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ORIGINAL ARTICLE

An assessment of total RMR classification system using unified simulation model based on artificial neural networks

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Abstract Engineering design has great importance in the cost and safety of engineering structures. Rock mass rating (RMR) system has become a reliable and widespread predesign system for its ease of use and variety in engineering applications such as tunnels, foundations, and slopes. In RMR system, six parameters are employed in classifying a rock mass: uniaxial compressive strength of intact rock material (UCS), rock quality designation (RQD), spacing of discontinuities (SD), condition of discontinuities (CD), condition of groundwater (CG), and orientation of discontinuities (OD). The ratings of the first three parameters UCS, RQD, and SD are determined via graphic readings where the last three parameters CD, CG, and OD are estimated by the tables that are composed of interval valued linguistic expressions. Because of these linguistic expresions, the estimated rating values of the last three become fuzzy especially when the related conditions are close to border of any two classes. In such cases, these fuzzy situations could lead up incorrect rock class estimations. In this study, an empirical database based on the linguistic expressions for CD, CG, and OD is developed for training Artificial Neural Network (ANN) classifiers. The results obtained from graphical readings and ANN classifiers are unified in a simulation model (USM). The data obtained from five different tunnels, which were excavated for derivation purpose, are used to evaluate classification results of conventional method and proposed model. Finally, it is noted that more accurate and realistic ratings are reached by means of proposed model.

Keywords ANN · RMR · Rock Mechanics · Classification · USM

1 Introduction

Rock masses are complex materials, which exhibit different properties so that they are divided into structural regions which show uniform features rather than the others in classifications. Quantitative rock mass classifications are based on the experiences of engineers and designers and provide communications between them [1].

For this reason, some classification systems were proposed in design of engineering applications. Like many other classification systems in use in engineering geological practice, rock mass classifications often involve criteria on which values are assigned in linguistic terms [2].

As being one of the classification systems, RMR is used more abundantly. The system, also known as geomechanics classification, was proposed in 1973 and modified according to the experiences of new cases (tunnel projects) and to adapt with the standards. Despite the changes made over years, the system remains the same in principle [3]. The RMR system has been used in many tunnel projects as one of the indicators to define the support or excavation classes [4].

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In this study, the latest version (1989) of the system which utilizes six parameters for total RMR sum is used. In estimation of total RMR, an additional sixth parameter adjusts the basic RMR sum (Table 1) due to the engineering application. This parameter is used for estimating the effect of strike and dip orientations (OD) of discontinuities as linguistic terms (Table 4). Numerical values are assigned to estimate the quantitative value of the effect of the orientation of discontinuity.

There is a need to account for fuzzy variation of rock parameters approximately after taking uncertainty into account. Thus, it is better to assign a range of ratings for each parameter [1]. According to Hoek and Brown, a classification must be a non-linear process [5]. ANNs have the potential to map complex and non-linear relations between input and output variables of a system and so they are commonly used in non-linear engineering problems. In design of engineering projects, neural network systems can be used to confirm and refine design solutions [6].

Integration of the conventional and intelligent system modeling methods can be used in comparison of the different methods. For example, a model or a method could be embedded in another model or a method and could provide to enhance the other's capability [7].

2 Method

In this study, conventional method and ANN-based USM are compared and evaluated. Tunnels that have rock mass parameter values close to borderlines are selected to evaluate.

2.1 Evaluation of total RMR in conventional method

In RMR classification, also known as geomechanics classification, the rock mass in a given site is divided into structural regions of certain similar features. The following six parameters are determined for each structural region to classify a rock mass:

1. Uniaxial compressive strenght of rock material (UCS).
2. Rock quality designation (RQD).
3. Spacing of discontinuities (SD).
4. Condition of discontinuities (CD).
5. Condition of groundwater (CG).
6. Orientation of discontinuities (OD).

