Journal of Petroleum
Science and Technology

An Estimation of Required Rotational Torque to Operate Horizontal Directional Drilling Using Rock Engineering Systems

Hadi Fattahi

Department of Mining Engineering, Arak University of Technology, Arak, Iran

ABSTRACT

Horizontal directional drilling (HDD) is widely used in soil and rock engineering. In a variety of conditions, it is necessary to estimate the torque required for performing the reaming operation. Nevertheless, there is not presently a convenient method to accomplish this task. In this paper, to overcome this difficulty based on the basic concepts of rock engineering systems (RES), a model for the estimation of rotational torque to operate horizontal directional drilling is presented. The newly proposed model involves seven parameters (axial force on the cutter/bit (P), rotational speed (revolutions per minute) of the bit (N), the length of drill string in the borehole (L), the total angular change of the borehole (K_L), the radius for the i^{th} reaming operation (D_i), the mud flow rate (W), and the mud viscosity (V)) effective on required rotational torque to operate horizontal directional drilling while keeping simplicity as well. The performance of the RES model is compared with multiple regression models. The estimation abilities offered using RES and multiple regression models were presented by using field data given from nine projects. The results indicate that the RES-based model predictor with a higher coefficient of determination (R_2), a smaller mean square error (MSE), a lower root mean square error (RMSE), and a lower mean absolute percentage error (MAPE) performs better than the other models.

Keywords: Rock Engineering Systems, Rotational Torque, Horizontal Directional Drilling, Multiple Regression Models

INTRODUCTION

The horizontal directional drilling (HDD) has been extensively used throughout the world to construct underground pipeline systems [1]. Most pipelines, including those employing HDD, are installed in soil formations for which engineers have accumulated a great amount of experience [2,3]. Reasonable mechanical models and corresponding equations have therefore been developed for calculating various construction-related parameters. However, there is a lack of such a methodology in more difficult situations. A major concern of many HDD projects is what the amount of rotational torque should be used. However, relatively little quick research has been conducted in this area. In the field, Lan et al. [2] utilized a regression model for

***Corresponding author**
Hadi Fattahi
Email: h.fattahi@arakut.ac.ir
Tel: +98 86 33400793
Fax: +98 86 33400793

Article history
Received: August 20, 2016
Received in revised form: May 17, 2017
Accepted: June 25, 2017
Available online: January 07, 2018

predicting rotational torque.

Also, some research works were carried out using artificial intelligence methods in the areas of drilling engineering. For example, Adel and Zayed [4] used adaptive neuro-fuzzy inference system (ANFIS) model to design the HDD productivity prediction model for underground pipe installations in clay soil. Akin and Karpuz [5] used artificial neural networks (ANN) for estimating drilling parameters for diamond bit drilling operations. Monfared et al. [6] presented an ANFIS model for the advanced prediction of bottom hole circulating pressure in underbalanced drilling operations.

The empirical and artificial intelligence methods, which are based upon the data surveying from different drilling operations in a certain range of rock types, cannot be generalized for various ground conditions. Furthermore, all of the above models do not simultaneously consider all the pertinent parameters in the modeling. Under such limitations or constraints, the prediction of rotational torque to operate horizontal directional drilling needs new innovative methods such as the RES-based model, capable of accounting unlimited parameters in the model. The rock engineering systems (RES) concept has been applied to a number of rock engineering fields such as hazard and risk assessment of rockfall [7], the evaluation and classification of the coal spontaneous combustion potential [8], the prediction of backbreak in bench blasting [9], rock mass characterization for indicating natural slope instability [10], the prediction of the advance rate in rock TBM tunneling [11], quantitative hazard assessment for tunnel collapses [12], the assessment of geotechnical hazards for tunnel boring machine (TBM) tunneling [13], the prediction of flyrock distance in surface blasting [14], the prediction of deformation modulus of rock mass [15], the prediction of TBM penetration rate [16], the prediction of rock fragmentation by blasting [17], and the prediction of out-of-seam dilution in longwall mining [18]. It has also been widely applied to different engineering problems such as environmental studies on the disposal of spent fuel [19], forest ecosystems [20,21], radioactive waste management [22,23], traffic induced air pollution [24], risk of reservoir pollution [25], and the prediction of the safety factor for circular failure slope [26].

In this paper, the RES-based model, capable of accounting for many parameters in the model, was used to carry out the prediction of rotational torque to operate HDD. To validate the performance of the model proposed, it was first applied to field data given in open source literatures. Furthermore, the results obtained are compared with those of the multiple regression models using the same data.

EXPERIMENTAL PROCEDURES

Database Information

The required rotational torque at the drill rig depends on various factors, including geological conditions, drilling methods, reamer cutter/bit sizes and types, rotary speed, axial force on bit, drilling mud properties, borehole diameter, length of drill string in the borehole, and borehole trajectory [2, 27, 28].

To establish RES-based method for the prediction of rotational torque to operate horizontal directional drilling, providing a dataset which includes a wide geographic distribution is the most important requirement. To achieve this, datasets given in the previous paper is borrowed [2]. The dataset (including 84 datasets) has been collected from nine projects (project A, project B, project C, project D, project E, project F, project G, project H, and project I), using HDD for the China west–east natural gas transmission pipeline. Information regarding the mechanical parameters of rock strata (mainly sandstone, mudstone, and gravels) has also been collected from these projects. However, due to different measurements made in each project, and practical difficulties in attempting to collect the wide range of information, some data are limited. A detailed description of the database can be found below [2].

