Estimation of Rock Joint Trace Length in Scanline Sampling Using Artificial Neural Network (ANN)

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Abstract

Geometrical modeling of jointed rock massneeds the geometrical parameters of joints such as orientation, spacing, trace length, shape, and location.The trace length of rock joints is an important design parameter in rock engineering and geotechnics because affecting rock mass strength. It controlsthe stability of the rock slope and tunnels in jointed rock masses. This parameter is usually determined through a joint survey in the field. It is complicated to obtain the parameters because a complete joint plane within rock mass cannot be observed directly. Thedevelopment of predictive models to determinerock joint length seems to be essential in rock engineering.In this paper, an attempt was made to develop an artificial neural network (ANN) modelto predict rock joint length. For this aim, a database of scanline joint sampling of Sarshiw andesites in Iran was surveyed, whichintersection distance of the joint on the scanline, spacing, aperture, orientation (dip and dip direction), roughness, Schmidt rebound of the joint's wall, type of joint termination, joint trace lengths in both sides of the scanline were measured. Final results indicated that this technique could predict joint trace length with high R^2 and minimum RMSE equal to 0.8667 and 1.93,respectively.

Keywords: *Rock Joint, Joint Trace Length, Scanline Sampling, Artificial Neural Network.*
DOI Number: :10.14704/nq.2022.20.8.NQ44175 NeuroQuantology 2022 ;20(8):1616-1625

1. Introduction

A rock mass consists of intact rock and discontinuities, which significantly affects the rock mass strength and deformability [1].Joints and related features are certain types of discontinuities in the rocks. Discontinuity is the general term used in rock mechanics for any weak mechanical plane in a rock mass having zero or low tensile strength [2].A Joint is a discontinuity plane of natural origin. No visible displacement [3] is found in all component rocks within about 1km of the Earth's surface, at all orientation and sizes ranging from a few millimeters to several hundred meters [4].

The origin of certain joints is related to relatively simple mechanisms such as the columnar jointing formed by stress-induced during the cooling of basalts and the slabbing joints caused by diurnal temperature changes on exposed rock faces [4].Price [5]stated that joints in horizontally bedded rocks might be generated by stress changes induced by geological uplift. Another type of joint probably causedby the unloading of the rock mass when the cover is eroded, breaks developed as a product of exfoliation along the foliation planes in metamorphic rocks and along the bedding planes in sedimentary rocks [2].They directly or indirectly influence the strength of the rock mass [6].

A joint's length describes the potential failure plane [6]. It determines the size of the rock blocks that form within a rock mass [7], whichstability of traffic tunnels in discontinuous rock mass at a shallow depth is primarily affected by the stability of rock blocks. Although some researchers have shown which geometrical characteristics of joints, especially their length, strongly affect the fluid-mechanical behavior of rock masses [8, 9].Joint trace length is one of the most significant parameters affecting rock mass strength and controlling rock slope and underground space stability. Thereforejoint geometry parameters must be measured precisely.

In the field survey, it is common to measure joints from a given minimum length (truncation), and this truncation error results in the overestimation of joint lengths.Einstein [10]and Brown ET[11]suggested that joint trace length can be crudely quantified only roughly by observing the discontinuity trace length on a rock exposure surface. The joint size is one of the most challenging properties to measure accurately [4,11, 12].This is because rock exposures are small and only two-dimensional.

According to those mentioned above, all joint characteristics have been made due to the same mechanism, such as basalt cooling, temperature changes, folding, etc. Since some researchers addressed changes in spacing, trace length, and appearance of rock mass joints as weathering progresses [13-16]. Palmsrom A [2] addressed which joint trace length is proportional to the joint aperture,andthe shape and size of joints are primarily related to the rocks they penetrate and the rock mass's size and geometry.

This study introduces a new technique for joint trace length estimation. The new method is derived using the artificial neural network (ANN). New techniques such as ANNs have been employed in developing predictive models for complex problems in recent years.This technique can generalize a solution from the pattern presented during training. Once the network is trained with sufficient sampledatasets, predictionscanbe made based onpreviouslearning [17]. Anincreasein ANNs applicationshasbeenobservedinrockmechanics, geotechnics,andengineeringgeology [16-25]. These applications demonstrate that ANNs are efficient in solving problems ingeosciences in which many parameters influence the process. This paper has attempted todevelopan ANN model to predict joint trace length based on common parameters that can be measured accurately.