- In classification, the sum of the first five parameters is divided into five ranges of values that give the basic

Table 1 Rock mass rating system (geomechanics classification of rock masses)

1	Strength of intact rock material	Point-load strength index (MPa)	> 10	4–10	2–4	1–2	For this low range, uniaxial compressive test is preferred
		Uniaxial compressive strength (MPa)	> 250	100–250	50–100	25–50	5–25 1–5 <1
	Rating		15	12	7	4	2 1 0
2	Drill core Quality RQD (%)		90–100	75–90	50–75	25–50	<25
	Rating		20	17	13	8	3
3	Spacing of discontinuities		>2 m	0.6-2m	200–600 mm	60–200 mm	<60 mm
	Rating		20	15	10	8	5
4	Condition of discontinuities		Very rough surfaces Not continuous No separation Unweathered wall rock	Slightly rough surfaces Separation < 1mm Slightly weathered walls	Very rough surfaces Separation < 1mm Highly weathered walls	Slickensided surfaces or Rouge < 5 mm or Separation 1-5 mm Continuous	Soft gouge > 5mm thick or Separation > 5mm continuous
	Rating		30	25	20	10	0
5	Groundwater	Inflow per 10 m tunnel length (L/min)	None	10	<25	25–125	>125
			Or	Or	Or	Or	Or
		Joint water pressure Ratio Major principle Stress	0	0–0,1	0.1–0,2	0.2–0,5	> 0.5
			Or	Or	Or	Or	Or
		General conditions	Completely dry	Damp	Wet	Dripping	Flowing
	Rating		15	10	7	4	0

RMR rating. Higher rating values indicate that the rock mass is in a better condition;

(a) In evaluation of the first three parameters ratings, the charts (Fig. 1) proposed by International Standards of Rock Mechanics (ISRM) are used, which remove abrupt changes in borderline cases and also that ratings occur between categories as shown in Table 1 [8].
(b) The 4th parameter CD is evaluated from Tables 2 and 3. General roughness and weathering situations of a rock mass are rated using the guidelines in Tables 2 and 3.
(c) The 5th parameter CG is evaluated from the fifth row of the Table 1.

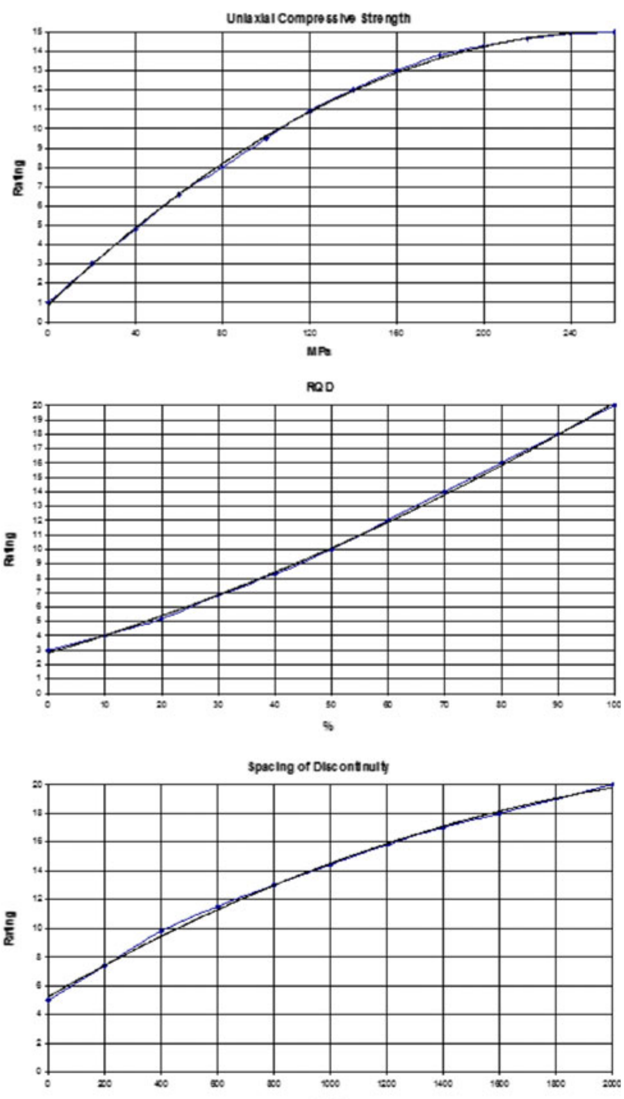

Fig. 1 Ratings of uniaxial compressive strength discontinuity length and a rock quality designation [3]

In this way, the sum of the five parameters' rating gives the basic RMR value of that structural region.