Each data set contains the parameters of the axial force on the cutter/bit (*P*), rotational speed (revolutions per minute) of the bit (*N*), the length of drill string in the borehole (*L*), the total angular change of the borehole (K_L), the radius for the i^{th} reaming operation (D_i), the mud flow rate (*W*), the mud viscosity (*V*), and the rotational torque (*M*).

Statistical Modeling

In reviewing the literature, addressing the parameters affecting the rotational torque to operate horizontal directional drilling, it is clear that many parameters can influence the rotational torque to operate horizontal directional drilling. However, the most important parameters, which are easily obtainable, are shown in Table 1.

At the first stage of the analysis, the significance of the parameters in the modeling was investigated based upon correlations between the individual independent variables and the actual measured the rotational torque to operate horizontal directional drilling. The coefficient of determination (R^2) was used as an indicator of correlation strength. R^2 values for independent variables versus the rotational torque to operate horizontal directional drilling are presented in Table 2. It can be concluded that W and V have negligible effects on the rotational torque to operate horizontal directional drilling and should be excluded in the regression modeling. Therefore, for a further statistical analysis and the development of a prediction model, five independent variables were selected.

Table 1: The statistical description of the dataset utilized for the construction of the models.

Parameter	Symbol	Min.	Max.	Average	Standard Deviation
Axial force on the cutter/bit	*P*	2	30.50	13.84	5.71
Rotational speed of the bit (r/min)	*N*	15	50	31.58	12.38
Length of drill string in the borehole (m)	*L*	116.68	586.06	322.56	129.03
Total angular change of the borehole	K_L	1.09	3.54	2.42	0.5366
Radius for the i^{th} reaming operation (mm)	D_i	457.2	1117.6	760.79	185.33
Mud flow rate (L/min)	*W*	500	4000	2233.09	1033.04
Marshal Funnel Mud viscosity (s)	*V*	42	88	63.51	14.13
Rotational torque (kN.m)	*M*	4	40	21.02	8.0132

Table 2: Relations between individual independent variables and rotational torque.

Independent variables	Regression line	R^2	N
P	M = 0.6023 P + 12.682	0.1842	84
N	M = 0.1953 N + 14.85	0.1000	84
L	M = 0.0397 L + 8.2141	0.4085	84
K_L	M = 7.1124 K_L + 3.8158	0.2269	84
D_i	M = 0.0185 D_i + 6.9716	0.1823	84
W	M = 0.0014 W +17.915	0.0321	84
V	M = 0.0676 V + 16.724	0.0142	84

Multiple Linear Regression Analysis

In this paper, a multiple linear regression (MLR) analysis was carried out among P, N, L, K_L, and D_i as the independent variables and rotational torque to operate horizontal directional drilling as the dependent variable using the commercial software package for standard statistical analysis (SPSS). Based on the statistical analysis, the predictive model is as follows:

$$M = -4.810 + 0.435P - 0.019N + 0.033L - 1.591K_L + 0.017D_i \quad (1)$$

A multicollinearity analysis was carried out to check whether two or more independent variables are highly correlated. In the case of occurring multicollinearity, the redundancy of the independent variables could be expected, which can lead to erroneous results. One of the most common tools for finding the degree of multicollinearity is the variance inflation factor (VIF). It varies from 1 to infinity. Generally, if the calculated VIF is greater than 10, there may be a problem with multicollinearity [29]. The VIF values of the independent variables in Equation 2 were calculated and are shown in Table 3.

Table 3: Multiple linear regression coefficients and collinearity statistics for Equation 2.

Independent variables	Unstandardized coefficients		Standardized coefficients	95.0% Confidence interval for B		Collinearity statistics		t values	Determination coefficient (R^2)	Standard error of an estimate
	B	Standard error	Beta	Lower bound	Upper bound	Tolerance	VIF			
(Constant)	-4.810	4.841	-	-14.519	4.899	-	-	-0.994	0.575	6.019
P	0.435	0.151	0.307	0.133	0.738	0.710	1.408	2.888		
N	-0.019	0.070	-0.027	-0.160	0.122	0.784	1.276	-0.269		
L	0.033	0.010	0.518	0.013	0.053	0.337	2.966	3.358		
K_L	-1.591	2.383	-0.103	-6.370	3.188	0.338	2.955	-0.668		
D_i	0.017	0.004	0.379	0.008	0.026	0.854	1.171	3.910		

Also, the regression statistics and the analysis of variance (ANOVA) of Equation 1 are shown in Table 4. The model statistic value *F* and significance (Sig.) are used to provide enough evidence to reject the hypothesis of "no effect." From Table 4, an *F* value of 14.336 and a Sig. value of 0.000 (less than 0.05) were obtained, which shows that the null hypothesis can be rejected.

Table 4: Analysis of variance (ANOVA) for Equation 2.

	Sum of Squares	*df*	Mean Square	*F*	Sig.
Regression	2596.970	5	519.394	14.336	0.000
Residual	1920.174	53	36.230	-	-
Total	4517.144	58	-	-	-

Multiple Nonlinear Regression Analysis

In this paper, power, logarithmic, and exponential models using the same independent variables, employing the rotational torque to operate horizontal directional drilling as the dependent variable, and using the same sets of data were used to carry out the nonlinear regression modeling. The mathematical equation obtained for the power model is given by:

$$M = 0.001515(P)^{0.2697}(N)^{0.06084}(L)^{0.51676}(K_L)^{-0.36927}(D_i)^{0.55256} \quad (2)$$

For logarithmic regression modeling, the relation is defined by:

$$\begin{aligned} M &= -139.954 + 5.532\ln(P) + 1.443\ln(N) + \\ &\quad 12.349\ln(L) - 8.707\ln(K_L) + 11.960\ln(D_i) \end{aligned} \quad (3)$$

Finally, the exponential relation for the regression modeling reads:

$$\begin{aligned} M &= \exp(1.7928 + 0.01542P - 0.000084N + \\ &\quad 0.001122L + 0.008123K_L + 0.000799D_i) \end{aligned} \quad (4)$$

A comparison between the values of the rotational torque predicted by the multiple regression models and the measured values for 59 datasets in the training phases is shown in Figure 1.