2. Rock jointsproperties

Since this paper deals with the collection and use of joint geometrical properties, it is considered appropriate to reiterate some relevant terms briefly. Figure 1 illustrates the parameters which are measured in the joint survey.

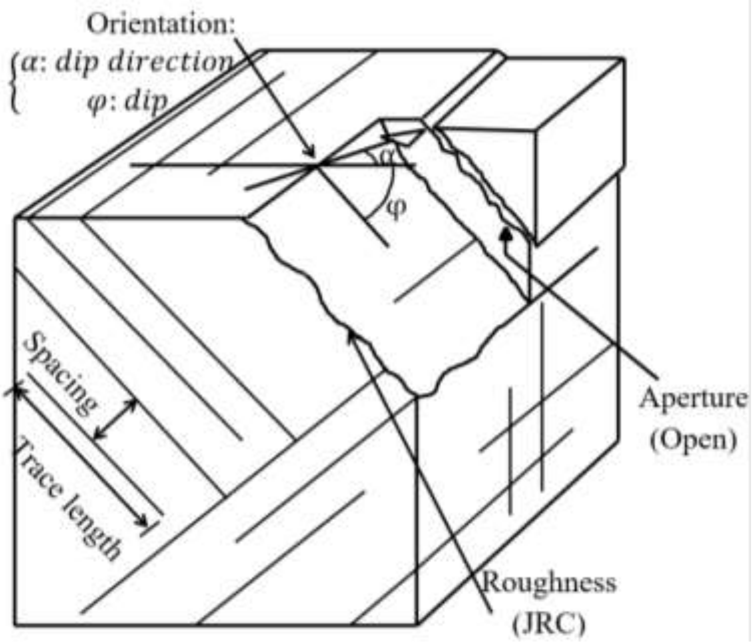


Figure 1. Illustration of joints in rock masses (Adopted from [26])

Joint spacing is a measure of jointing intensity in a rock mass, that is, the number of joints per unit distance normal to the orientation of the set. It is taken as the perpendicular distance between adjacent joints [6].This paper used intersection distance (distance along the scanline to the intersection point with the joint) to describe joint spacing.

Aperture is the perpendicular distance separating adjacent rock walls of an open joint in which the intervening space is filled with air or water [11]. The apertures of natural discontinuities are likely to vary widely over the extent of the joint [27].

Joint orientation describes the attitude of the joint in space. The plane of a joint in space is defined by the dip of the line of steepest declination measured from horizontal and by the dip direction measured clockwise from true north.

Joint roughness describes surface irregularities with a wavelength less than 100mm and can be expressed in Barton's Joint roughness coefficient (JRC). The value of JRC can be estimated by visually comparing the joint surface condition with standard profiles [28]. JRC varies from zero for smooth, planar, and particularly slickenside surfaces to as much as 20 for rough, undulating surfaces.

A joint is a three-dimensional discontinuity composed of two matching surfaces called joint walls.**Joint wall condition** is a main joint characteristic that reflects its weathering process. Thus, we used the Schmidt rebound number to represent this effect in the joint walls.

Joint trace length as observed in an exposure. This is the distance from the intersection point on the scanline to the end of the joint trace. There will be two semi-trace lengths associated with each discontinuity: one to the left and one to the right of a scanline along the maximum dip line of the face.It can be helpful to keep a record of the nature of the termination of each semi-trace. 1: Discontinuity trace terminates in intact rock material, 2: termination at another discontinuity, 3: termination is obscured. A trace can be obscured by blocks, rock, scree, soil, vegetation, or extending beyond the exposure limits [4].