- The 6th parameter is the adjustment of basic RMR that regards the influence of dip orientation and strike (OD). Evaluation of the sixth parameter depends on engineering structures such as tunnel, mine, slope, or foundation. In tunneling, OD is determined by linguistic terms such as 'fair' (Table 4). Finally, rating of OD is scored as shown in Table 5."
- For total RMR rating, each tunnel is evaluated using basic RMR ratings and adjusting them by means of adding the OD ratings.

2.2 Evaluation with unified simulation model (USM)

USM shown in Fig. 2 is composed of three parts;

- Ratings of UCS, RQD, and SD are estimated assigning functions to the graphics in the first part of Fig. 1 whose charts are redrawn by means of curve fitting and obtained functions are used in USM.
- In the USM, CD and CG ratings are estimated by means of an ANN which determines conditions of both discontinuities and groundwater (ANN-CD&CG).
- In the third part, OD ratings are estimated by evaluating the effect of strike and dips parameters by a second ANN, called ANN-OD.

Structural properties of these two ANN models will be given as follows.

2.2.1 ANN classifiers

Contrary to the traditional method, ANN learns the solution from a set of training data as an alternative calculation method. Especially from human brain, this opinion is stemmed from biological neural system [9]. ANN is composed of neurons which generally are fully connected to each others by means of layers. A Multi Layer Perceptron (MLP) ANN structure shown in Fig. 3 consists of one input layer (X_i), one or more hidden layer(s), and one output layer (y_k). All the layers of the MLP are fully connected to each others [10]. An effective training algorithm based on back propagation of the error has made MLP ANN widely used [11].

To perform a rapid convergence in training phase, inputs of ANNs are (not compulsory but in general) normalized by a factor due to amplitude of the related possible maximum input values. But if such a way is applied in, we need to pay attention to redivide an input with the same factor also in the testing phase. In the training and testing phase of the ANNs, relatively great input ranges are normalized by 100, while relative smallers are normalized by 10.

Table 2 Guidelines for classification of CD

Parameter	Rating					
Discontinuity length		< 1 m (6)	1–3 m (4)	3–10 m (2)	10–20 m (1)	>20 m (0)
Separation		None (6)	<0.1 mm (5)	0.1–1 mm (4)	1–5 mm (1)	>5 mm (0)
Roughness		Very rough (6)	Rough (5)	Slightly rough (3)	Smooth (1)	Slickensided (0)
Infilling		Hard filling		Soft filling		
	None (6)	<5 mm (4)	>5 mm (2)	<5 mm (2)	>5 mm (0)	
Weathering	Unweathered (6)	Slightly weathered (5)	Moderately weathered (3)	Highly weathered (1)	Decomposed (0)	

Table 3 Data combination which is used to synthesize inputs–output database of ANN-CD&CG for the training and testing phases

Discontinuity length (m)	Separation (mm)	Infilling (mm)	Groundwater (lt/min)	Rating
0.5	0	0	0	0 ~ 33
2	0.05	2.5	5	
6.5	0.55	6	17.5	
15	3	−2.5	75	
21	6	−6	126	

Table 4 Effect of discontinuity strike and dip orientations (OD) in tunneling

Strike perpendicular to tunnel axis			
Drive with dip		Drive against dip	
Dip 45–90	Dip 20–45	Dip 45–90	Dip 20–45
Very favorable	Favorable	Fair	Unfavorable
Strike parallel to tunnel axis		Irrespective of strike	
Dip 20–45	Dip 45–90	Dip 0–20	
Fair	Very unfavorable	Fair	

ANN designed for condition of discontinuities and condition of groundwater (ANN-CD&CG) A database for CD and CG is built by means of parameter ratings which are given by the tables. Six hundred and twenty five possible situations of ratings are selected, and related scores are derived from Tables 1 and 2, item 5. This database is used in training and testing of the ANN-CD&CG; in this way, 313 and 312 out of 625 data of ANN inputs–output pairs are used in training and testing phases, respectively.

The ranges of training and testing data used in the ANN-CD&CG classifier are given in Table 3. The parameters are trained in a MLP. The Levenberg–Marquard Backpropagation learning algorithm is used in training Feed-Forward MLP [13].