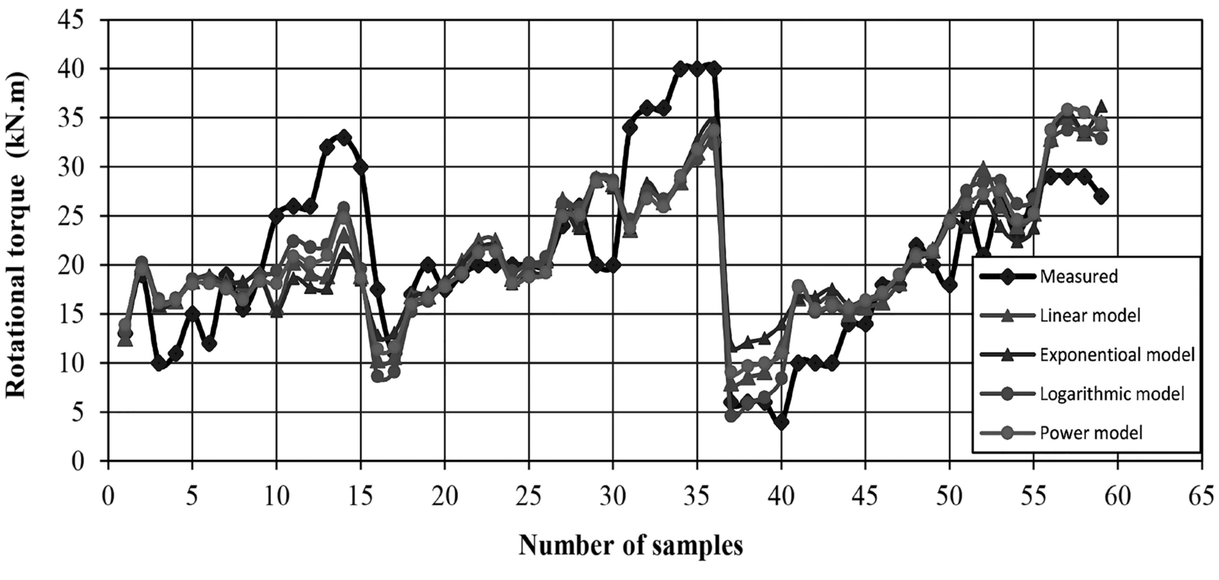


Figure 1: Comparison between the measured and predicted rotational torque for the training data.

Rock Engineering Systems

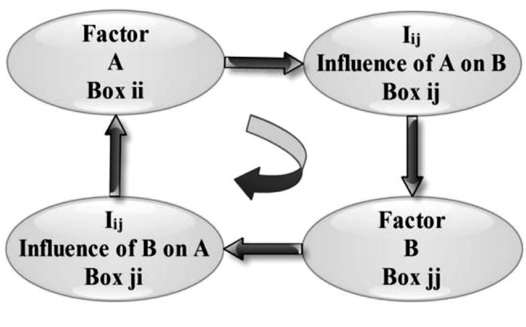
One of the powerful approaches towards solving difficult engineering problems is RES. The concept of RES was introduced by Hudson [30]. The RES is a method of structuring all the ways in which the parameters and variables of rock mechanics can affect one another-the rock mechanics interactions. The key element in RES is the interaction matrix. The interaction matrix is both a basic analytical and a presentational technique for characterizing the important parameters and the interaction mechanisms in a rock engineering system. The generation of the interaction matrix can help with the weight of parameters within the rock mass system as a whole.

In the interaction matrix, the principal parameters affecting the system are located along the leading diagonal of the matrix, and the effects of each individual parameter on any other parameter (interactions) are placed on the off-diagonal cells. The assignment of values to the off-diagonal cells is called coding the matrix. A problem having only two parameters is the simplest interaction matrix, as revealed in Figure 2a. Also, a general view of the coding of the interaction matrix is shown in Figure 2b.

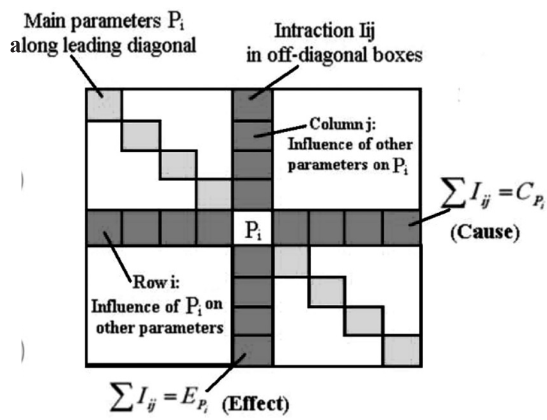
The row passing through P_i represents the influence of P_i on all other parameters in the system, while the column through P_i shows the effects of other parameters, or the remainder of the system, on P_i. In principle, there is no limit to the number of parameters that may be included in an interaction matrix. Different procedures such as the 0-1 binary, expert semi-quantitative (ESQ) [30], and the continuous quantitative coding (CQC) [31] were proposed for numerically coding the interaction matrix. Among the coding procedures, the ESQ coding is the most commonly used. According to this coding technique, the interaction intensity is denoted by values from 0 (no interaction) to 4 (critical interaction) as shown in Table 5.