3. Joint trace length measurement using scanline sampling

Joint surveys are an integral component of site characterization studies in rock engineering because rock masses' strength, deformation, and flow behavior strongly influencerock mass discontinuities' geometry and engineering properties [29].The success of discontinuous analysis greatly depends on how correctly in situ joints are surveyed and modeled for the study [30].The size parameter is commonly determined by surveys of fracture trace lengths along exposed rock faces using either line-sampling or window-sampling techniques [31].Because of the research purpose, scanline sampling was conducted for the joint survey.Figure 2 shows the Scanline sampling and type of joint termination.

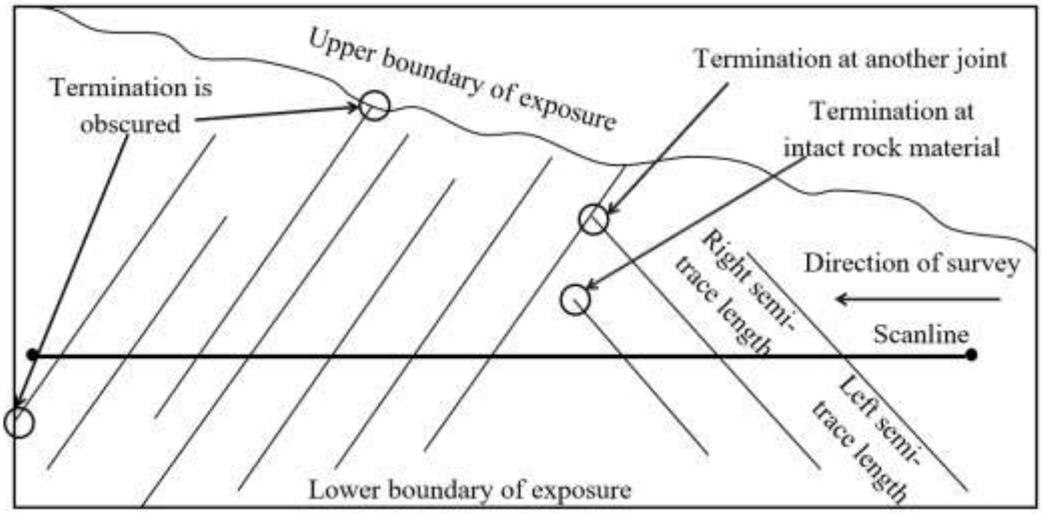


Figure 2. Scnline sampling and type of joint termination

The scanline sampling technique involves measuring all the joints that intersect a scanline along its length. A measuring tape is usually used as a scanline, and the properties of only those joints cross the tape are recorded.

According to the suggestions of Stephen D. Priest [4], a clean, approximately planar rock face is selected that is large relative to the size and spacing of discontinuities exposed. As a rough guide, the sample zone should contain between 150 and 350 discontinuities, of which about 50% should have at least one end visible. So, exposure of Sarshiw andesites, located 40 km away from Marivan city in Kurdistan province in the west of Iran, was selected for this purpose.