Structural and operational properties of the ANN-CD&CG can be summarized as follow:

1. Discontinuity, separation, infilling, and groundwater are the four inputs of the MLP.
2. There is one output as discontinuity length and groundwater condition are calculated as ratings. Output layer of the neuron's activation function is chosen linearly.
3. The activation functions of neurons in the hidden layer(s) are chosen hyperbolic tangent. In addition to the hybrid structures of ANNs network optimization proposed by Lagaros et al. [12], architectures of ANNs are generally determined empirically. In this study, optimum hidden layer(s) and number of neurons in each layer are experimentally determined.
4. All the initial weights of the network are determined using Nguyen-Widrow algorithm [14].
5. Discontinuity, separation, and infilling parameters are divided by 10, and groundwater is divided by 100 to obtain training and testing data of the network. To normalize, discontinuity length and groundwater condition are also divided by 100 to increase the sensibility of the network to the minor changes.
6. 313 and 312 out of 625 data which were built for the parameters represent inputs and output of the network are used in training and testing, respectively.

Table 5 Rating adjustment for OD

Strike and dip orientations of discontinuities		Very favorable	Favorable	Fair	Unfavorable	Very unfavorable
Ratings	Tunnels and mines	0	−2	−5	−10	−12

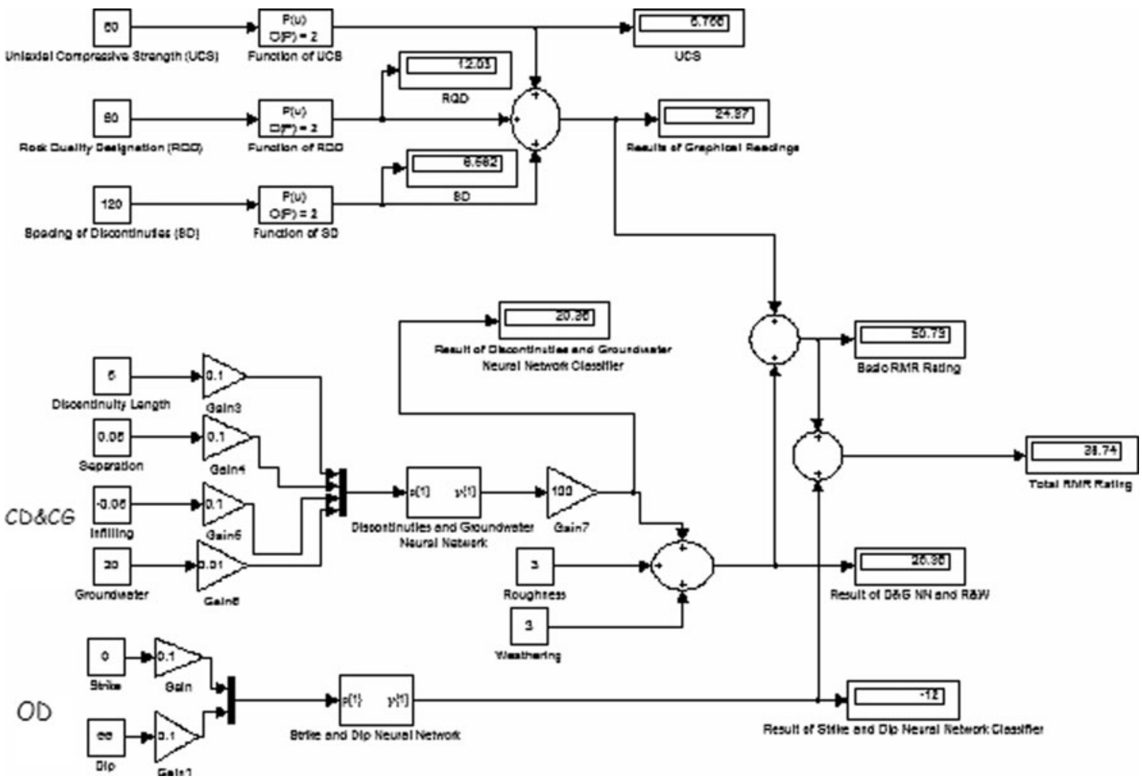

Fig. 2 Unified simulation model for total RMR rating

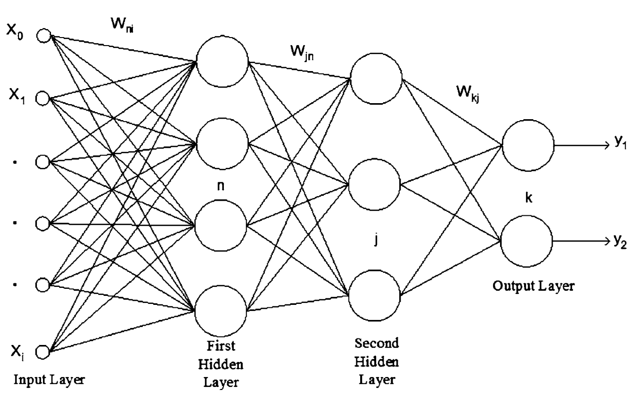

Fig. 3 ANNs structure

ANN designed for orientation of discontinuities (ANN-OD) A database for OD conditions is built by means of parameter ratings. This database is used in training and testing of ANN-OD classifier. The training and testing database, which is relatively shorter for depicting than that of ANN-CD&CG, is given in Table 6. The parameters given in Table 6 are trained in a MLP. The Levenberg–Marquard Backpropagation learning algorithm is used in training Feed-Forward MLP [13].

