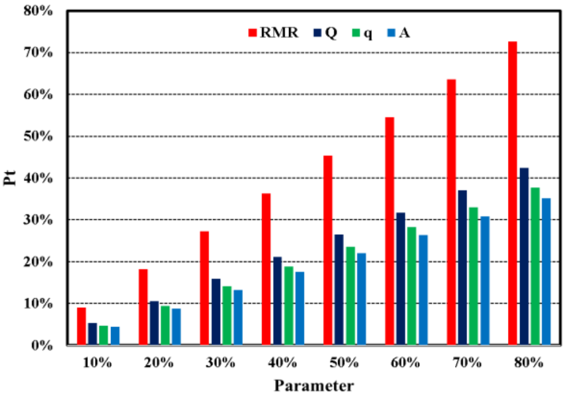

Fig. 8. Effect of independent variable parameters variation on tunnel face advance.

4.2. RES Analysis

As previously mentioned, quantifying the interaction matrix is a pivotal component of the RES method. The initial step involves establishing an interaction matrix that delineates the effective parameters impacting tunnel face advance. Following the construction of this matrix, it becomes necessary to 'code' the off-diagonal components, a process that highlights their significance and facilitates the matrix's mathematical utilization.

To overcome the limitations of traditional coding methods, our approach involves a novel coding method implemented within the RES systems framework. The main weakness of the traditional coding methods lies in the uncertainties surrounding the assignments of values in each interaction. To address this, we propose a novel coding method for the interaction matrix to be implemented within the RES systems framework. In this method, the value of interaction between each pair of parameters is derived from a statistical analysis involving independent and dependent variables. Consequently, the strength of the relationship between each primary parameter is indicated by the coefficient of determination, R^2. Therefore, the main parameters are found on the main diagonal of the interaction matrix, while a coefficient of determination represents the relationships between parameters found off-diagonal. Following the provided explanations, we coded the interaction matrix using four main parameters analyzed through regression analysis. The correlation results between the variable parameters, based on polynomial regression analysis, can be viewed in Table 3.

Table 3. The correlation between main parameters in the polynomial regression analysis.

Parameters		Regression equation	R^2
Dependent	Independent		
RMR	Q	$RMR = -3.8022Q^2 + 9.3998Q + 41.856$	0.2239
RMR	q	$RMR = -1.0457q^2 + 0.4724q + 49.34$	0.1597
RMR	A	$RMR = 0.1004A^2 - 8.9657A + 242.71$	0.1225
RMR	P_t	$RMR = -0.6734P_t^2 + 9.5418P_t + 23.622$	0.5097
Q	RMR	$Q = 0.0072RMR^2 - 0.6859RMR + 17.386$	0.4645
Q	q	$Q = 0.0377q^2 + 0.0252q + 1.1048$	0.03926
Q	A	$Q = -0.0101A^2 + 0.9445A - 20.131$	0.2436
Q	P_t	$Q = 0.1543P_t^2 - 1.2964P_t + 3.7443$	0.3757
A	RMR	$A = 0.0215RMR^2 - 2.0117RMR + 85.095$	0.1706
A	Q	$A = 1.0222Q^2 - 2.0516Q + 39.508$	0.1627
A	q	$A = 0.289q^2 - 1.8972q + 41.228$	0.04195
A	P_t	$A = 0.9854P_t^2 - 6.0401P_t + 47.611$	0.1333
q	RMR	$q = 0.0018RMR^2 - 0.2034RMR + 7.2434$	0.1611
q	Q	$q = -0.3657Q^2 + 1.5191Q + 0.5458$	0.09682
q	A	$q = 0.0075A^2 - 0.6897A + 17.172$	0.08591
q	P_t	$q = 0.0331P_t^2 - 0.7064P_t + 3.6427$	0.3832
P_t	RMR	$P_t = -0.0054RMR^2 + 0.5741RMR - 11.709$	0.6047
P_t	Q	$P_t = 0.1598Q^2 - 1.3139Q + 4.4917$	0.3341
P_t	q	$P_t = -0.1853q^2 + 0.0064q + 3.7636$	0.4129
P_t	A	$P_t = 0.0095A^2 - 0.859A + 22.127$	0.0854

According to the obtained R^2 values, the interaction between the parameters has been established and is displayed in Table 3. In this interaction matrix, the main and effective parameters (RMR, Q, q, A) influencing the tunnel face advance (P_t) are situated on the main diagonal. The values representing the intensity of the influence one parameter has on another are placed in off-diagonal positions. To quantify the off-diagonal elements, the R^2 coding method has been utilized (see Table 3).

Table 4. The interaction matrix of RES.

RMR	0.4645	0.1611	0.1706	0.6047	1.4009
0.2239	Q	0.09682	0.1627	0.3341	0.81752
0.1597	0.03926	q	0.04195	0.4129	0.65381
0.1225	0.2436	0.08591	A	0.0854	0.53741
0.5097	0.3757	0.3832	0.1333	P_t	1.4009
1.0158	1.12306	0.72703	0.50855	1.0158	

The cause (C) and effect (E) values, depicting the interactive intensity and dominance of each parameter illustrated by the sum (C+E) and subtraction (C-E) of the C and E values, and the weighting factor (αi), are presented in Table 5.