4. Artificial neural network (ANN)

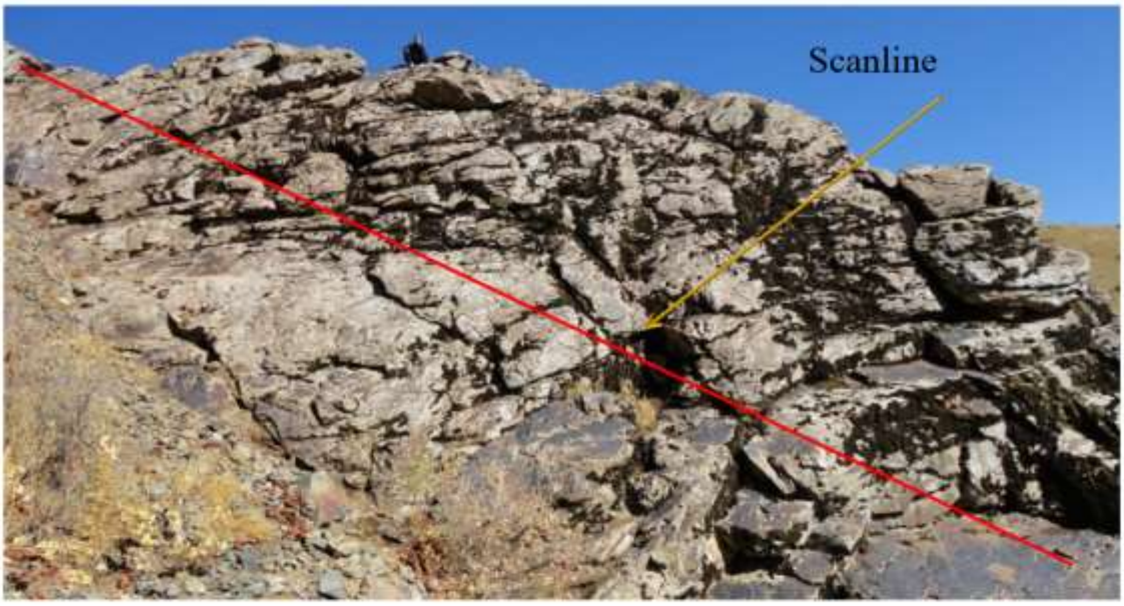
Artificial neural networks are computational models inspired by biological nervous systems. Prediction, classification, recognition, etc., can be simulated by ANNs using simple processing elements called neurons [32]. A multilayer network consists of at least three layers, input, hidden, and output layers. The number of neurons in input and output layers equals the number of input and output parameters. The number of neurons in the hidden layer is significant and usually calculated by trial and error [33, 34]. Although several heuristic suggestions have been proposed for this aim, most researchers apply a trial-and-error process [35]. Usually,involving one or two hidden layers is sufficient for modeling complicated or straightforward problems by ANNs [36]. Various types of ANNs can be used in prediction or classifying problems; Feed-Forward Back-Propagation (FFBP) networks are more prevalent in prediction issues. The network calculates its outputs using initial weights and training data biases in the feed-forward pass. In backward propagation pass, weights and biases are adjusted to compare the network output values and the actual target values until the network outputs match the targets. Error signals propagate back from the last layer toward the first layer in defined cycles called epochs [37, 41].

The other essential parameters for neural networks are learning rate and momentum coefficient. In the back-propagation algorithm, the learning rate is multiplied by the negative of the gradient to adjust the weights and biases; the momentum coefficient has a stabilizing effect training process. Most researchers have suggested values between 0.001 and 0.1 for learning rate and between 0.4 and 1 for momentum coefficient [38, 39]. Also,the transfer function is essential for transforming the weighted sum of all signals hitting each neuron to determine its firing intensity. The most frequently transferred functions are sigmoid and linear [40].The designed network is the best-trained network by selecting the optimum structure. It can be applied for testing new data to predict any unknown relationship between given inputs and their respected outputs.

5. Description of data collection

Data collection is one of the most critical stages in ANN modeling. In this study, rock exposure of Sarshiw andesites was surveyed (figure 3).

Figure 3.A view of rock exposure of Sarshiw andesites



Here, rock exposure was surveyed using scanline sampling,anddescriptions of scanline and rock exposure are shown in table 1. The parameters such as rock type, exposure orientation, scanline orientation, intersection distance of the joint on scanline (distance along the scanline to the intersection point with the joint), spacing, aperture, joint orientation (dip and dip direction), roughness, Schmidt rebound of the joint's wall, type of joint termination (1 and 2 are the codes for termination at intact rock material and another joint respectively and 3: termination is obscured), joint trace lengths in both side of the scanline were measured.

Table 1. descriptions of scanline and rock exposure

Orientation of rock exposure:	Dip Direction (degree):208 , Dip (degree):65
Orientation of scanline:	Trend (degree): 97, Plunge (degree): 40
Joints that intersect the scanline:	226
Joints that terminate at the intact rock:	70
Joints that terminate at another joint:	97
Joints which its termination is obscured:	59

The present study, 167data entries were prepared and divided into training and testing data sets using random methods. Among the total datasets, 20% were chosen to test and validate the model. Table 2showsinput and output parameters along with their symbols. Also, a list of sample data for training the ANN model is given in table 3.