Structural and operational properties of ANN-OD classifier can be summarized as follow:

Table 6 The training–testing data for ANN-CD&CG classifier

Strike	Dip	Rating	Strike	Dip	Rating
0	−90	−7.44	45	45	−3.24
0	−45	−3.90	45	90	−5.46
0	−33.50	−3.48	90	−90	−3.48
0	−10	−3.48	90	−45	−7.44
0	0	−3.48	90	−33.50	−7.44
0	10.60	3.54	90	−10	−3.48
0	20.50	−4.05	90	0	−3.48
0	32	−3.48	90	10.60	−3.54
0	45	−3.90	90	20.50	−4.08
0	90	−7.44	90	32	−2.04
0	38	−5	90	45	−1.92
0	66	−12	90	90	−0.48
45	−90	−6	90	82	−5
45	−45	−6	90	40	−10
45	−33.5	−6	90	65	−2
45	−10	−4.08			
45	0	−4.08			
45	10.60	−4.08			
45	20.50	−3.24			
45	32	−3.24			

1. MLP has two inputs: strike and dip.
2. There is one output which is rating of strike and dip conditions (OD). Output layer of the neuron's activation function is chosen linearly.

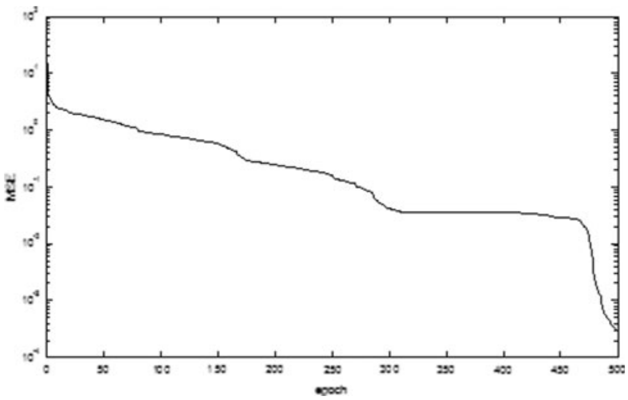

Fig. 4 MSE values of the ANN-OD

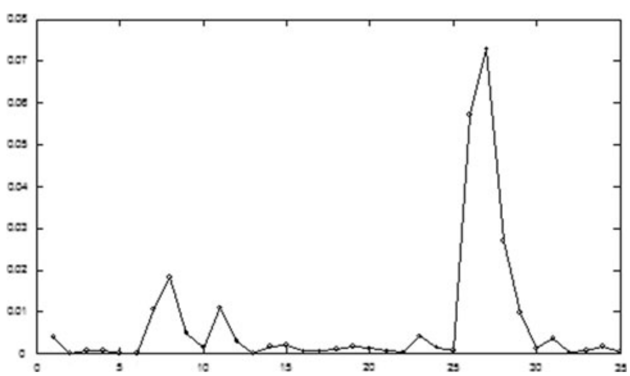

Fig. 5 AEV's of the ANN-OD

3. The activation functions of 16 neurons in the hidden layer are chosen hyperbolic tangent.
4. All the initial weights of the network are determined using Nguyen-Widrow algorithm [14].
5. Strike and dip parameters are divided by 10 to obtain training data of the network.

3 Results and discussion

Two neural network classifiers are analyzed in Sect. 2 to constitute the total RMR rating in USM.

To a given problem, the number and structure of operation units of input and output layers differ in any ANN applications. In order to determine an optimum architecture, every training data were investigated for different number of hidden layer(s) and neurons.