Table 5: Expert semi-quantitative (ESQ) method for interaction matrix coding [30].

Code number	Concept
0	No interaction
1	Weak interaction
2	Medium interaction
3	Strong interaction
4	Critical interaction



(a)



(b)

Figure 2: Interaction matrix in a rock engineering systems (RES) approach; a) two-parameter interaction matrix and b) a general view of the coding of the interaction matrix (modified after [30]).

In the interaction matrix, the sum of a row is called the "Cause" value and the sum of a column is called the "Effect" value, denoted as coordinates (C, E) for a particular parameter. The coordinate values for each parameter can be plotted in cause and effect space, forming the so-called C–E plot. The interactive intensity value of each parameter is denoted as the sum of the C and E values (C+E), and it can be used as an indicator of parameters' significance in the system. That is, the weight of parameter *i*, indicated by a_i, is given by its "parameter interaction intensity" ($C_i + E_i$) divided by the (total) sum of interaction intensities of all the parameters in the system [30].

$$a_i = \frac{(C_i + E_i)}{(\sum_{i=1}^{n} C_i + \sum_{i=1}^{n} E_i)} \times 100 \tag{5}$$

An RES-based Model for Risk Assessment and Prediction of Rotational Torque

The principles of RES were used in the vulnerability index (VI) methodology concept, first introduced by Benardos and Kaliampakos [13] to identify the vulnerable areas that may pose threat to the TBM tunneling operation. As there is an obvious relation between advance rate and the associated risk encountered, this concept was also used to predict advance rate in the TBM tunneling.

In this research, a similar methodology, inspired by the works carried out by Faramarzi et al. [9], Benardos and Kaliampakos [13], and Faramarzi et al. [17] is adopted to define a model, predicting rotational torque to operate horizontal directional drilling. In defining the model, three main steps must be taken into account. The first step is to identify the parameters that are responsible for the occurrence of risk, to analyze their behavior, and to evaluate the significance (weight) of each parameter in the overall risk conditions. In this step, the RES principles can be used to assess the weight of the parameters involved.

In the second step, the vulnerability index (VI) can be determined:

$$VI = 100 - \sum_{i=1} a_i \frac{Q_i}{Q_{max}} \tag{6}$$

where a_i is the weighting of the ith parameter, Q_i is the value (rating) of the i^{th} parameter, and Q_{max} is the maximum value assigned for i^{th} parameter (normalization factor) [13].

Based upon the VI estimated and the classification of the VI, which is divided into three main categories with different severity of the normalized scale of 0-100 (Table 6) [13]. In category I, small scale problems are expected, that cannot significantly affect the results. In category II, which must be taken into account. In category III, which might cause several difficulties during the loading and unloading must be considered.

Table 6: Classification of the VI (Benardos and Kaliampakos [13]).

Risk description	Low-medium	Medium-high	High-very high
Category	I	II	III
VI	0-33	33-66	66-100

In the third step, a relation between rotational torque to operate horizontal directional drilling and VI can be determined. Based upon this new relation, the rotational torque for every in situ test can be obtained by having VI. The most important parameters used to define the RES-based model are presented in Table 7.

Table 7: The most important parameters used to define the RES based model.

	Parameter	Symbol
P_1	Axial force on the cutter/bit (kN×10)	P
P_2	Rotational speed of the bit (r/min)	N
P_3	Length of drill string in the borehole (m)	L
P_4	Total angular change of the borehole	K_L
P_5	Radius for the ith reaming operation (mm)	D_i
P_6	Mud flow rate (L/min)	W
P_7	Mud viscosity (s)	V

Interaction Matrix and Rating of Parameters

Interaction Matrix

The seven principal parameters affecting the rotational torque are located along the leading diagonal of the matrix and the effects of each individual parameter on any other parameters (interactions) are placed on the off-diagonal cells. Assigning values to off-diagonal cells and coding the matrix were carried out using the ESQ coding method and were based on the judgments of experts as proposed by Hudson [30].

It should be noted that, at this point, the selection process of experts involves the identification of the expertise relevant to the elicitation process and the selection of the subset of the experts who best fulfill the requirements for expertise within the existing time and resource constraints. In some cases, the selection of appropriate experts is straightforward, but in other cases, an appropriate expert group will need to be defined by the researcher according to the experts' availability and the requirements of the elicitation. Experts should be selected using explicit criteria to ensure transparency and to establish that the results represent the full range of views in the expert community. Common metrics for identifying experts include qualifications, employment, memberships in professional bodies, publication records, experience, peer nomination, and perceived standing in the expert community. In this study, based upon the views of three experts, working in the field of rock engineering for many years, the interaction matrix for the parameters affecting the rotational torque is established as presented in Table 8.

Table 8: Interaction matrix for the parameters affecting rotational torque to operate horizontal directional drilling.

P_1	1	0	0	0	3	1
1	P_2	0	0	0	2	0
3	0	P_3	1	1	0	1
3	0	2	P_4	1	2	1
3	1	0	0	P_5	3	0
1	0	0	0	0	P_6	1
1	1	0	0	0	1	P_7

Table 9 tabulates cause (C), effect (E), interactive intensity (C+E), dominance (C–E), and the weight of each parameter (a_i). As it can be seen in Table 9, burden has the highest weight in the system and highly controls other elements. The E–C histogram for each parameter is illustrated in Figure 3. The points below the C=E line are called dominant, and the points above the C=E line are called subordinate.