Table 2. Description of input and output parameters in the ANN modeling used for prediction of joint trace length

Type of data	Parameter	Symbol	Max.	Ave.	Min.	Std. dev.
Input parameters	Intersection distance (m)	ID	138.1	75.9	3.3	36.2
	Aperture (mm)	A	52.0	6.3	0.5	10.6
	Dip Direction (degrees)	DD	326.0	212.3	90.0	86.5
	Dip angle (degrees)	D	90.0	67.3	30.0	17.5
	Left Termination	LT	2.0	1.3	1.0	0.4
	Right Termination	RT	2.0	1.7	1.0	0.5
	Roughness (JRC)	R	11.0	1.8	1.0	2.0
	Schmidt Rebound	SR	76.0	59.9	40.0	10.4
Output parameters	Trace length (m)	TL	14.2	4.6	0.8	3.8

Table 3. Sample of the dataset used for ANN modeling for prediction of joint trace length

Intersection distance (m)	Aperture (mm)	dip direction (degrees)	Dip angle (degrees)	Termination		Roughness (JRC)	Schmidt Rebound	Semi-trace length (m)	
				Left	Right			left	right
3.25	1	313	67	1	1	7	70	0.67	1.5
11.8	0.5	173	88	1	2	5	74	1.24	0.58
14.1	28	158	30	2	2	3	74	0.85	1.28
17.75	52	17	34	1	1	1	76	0.71	2.27
19.23	38	14	25	1	2	5	70	0.5	4.85
80.64	0.5	7	12	2	1	5	40*	2.18	1.72
80.72	6	7	12	1	1	1	40*	85	1.76
92.82	0.5	97	3	1	2	11	58	2.75	1.35
93	3	164	89	2	2	7	58	1.96	0.24

*joint wall had been affected by hydrothermal alteration

6. Joint trace length prediction using ANN

Training a neural network depends on the best selection of network parameters such as the number of hidden layers and their interconnected neurons, type of transfer functions, learning rate value, and momentum coefficient. A modification process should be used to achieve this aim so that the network root mean square error (RMSE) reaches a minimum threshold. The network with minimum RMSE and a high coefficient of determination (R^2) is selected as the best-trained network and is applied to predictjoint trace length in this study. RMSE is calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(T_P - T_M)^2} \quad (1)$$

where T_P, T_T,and n arethe *i*thmeasuredelement, *i*thpredictedelement,andthenumberofdatasets, respectively.

To best recognize the relation between inputs and outputs by ANN, it is essential to normalize the input-output values within the range [0 1] or [-1 1]. Normalization was performed to the range [0 1], using the following equation:

$$Normalized\ value = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (2)$$

where X is the actual value, X_{min} is the minimum real value, and X_{max} is the maximum real value.

The process of determining network parameters is commonly fulfilled by thetrial-and-error method. In this study, a feed-forward back-propagation network with one hidden layer involving 12 neurons with Log-sigmoid transfer function in the hidden layer and pure line transfer function in the output layer, learning rate and momentum coefficient equal to 0.1 and 0.7, respectively, was selected as the best-trained network. The structure of this network is illustrated in figure 4.