Considering both training and testing, the architecture of the ANN-CD&CG for one hidden layer with sixteen neurons gives the best solution.

Also, the same architecture was used for the second classifier, which is named as ANN-OD. The iteration steps and the corresponding MSEs of the ANN-OD are given in Fig. 4 as an example.

Absolute error values (AEV) are also given in Fig. 5, which is built by the network for training data due to target vectors. The couples of min and max AEV for training data are 3.5548×10^{-5} to 7.2907×10^{-2}. Percentage of mean AEV are determined as 0.0199 for the training data.

After the training, the MSE—percentage MSE values of ANN-CD&CG and ANN-OD classifiers are evaluated as 8.9469×10^{-6} to 1.4315×10^{-6} and 2.8756×10^{-4} to 8.2161×10^{-4}, respectively. Trained networks were used

Table 7 OD rating adjustments of the tunnels

Tunnels	1	2	3	4	5
Strike and dips	Strike is perpendicular to tunnel axis (90°) and drive is against dip (82°)	Strike is perpendicular to tunnel axis (90°) and drive is against dip (40°)	Strike is perpendicular to tunnel axis (90°) and drive is with dip (65°)	Strike is parallel to tunnel axis (0°) and dip is (38°)	Strike is parallel to tunnel axis (0°) and dip is (66°)
Rating adjustment for OD	Ratings of tunnels (conventional/USM)				
	−5/−5.001	−10/−9.998	−2/−2	−5/−4.989	−12/−12

Table 8 Total RMR ratings

Total RMR ratings (conventional—USM)									
Tunnel 1		Tunnel 2		Tunnel 3		Tunnel 4		Tunnel 5	
73.00	65.77	60.90	58.92	90.00	89.93	53.70	52.44	40.90	39.58
Good Rock	Good Rock	Good Rock	Fair Rock	Very Good Rock	Very Good Rock	Fair Rock	Fair Rock	Fair Rock	Poor Rock

in USM model design as ANN classifiers to determine total RMR rating.

In the assessment of the tunneling cases, five data sets of different rock masses were used as classification parameters in this study. In Table 7, the comparison of OD rating adjustments of conventional method and ANN-OD model is given.

The total rating results obtained from the conventional and USM methods compared in Table 8. Then, rock mass classes are determined by means of Table 9.

The values obtained from conventional and USM belong to 5 different derivation tunnels parameters. Parameters of CD are given in the first 5 rows, and the CG is given in the sixth row in Table 10. Also, the numerical values correspond to linguistic terms are given in the same table.

In USM, infilling is divided into two parts depending on hard or soft filling. For instance, when the separation is 0.05 mm and infilling is hard then its value is taken as +0.005 and is taken −0.005 when infilling is soft with the 0.05-mm separation. These values are used as inputs of ANN-CD&CG in the USM.

The change of inflow of groundwater to the tunnel (CG) is represented between 0 and 126 lt/min in USM.

The difference of ratings between two methods reaches up to 7.43. This change is because of having the same value for a wide range in conventional method.

Regarding to the total RMR sum, rock masses of the 2nd and 5th cases fall into good and fair rock classes in conventional method whereas good and fair rock classes in USM as shown in Table 8, respectively.

Using the guides given in Tables 1, 2, and 3, descriptions and measurements of SD for the cases are carried out (Table 10).

Table 9 Rock mass classes determined from total ratings

Class no	I	II	III	IV	V
Description	Very good rock	Good rock	Fair rock	Poor rock	Very poor rock
Rating	100 ← 81	80 ← 61	60 ← 41	40 ← 21	<20

Table 10 Input values of the cases for the CD and CG parameters

Parameter	Tunnels				
	1	2	3	4	5
CD					
Discontinuity length (m)	6.5	8	10	2.5	5
Separation (mm)	0.05	0.4	0.01	1	0.05
Infilling (mm)	0.04	0.3	0.01	1	−0.05
Roughness (rating)	3	3	5	3	3
Weathering (rating)	6	5	6	3	3
CG					
Groundwater (lt/min)	4	1	0	10	20