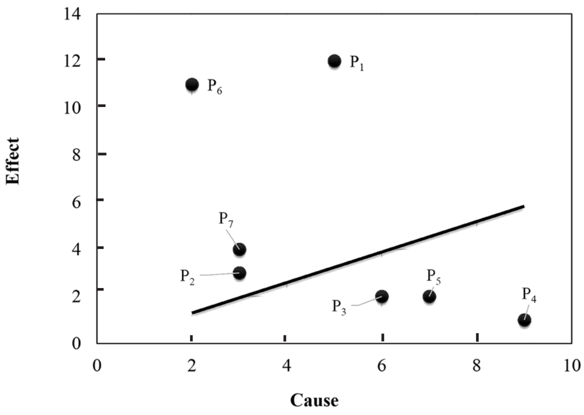


Figure 3: C-E plot for principal parameters of rotational torque to operate horizontal directional drilling.

Table 9: Weight of the principal parameters of rotational torque to operate horizontal directional drilling.

Main factor	C	E	C-E	C+E	a_i (%)
P	5	12	-7	17	24.28
N	3	3	0	6	8.57
L	6	2	4	8	11.43
K_L	9	1	8	10	14.29
D_i	7	2	5	9	12.86
W	2	11	-9	13	18.57
V	3	4	-1	7	10
Total	**35**	**35**	**0**	**70**	**100**

Rating of Parameters

The rating of the parameter values was carried out based upon their effect on the rotational torque to operate horizontal directional drilling. Totally five classes of rating from 0 to 4 were considered, where 0 denotes the worst case (the most unfavorable condition) and 4 expresses the best (the most favorable condition) [30]. The rating of each parameter is presented in Table 10. The ranges of parameters in Table 10 were proposed based on the judgments of three experienced experts in the field of drilling engineering.

Table 10: Proposed ranges of the parameters effective on rotational torque.

Parameters	Values and ratings					
P (kN×10)	Value	0-2.5	2.5-5	5-10	10-15	>15
	Rating	0	1	2	3	4
N (r/min)	Value	<10	10-20	20-30	30-40	>40
	Rating	0	1	2	3	4
L (m)	Value	<100	100-200	200-300	300-400	>400
	Rating	0	1	2	3	4
K_L	Value	<1	1-1.5	1.5-2	2-2.5	>2.5
	Rating	0	1	2	3	4
D_i (mm)	Value	<600	600-800	800-1000	1000-1200	>1200
	Rating	0	1	2	3	4
W (L/min)	Value	<500	500-1000	1000-2000	2000-3000	>3000
	Rating	0	1	2	3	4
V (s)	Value	-	<50	50-60	60-70	70<
	Rating	-	1	2	3	4

RESULTS AND DISCUSSION

Risk Analysis and Rotational Torque to Operate Horizontal Directional Drilling Prediction

In many areas of information science, finding predictive relationships from data is a very important task. The initial discovery of relationships is usually performed with a training set, while a test set is used for evaluating whether the discovered relationships are correct. More formally, a training set is a set of data used to discover potentially predictive relationships. A test set is a set of data used to assess the strength and utility of a predictive relationship.

In the current study, a dataset which includes 84 data points was employed, while 59 data points (70%) were utilized to determine the associated VI for each data point using Equation 6; the remainder data points (25 data points) were employed for the assessment of the degree of accuracy and robustness.

To make the methodology more understandable, an example of determining VI for data point No.1 is shown in Table 11. Variations in the VI for the 59 data points are shown in Figure 4. As it can be seen, the mean of VI is close to 34, showing that the level of risk is in the second category (Medium-High).

Table 11: Parameter values and the corresponding VI for data point No. 1.

Parameter	P (kN×10)	N (r/min)	L (m)	K_L	D_i (mm)	W (L/min)	V (s)
Value or description	11.5	15	146.01	1.177	558.8	3400	62
Value rating (Qi)	3	1	1	1	0	4	3
Weight (a_i(%))	24.285	8.571	11.428	14.285	12.857	18.571	10
VI	47.142	-	-	-	-	-	-