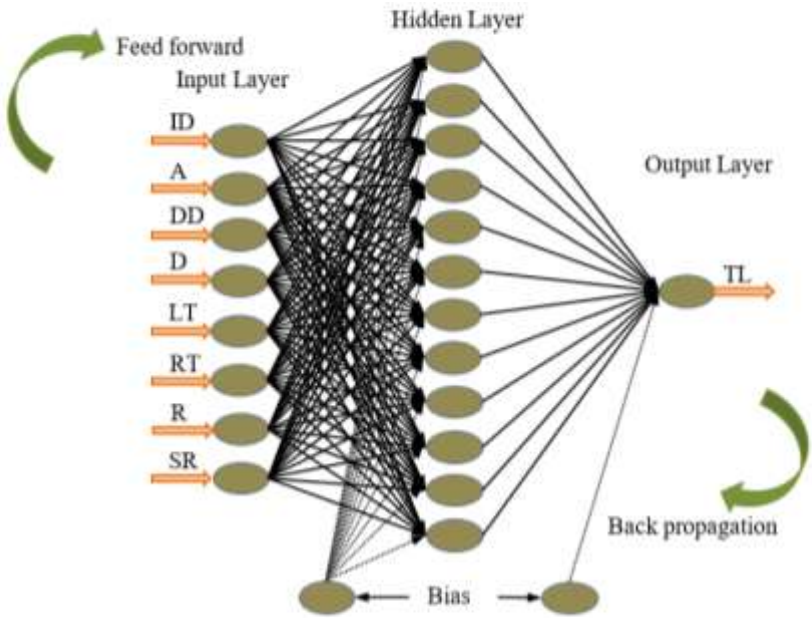


Figure 4Structure of the ANN for predicting joint trace length

The optimum achieved network was employed to predict joint trace length with new test data. The network performance was identified by measuring RMSE and R^2 for the testing process. Figure 5 shows the relation between predicted and measured joint trace length graphically. The final results indicated that this network could predict joint trace length in rock exposure with high R2 and minimum RMSE of 0.8667 and 1.93,respectively.

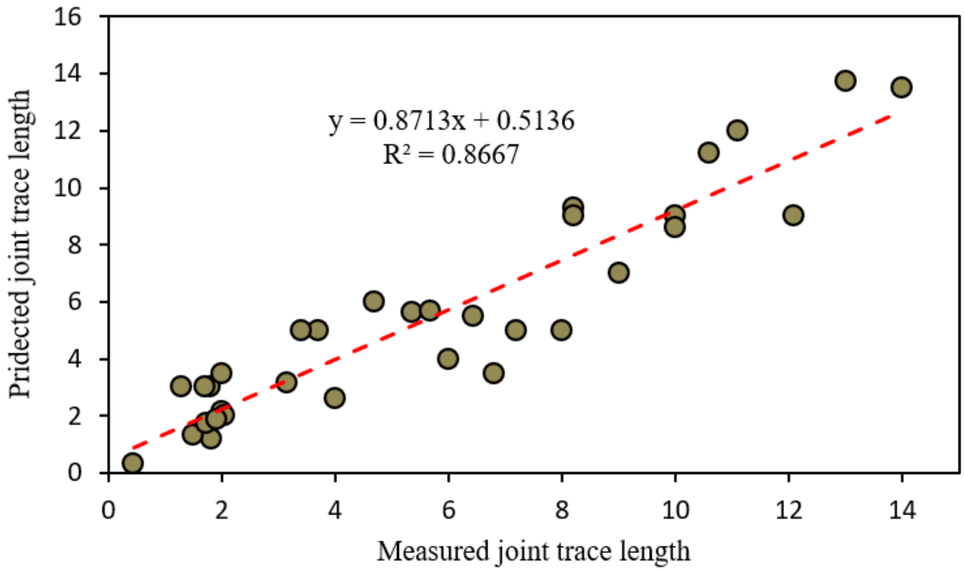


Figure 5. Correlation between measured and predicted joint trace length of considered artificial methods

7. Conclusions

A rock mass consists of intact rock

and discontinuities. A Joint is a discontinuity plane of natural origin with no visible displacement. Its trace length is one of the most significant joint parameters affecting rock mass strength and control rock slope and underground stability. Because rock exposures are small and only two-dimensional, the joint length is one of the most challenging properties to measure accurately. Since joint characteristics have been made due tothe same mechanism, such as basalt cooling, temperature changes, folding, etc., obscured joint trace length using the prediction techniques can be estimated. Artificial neural network applications have been observed in rock mechanics, geotechnics, and engineering geology. These applications demonstrate that ANNs are efficient in solving problems in geosciences in which many parameters influence the process.

This study developed a neural network model to predict joint trace length. A feed-forward back-propagation neural network with architecture 8-12-1 and RMSE of 1.93 was an optimum network. Itwasconcludedthatthe ANN resultsindicateveryclose agreementforthejoint trace lengthwiththe surveydatasets. Considering the above results, it can be concluded that the ANN model can predict obscured joint trace length.

8. Acknowledgments

The authors would like to thank all persons for their help in collecting joint geometry properties.

9. Funding

The authors received no financial support for this article's research, authorship, and publication.

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