Table 11 Parameters of tunnels for basic RMR

Parameter	Input data				
Tunnels	1	2	3	4	5
1. Uniaxial compressive strength, UCS (MPa)	150	125	245	95	60
2. Drill core quality RQD (%)	85	85	92	73	60
3. Spacing of discontinuity, SD (mm)	285	190	1800	155	120
4. Discontinuity, CD, and groundwater, CG	Very rough surfaces	Slightly rough surfaces	Very rough surfaces	Very rough surfaces	Slightly rough surfaces
	Separation < 1 mm	Separation < 1 mm Slightly weathered walls	Separation < 1 mm	Separation < 1 mm	Separation < 1 mm Slightly weathered walls

Parameter	Ratings (Conventional – USM)									
Tunnels	1		2		3		4		5	
1. UCS (MPa)	12.30	12.43	11.20	11.13	14.90	15.06	9.00	9.25	6.70	6.60
2. RQD (%)	17.00	17.15	17.00	17.15	18.10	18.72	14.20	14.60	11.90	12.03
3. SD (mm)	8.70	8.31	7.70	7.33	19.00	19.12	7.50	6.96	7.30	6.58
4. CD and CG	40.00	32.88	35.00	33.30	40.00	39.04	28.00	26.62	27.00	26.36
Basic RMR rating	78.00	70.77	70.90	68.92	92.00	91.93	58.70	57.43	52.90	51.58

Basic RMR rating is calculated by means of Table 11. For total RMR rating, the sixth parameter, the effect of OD, is evaluated in Table 7. Rock mass classes of the tunnels are determined by means of Table 9 due to their total RMR ratings.

4 Conclusion

Bieniawski reported the deficiency stems from the abrupt changes in borderline cases [3]. Since ANN in USM take whole effects into consideration, in details, more sensitive and exact results are obtained.

The rock masses discussed in 2nd and 5th tunnels therefore fall in a more realistic class, that is, fair and poor rock classes, whereas good and fair rock classes in conventional method which makes a rougher evaluation as indicated. This rough evaluation possibly will cause mis-evaluation of support of rock tunnels and contractual problems. It could be concluded that RMR overestimates the rock classes considering these five cases (tunnels).

Taking into consideration the values of % 1.4315×10^{-6} and 2.8756×10^{-4} of MSEs for ANN-CD&CG and ANN-OD, ANN classifiers used in USM estimate more effective total RMR. Developing a single ANN classifier consisting of all parameters as inputs is proposed for future works.

References

1. Singh B, Goel RK (1999) Rock mass classification, a practical approach in civil engineering. Elsevier Science, Oxford
2. Aydin A (2004) Fuzzy set approaches to classification of rock masses. Eng Geol 74(3–4):227–245
3. Bieniawski ZT (1989) Engineering rock mass classifications. Wiley, New York
4. Stille H, Palmstom A (2003) Classification as a tool in rock engineering. Tunnel Underground Space Technol 18:831–845
5. Hoek E, Brown ET (1997) Practical estimation of rock mass strength. Int J Rock Mech Mining Sci 34(8):1165–1186
6. Feng X-T, Hudson JA (2004) The ways ahead for rock engineering design methodologies. Int J Rock Mech Mining Sci 41:255–273
7. Feng XT, Zhang ZQ, Li TJ (2001) On uniqueness of identification of rock mass mechanical parameters using inverse displacement back analysis. In: Proceedings of 9th international conference of the association for computer methods and advances in geomechanics. A.A. Balkema, Rotterdam
8. ISRM (International Society for Rock Mechanics) (1982) Rock characterization, testing and monitoring. In: Brown ET (ed) ISRM suggested methods. Pergamon, London, p 211
9. McCulloch WS, Pitts W (1943) A logical calculus of the ideas immanent in nervous activity. Bull Math Biophys 5:115–133
10. Haykin S (1999) Neural networks a comprehensive foundation, 2nd edn. Prentice-Hall, Upper Saddle River. ISBN: 0-13-273350-1
11. Rumelhart DE, Hinton GE, Williams RJ (1986) Learning representations by back-propagating errors. Nature 323:533–536
12. Lagaros ND, Papadrakakis M (2004) Learning improvement of neural networks used in structural optimization. Adv Eng Softw 35:9–25
13. Hagan MT, Menhaj MB (1994) Training feedforward networks with the Marquardt algorithm. IEEE Trans Neural Netw 5(6):989–993
14. Nguyen D, Widrow B (1990) Improving the learning speed of 2-layer neural networks by choosing initial values of the adaptive weights. Int Joint Conf Neural Netw 3:21–26