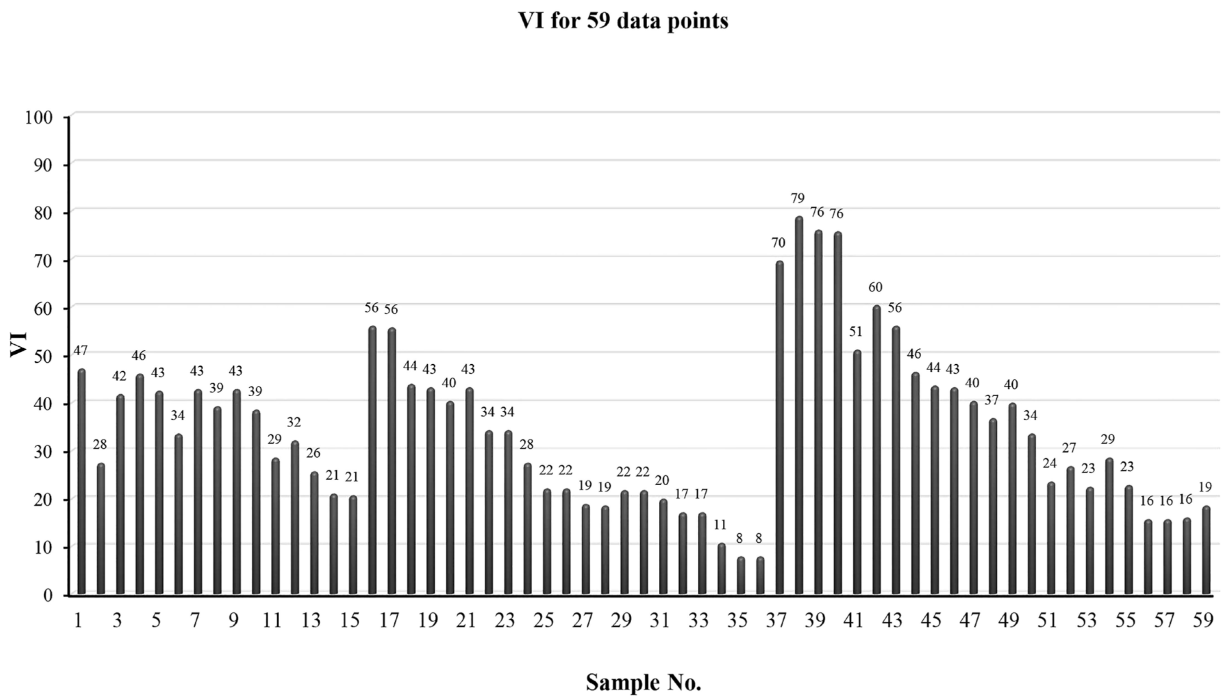


Figure 4: VI for 59 data points.

Based on the calculated VI and the measured rotational torque to operate horizontal directional drilling for 59 data points, an exponential regression analysis was carried out (Figure 5, and Equation 7) with a coefficient of determination (R^2) of 0.84 was obtained. This relation can be used as a predictive model to predict rotational torque to operate horizontal directional drilling (M) based on VI.

$$M\ (kN.m) = 48.41\exp\left(-0.027VI\right) \tag{7}$$

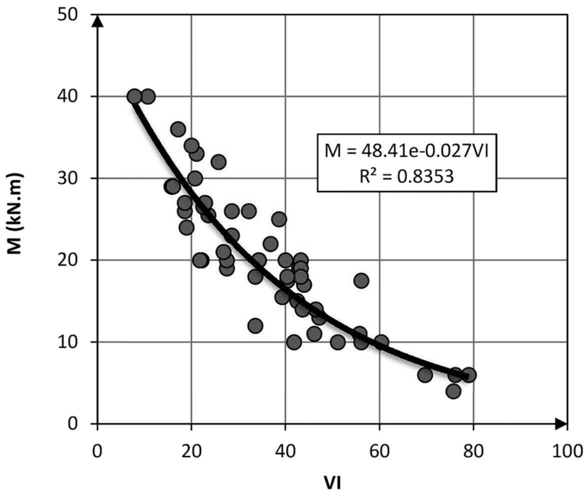


Figure 5: Rotational torque (M)–VI predictive model.

Evaluation of the Performance of Models

For a total of 84 data points, a comparison was made between the predicted and the measured rotational torque to operate horizontal directional drilling using different models as shown in Figure 6.

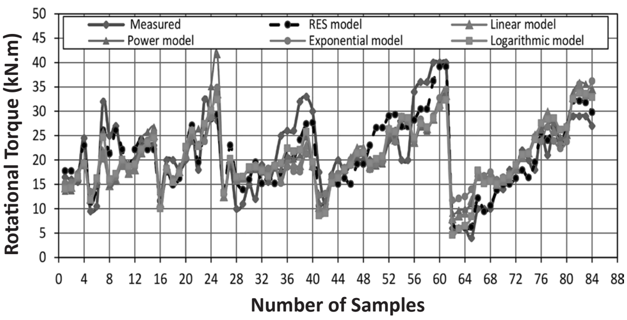


Figure 6: A comparison between the measured and predicted rotational torque for the total data points.

To verify the performance of the model, five statistical criteria, namely mean squared error (MSE), root mean squared error (RMSE), squared correlation coefficient (R^2), and mean absolute percentage error (MAPE) were chosen to be the measure of accuracy. if t_k, $\hat{t}_k$, and n are the actual value, the predicted value of the k^{th} observation, and the number of observations respectively, then the RMSE, MSE, R^2, and MAPE could respectively be defined as follows:

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(t_k - \hat{t}_k)^2 \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(t_k - \hat{t}_k)^2} \tag{9}$$

$$R^2 = 1 - \frac{\sum_{k=1}^{n}(t_k - \hat{t}_k)^2}{\sum_{k=1}^{n} t_k^2 - \frac{\sum_{i=1}^{n}\hat{t}_k^2}{n}} \tag{10}$$

$$MAPE = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{t_k - \hat{t}_k}{t_k}\right| \times 100 \tag{11}$$

The results of the performance analysis of different models for training and testing data are shown in Tables 12 and 13. As it can be seen from the performance indices, the RES-based model shows the best agreement with the measured rotational torque and works better in comparison with the other models. It is worth mentioning that the presented RES predictive model (Equation 7) was developed based upon the limited sets of data from the China west-east natural gas transmission pipeline, so it cannot be generalized for all the operations. However, it is open for more development if more data are available.

Table 12: Performance analysis of different models for the training data.

Models	MSE	RMSE	R^2	MAPE	Observation
Linear	0.0251	0.1585	0.5749	29.39	**59**
Exponential	0.0276	0.1661	0.5337	31.08	**59**
Logarithmic	0.0209	0.1444	0.6470	29.73	**59**
Power	0.0228	0.1509	0.6160	27.84	**59**
RES	**0.0116**	**0.1075**	**0.8065**	**21.85**	**59**

Table 13: The results of the performance analysis of the different models for the testing data.

Models	MSE	RMSE	R^2	MAPE	Observation
Linear	0.0164	0.1281	0.4954	24.306	**25**
Exponential	0.0186	0.1364	0.3998	23.756	**25**
Logarithmic	0.0130	0.114	0.5791	22.1924	**25**
Power	0.0231	0.1521	0.4251	26.6694	**25**
RES	**0.0050**	**0.0709**	**0.8216**	**13.8612**	**25**

As it was mentioned, it seems that RES is a more accurate method in predicting rotational torque during testing and training steps. However, this strong statement needs more approvals. As a matter of fact, there is one question which is yet required to be answered in this section: whether different fractions of training and testing data may change the performance of the models. This question would require many attempts with different fractions of data to show how the performance of the models may change with different numbers of training and testing data [32,33].