Table 5. The weighting of the effective parameters in the tunnel face advance

NO.	Parameter	C	E	C+E	C-E	α_i (%)
1	RMR	1.4009	1.0158	2.4167	0.3851	35.62
2	Q	0.81752	1.12306	1.94058	-0.30554	28.60
3	q	0.65381	0.72703	1.38084	-0.07322	20.35
4	A	0.53741	0.50855	1.04596	0.02886	15.42
Sum		3.40964	3.37444	6.78408	0.0352	100

Fig. 9 depicts the Cause-Effect diagram delineating the effective parameters influencing tunnel face advance. In the diagram, points situated above and below the C-E line are designated as subordinate and dominant, respectively. Here, the parameters RMR, Q, q, and A are denoted with numbers 1 through 4, as referenced in Table 5. The diagram reveals that RMR and A function as subordinate parameters, whereas Q and q assume roles as dominant parameters.

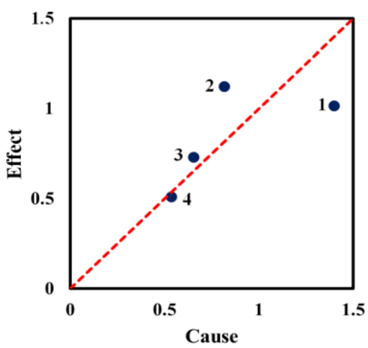

Fig. 9. Cause-effect diagram for the effective parameters of the tunnel face advance.

Furthermore, the values of dominance (C - E) and interactive intensity (C + E) for each parameter are shown in Fig. 10. Based on Table 5 and Fig. 9, RMR, Q, q, and A have the highest weights in the RES system, respectively.

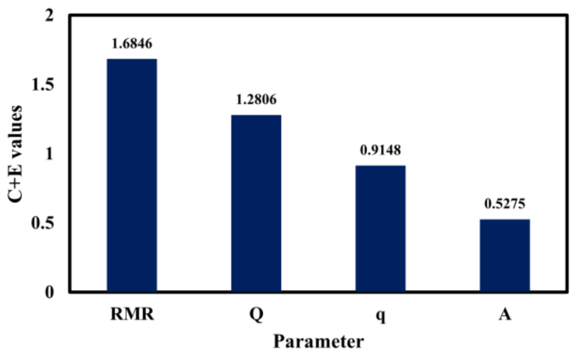

Fig. 10. C+E value versus main parameters.

Beyond employing the polynomial regression method, this study also incorporated linear and power methods to compute and juxtapose the results. The influences of the various parameters on progress through these three approaches are delineated in Table 6. Consistently, all methods emphasize the substantial effects of the parameters RMR, Q, q, and A, listed in descending order of impact. In this study, the polynomial trend line served as the preferred tool for coding the interaction matrix, grounded in its realistic portrayal of non-symmetrical matrices and its meticulous evaluation of the relationships between parameters. Overall, each method demonstrated consistent trends and effectiveness, endorsing their logical relevance in this context.

Table 6. Parameters effects on the tunnel face advance in three methods.

Parameter	Polynomial	Liner	Power
	α_i (%)		
RMR	35.62	35.97	38.21
Q	28.61	28.32	29.06
q	20.35	26.01	20.76
A	15.42	9.70	11.97
Sum	100.00	100.00	100.00

5. CONCLUSIONS

In this paper, an improvement to the rock engineering system (RES) coding method is presented through the use of a novel coding technique. A key innovation in this paper involves coding the main diagonal matrix through statistical analysis without relying on human judgment. The primary effective parameters influencing tunneling progress were investigated using two main methods, MLR and RES, demonstrating concordant results. For the first time, a new hybrid method for coding the interaction matrix was utilized. This approach entailed coding the interaction matrix based on the R-square value, subsequently validated through analytical strategies. The R-square interaction matrix was devised employing three regression methods—polynomial, linear, and power—and the outcomes were compared, confirming the consistent significance and relevance of the parameters. This new method offers considerable benefits. Firstly, it eliminates the necessity for expert parameter values in the interaction matrix formulation, and secondly, in the polynomial regression method, a non-symmetric and more realistic interaction matrix is created compared to conventional approaches. The hybrid method was applied in a case study involving the Azad tailrace tunnel, emphasizing the paramount significance of the RMR parameter, followed by proportional reductions in Q (system), q (specific charge), and A (area).

Considering the non-unique nature of interaction matrix codes, probabilistic coding can be performed non-deterministically, thereby addressing the uncertainties inherent in RES analysis. This technique consequently identifies parameters with the highest likelihood of being dominant or subordinate and those most likely to be interactive. Thus, this proposed strategy stands as a simple yet potent tool for assessing the parameters influencing the cavability of rock masses in block-caving mines, aiding in decision-making amidst uncertainties. Similar strategies employing different parameters can be devised for tunneling projects in other geological settings.

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