According to Table 14, the MSE and R^2 of the RES model (for training/testing=70/30) is less than those of the other models in almost all of the cases indicating that it can be a better choice for the prediction process.

Table 14: Comparing the performance of RES model in the prediction of rotational torque at different fractions of the training and testing data.

Training/ testing (%)	Model	MSE (Train)	MSE (Test)	R^2 (Train)	R^2 (Test)
90/10	RES	0.0117	0.0064	0.8033	0.8122
80/20	RES	0.0119	0.0059	0.7909	0.7943
70/30	**RES**	**0.0116**	**0.0050**	**0.8065**	**0.8216**
60/40	RES	0.0164	0.0115	0.8055	0.8117
50/50	RES	0.0184	0.0125	0.7512	0.7344

CONCLUSIONS

In this paper, a RES-based model is proposed for predicting the rotational torque to operate horizontal directional drilling. The RES-based model is an expert-based model, which can deal with the inherent uncertainties in the geological systems. Also, it has the privilege of considering unlimited input parameters, which may have an effect on the system. Moreover, it has the merit of considering descriptive input parameters which are not applicable to statistical modeling and artificial intelligence methods.

It is concluded that the RES-based model with performance indices of R^2 = 0.8216, RMSE= 0.0709, MAPE= 13.86, and MSE = 0.0050 performs better than linear, power, logarithmic, and exponential models. It is evident that the prediction of the model constructed in this research is open for more development if more data (e.g. geological conditions) are available. This study shows that the RES-based model can be used as a powerful tool for modeling some problems involved in soil and rock engineering.

NOMENCLATURES

ANFIS	:Adaptive Neuro-Fuzzy Inference System
ANN	:Artificial Neural Networks
C	:“Cause” value
CQC	:Continuous Quantitative Coding
D_i	:The Radius for the ith Reaming Operation
E	:“Effect” value
ESQ	:Expert Semi-Quantitative
HDD	:Horizontal Directional Drilling
KL	:The Total Angular Change of the Borehole
L	:The Length of Drill String in the Borehole
M	:Rotational Torque
MAPE	:Mean Absolute Percentage Error
MSE	:Less Mean Square Error
N	:Rotational Speed (revolutions per minute) of the Bit
P	:Axial Force on the Cutter/Bit
R^2	:Coefficient of Determination
R_2	:Squared Correlation Coefficient
RES	:Rock Engineering Systems
RMSE	:Root Mean Square Error
Sig.	:Significance
SPSS	:Standard statistical analysis
TBM	:Tunnel Boring Machine
V	:The Marshal Funnel Mud Viscosity (s)
VI	:Vulnerability Index
VIF	:Variance Inflation Factor
W	:The Mud Flow Rate (L\min)

REFERENCES

1. Gokhale S., Hamm R., and Sterling R. “A Comprehensive Survey on the State of Horizontal Directional Drilling in North America Provides an Inside Look at This Increasingly Growing Industry,” *Directional Drilling*, **1999**, *7*(1), 20-23.

2. Lan H., Ma B., Shu B., and Wu Z., “Prediction of Rotational Torque and Design of Teaming Program Using Horizontal Directional Drilling in Rock Strata,” *Tunnelling and Underground Space Technology,* **2011**, *26*(2), 415-421.

3. Allouche E. N. “Implementing Quality Control in HDD Projects-a North American Prospective,” *Tunnelling and Underground Space Technology*, **2001**, *16*, 3-12.

4. Adel M. and Zayed T. “Productivity Analysis of Horizontal Directional Drilling”, Paper Presented at *the Pipelines 2009 Conference*, Pipelines 2009: Infrastructure’s Hidden Assets, **2009**,.

5. Akin S. and Karpuz C. “Estimating Drilling Parameters for Diamond Bit Drilling Operations Using Artificial Neural Networks,” *International Journal of Geomechanics*, **2008**, *8*(1), 68-73.

6. Feili Monfared A., Ranjbar M., Nezamabadi-Poor H., Schaffie M., and et al., “Development of a Neural Fuzzy System for Advanced Prediction of Bottomhole Circulating Pressure in Underbalanced Drilling Operations,” *Petroleum Science and Technology*, **2011**, *29*(21), 2282-2292.

7. Cancelli A. and Crosta G. “Hazard and Risk Assessment in Rockfall Prone Areas,” Risk and reliability in ground engineering. Thomas Telford, London, **1993**, 177-190.

8. Saffari A., Ataei M., and Ghanbari K. “Applying Rock Engineering Systems (RES) Approach to Evaluate and Classify the Coal Spontaneous Combustion Potential in Eastern Alborz Coal Mines,” *Int. Journal of Mining & Geo-Engineering*, **2013**, *47*(2), 115-127.

9. Faramarzi F., Farsangi M. E., and Mansouri H. “An RES-based Model for Risk Assessment and Prediction of Backbreak in Bench Blasting,” *Rock Mechanics and Rock Engineering*, **2013**, *46*(4), 877-887.

10. Mazzoccola D. and Hudson J. “A Comprehensive Method of Rock Mass Characterization for Indicating Natural Slope Instability,” *Quarterly*

Journal of Engineering Geology and Hydrogeology, **1996**, *29*(1), 37-56.

11. Moradi M. R. and Farsangi M A. E. “Application of the Risk Matrix Method for Geotechnical Risk Analysis and Prediction of the Advance Rate in Rock TBM Tunneling,” *Rock Mechanics and Rock Engineering*, **2013**, 1-10.

12. Shin H. S., Kwon Y. C., Jung Y. S., Bae G. J., and et al., “Methodology for Quantitative Hazard Assessment for Tunnel Collapses Based on Case Histories in Korea,” *International Journal of Rock Mechanics and Mining Sciences*, **2009**, *46*(6), 1072-1087.

13.Benardos A. and Kaliampakos D. “A Methodology for Assessing Geotechnical Hazards for TBM Tunnelling-illustrated by the Athens Metro, Greece,” *International Journal of Rock Mechanics and Mining Sciences*, **2004**, *41*(6), 987-999.

14. Faramarzi F., Mansouri H., and Farsangi M. A. E. “Development of Rock Engineering Systems-based Models for Flyrock Risk Analysis and Prediction of Flyrock Distance in Surface Blasting,” *Rock Mechanics and Rock Engineering*, **2014**, *47*(4), 1291-1306.

15. Fattahi H. and Moradi A. “A New Approach for Estimation of the Rock Mass Deformation Modulus: a Rock Engineering Systems-based Model,” *Bulletin of engineering geology and the environment*, **2017**, *75*, 1-12.

16. Fattahi H. and Moradi A. “Risk Assessment and Estimation of TBM Penetration Rate Using RES-Based Model,” *Geotechnical and Geological Engineering*, **2017**, *35*(1), 365–376.

17. Faramarzi F., Mansouri H., and Ebrahimi Farsangi M. “A Rock Engineering Systems Based Model to Predict Rock Fragmentation by Blasting,” *International Journal of Rock Mechanics and Mining Sciences*, **2013**, *60*, 82-94.

18. Bahri Najafi A., Saeedi G. R., and Ebrahimi Farsangi M. A. “Risk Analysis and prediction of Out-of-seam Silution in Longwall Mining,” *International Journal of Rock Mechanics and Mining Sciences*, **2014**, *70*, 115-122.

19. Skagius K., Wiborgh M., Ström A., and Morén L., “Performance Assessment of the Geosphere Barrier of a Deep Geological Repository for Spent Fuel: The Use of Interaction Matrices for Identification, Structuring and Ranking of Features, Events and Processes,” *Nuclear Engineering and Design*, **1997**, *176*(1), 155-162.

20. Avila R. and Moberg L. “A Systematic Approach to the Migration of< Sup> 137</Sup> Cs in Forest Ecosystems Using Interaction Matrices,” *Journal of Environmental Radioactivity*, **1999**, *45*(3), 271-282.

21. Velasco H., Ayub J., Belli M., and Sansone U., “Interaction Matrices as a First Step Toward a General Model of Radionuclide Cycling: Application to the 137 Cs Behavior in a Grassland Ecosystem,” *Journal of Radioanalytical and Nuclear Chemistry,* **2006**, *268*(3), 503-509.

22. Van Dorp F., Egan M., Kessler J. H., Nilsson S., and et al., “Biosphere Modelling for the Assessment of Radioactive Waste Repositories; the Development of a Common Basis by the BIOMOVS II Reference Biospheres Working Group,” *Journal of Environmental Radioactivity*, **1998**, *42*(2), 225-236.

23. Agüero A., Pinedo P., Simón I., Cancio D., and et al., “Application of the Spanish Methodological Approach for Biosphere Assessment to a Generic High-level Waste Disposal Site,” *Science of the Total Environment*, **2008**, *403*(1), 34-58.

24. Mavroulidou M., Hughes S. J., and Hellawell E. E. “A Qualitative Tool Combining an Interaction Matrix and a GIS to Map Vulnerability to Traffic

Induced Air Pollution," *Journal of Environmental Management*, **2004**, *70*(4), 283-289.

25. Condor J. and Asghari K. "An Alternative Theoretical Methodology for Monitoring the Risks of CO< sub> 2</sub> Leakage from Wellbores," *Energy Procedia*, **2009**, *1*(1), 2599-2605.

26. Fattahi H. "Risk Assessment and Prediction of Safety Factor for Circular Failure Slope Using Rock Engineering Systems," *Environmental Earth Sciences*, **2017**, *76*(5), 224.

27. Niżnik D. and Gonet A. "Identification of Rotational Torque and Power in HDD," *Archives of Mining Sciences*, **2007**, *52*(1), 49-60.

28. Maidla E. E. and Wojtanowicz A. K. "A Field Method for Assessing Borehole Friction for Directional Well Casing," *Journal of Petroleum Science and Engineering*, **1988**, *1*(4), 323-333.

29. Jammalamadaka S. R. "Introduction to Linear Regression Analysis," *The American Statistician*, **2012**, 1-222.

30. Hudson J. A. "Rock Engineering Systems : Theory and Practice," Horwood, Chichester, **1992.**

31. Lu P. and Latham J. P. "A Continuous Quantitative Coding Approach to the Interaction Matrix in Rock Engineering Systems Based on Grey Systems Approaches," Paper presented at *the Proc. 7th Int. Cong. of IAEG*., Balkema, Rotterdam, **1994**.

32. Fattahi H. "Applying Soft Computing Methods to Predict the Uniaxial Compressive Strength of Rocks from Schmidt Hammer Rebound Values," *Computational Geosciences*, **2017**, 1-17.

33. Gholami R., Moradzadeh A., Maleki S., Amiri S., and et al., "Applications of Artificial Intelligence Methods in Prediction of Permeability in Hydrocarbon Reservoirs," *Journal of Petroleum Science and Engineering*, **2014**, *122*, 643-656.