ADAPTIVE NEURO FUZZY INFERENCE SYSTEM BASED ON FUZZY C–MEANS CLUSTERING ALGORITHM, A TECHNIQUE FOR ESTIMATION OF TBM PENETRATION RATE

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ABSTRACT

The tunnel boring machine (TBM) penetration rate estimation is one of the crucial and complex tasks encountered frequently to excavate the mechanical tunnels. Estimating the machine penetration rate may reduce the risks related to high capital costs typical for excavation operation. Thus establishing a relationship between rock properties and TBM penetration rate can be very helpful in estimation of this vital parameter. However, establishing relationship between rock properties and TBM penetration rate is not a simple task and cannot be done using a simple linear or nonlinear method. Adaptive neuro fuzzy inference system based on fuzzy c–means clustering algorithm (ANFIS–FCM) is one of the robust artificial intelligence algorithms proved to be very successful in recognition of relationships between input and output parameters. The aim of this paper is to show the application of ANFIS–FCM in estimation of TBM performance. The model was applied to available data given in open source literatures. The results obtained show that the ANFIS–FCM model can be used successfully for estimation of the TBM performance.

Kewords: adaptive neuro fuzzy inference system; TBM; rock properties; penetration rate estimation; fuzzy c–means clustering algorithm.

1. INTRODUCTION

The use of tunnel boring machines (TBM) for tunneling project has been increasing steadily for the last 30 years [1]. The TBM performance estimation is one of the crucial and complex tasks encountered frequently to excavate the mechanical tunnels. Estimating the machine performance may reduce the risks related to high capital costs typical for excavation

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operation. Researches on the TBM performance include the study of advance rate, penetration rate and utilization. Advance rate is the ratio between excavated length and total available time. Penetration rate is the ratio of the length of tunnel excavated to the actual boring time during a continuous boring activity. Utilization refers to the percentage of the shift time that actual boring activity occurs, i.e., it refers to the ratio between actual penetration time and total available time in percent [2, 3].

Review of the literature shows that many methods of performance estimation and modeling for mechanical tunneling using TBM have been suggested by researchers. In this paper, the well–known research works are addressed. Aeberli and Wanner [4] studied effects of schistosity on TBM performance. McFeat-Smith and Tarkoy [5] presented different relations to predict the penetration rate for different types of machines in different geological conditions. This model is not generally valid and it has to be recalculated for each new project. Cassinelli, Cina [6] used a rock structure rating system for correlation with TBM performance. Nelson [7] studied TBM performance at several tunneling projects mainly in sedimentary rock formations by comparing the instantaneous penetration rate achieved with different rock properties. Sanio [8] developed a model to estimate the penetration rate indirectly. He pointed out that the ratio between the penetration rate perpendicular to the bedding and parallel to the bedding is equal to the ratio of the point load indices perpendicular and parallel to the bedding planes. Tarkoy [9] developed an empirical relationship between total hardness and TBM rate of penetration. Barton [10, 11] reviewed a wide range of TBM tunnels to establish the database for estimating penetration rate, utilization and advance rate. The Norwegian Institute of Technology (NTNU) has developed a comprehensive empirical performance estimation model that considers rock mass and intact rock properties as well as machine parameters [12, 13]. In the model, the machine specifications (including cutter size, type and number, machine thrust and torque requirements) along with laboratory measured indices, (drilling rate index, brittleness index, and cutter life index), and rock fracture data, are used to estimate the penetration rate [14]. Rostami and Ozdemir [15, 16] improved this model theoretically by estimating cutting forces as a function of intact rock properties, including tensile strength and uniaxial compressive of rock, and the cutter geometry. Yagiz and Ozdemir [17] and Yagiz [18] modified the CSM model by adding brittleness of intact rock and fracture properties of rock masses as indices into the model. Moradi and Farsangi [19] estimated the advance rate in rock TBM tunneling using the risk matrix method.

Besides these theoretical and empirical models, soft computing methods have been used to predict the rate of penetration. Grima, Bruines [20] used neuro–fuzzy methods to model the performance of TBM. Benardos and Kaliampakos [21, 22] utilized artificial neural networks for TBM performance prediction. Zhao, Gong [23] introduced a neural network–based model to predict TBM performance. Acaroglu, Ozdemir [24] introduced a fuzzy logic model to predict specific energy requirement for TBM performance prediction. In another attempt by Yagiz [25], two nonlinear prediction tools (artificial neural networks and non–linear multiple regression) presented for the estimation of TBM performance. Torabi, Shirazi [3] two main elements of the TBM performance including the rate of penetration and utilization factor investigated using artificial neural network and statistical package for social sciences. Yagiz and Karahan [26] predicted the hard–rock TBM penetration rate using the particle swarm optimization (PSO) technique.

In this paper, a new approach for data analysis named Adaptive neuro fuzzy inference system based on fuzzy c–means clustering algorithm (ANFIS–FCM) to estimate of TBM performance is demonstrated. In this model, uniaxial compressive strength (UCS), planes of weakness (DPW), alpha angle (α) and intact rock brittleness (BI) were utilized as the input parameters, while the rate of penetration was the output parameter. The estimation abilities offered using ANFIS–FCM is presented by using field data in open source literatures.

2. ADAPTIVE NETWORK–BASED FUZZY INFERENCE SYSTEM

A fuzzy inference system can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. Neural networks (NNs) are information–processing programs inspired by mammalian brain processes. NN are composed of a number of interconnected processing elements analogous to neurons. The training algorithm inputs to the NNs a set of input data and checks the NN output desired result. Combining NNs with fuzzy logic (FL) has been shown to emulate the human process of expert decision–making reasonably. In traditional NNs, only weight values change during learning, thus the learning ability of NNs is combined with the inference mechanism of the FL for a neuro–fuzzy decision–making system [27].

An adaptive neural network is a network structure consisting of several nodes connected through directional links. Each node is characterized by a node function with fixed or adjustable parameters. Once the fuzzy inference system (FIS) is initialized, NN algorithms can be utilized to determine the unknown parameters (premise and consequent parameters of the rules) minimizing the error measure, as conventionally defined for each variable of the system. Due to this optimization procedure the system is called adaptive [28].

The architecture of ANFIS consists of five layers, and a brief introduction of the model is as follows.

Layer 1: each node i in this layer generates a membership grades of a linguistic label. For instance, the node function of the ith node might be:

$$Q_i^1 = \mu_{Ai}(x) = \frac{1}{1 + \left[\left(\frac{x - v_i}{\sigma_i}\right)^2\right]^{b_i}} \tag{1}$$

where, x is the input to node i, and Ai is the linguistic label (small, large, …) associated with this node; and $\{\sigma_i, V_i, b_i\}$ is the parameter set that changes the shapes of the MF. Parameters in this layer are referred to as the "premise parameters".

Layer 2: Each node in this layer calculates the "firing strength" of each rule via multiplication:

$$Q_i^2 = W_i = \mu_{Ai}(x).\mu_{Bi}(y) \qquad i = 1,2 \tag{2}$$

Layer 3: The ith node of this layer calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths:

$$Q_i^3 = \bar{W}_i = \frac{w_i}{\sum\limits_{j=1}^{2} w_j}, \quad i = 1,2 \tag{3}$$

For convenience, outputs of this layer will be called "normalized firing" strengths.

Layer 4: Every node i in this layer is a node function:

$$Q_i^4 = \bar{W}_i f_i = \bar{W}_i (p_i x + q_i y + r_i) \tag{4}$$

where, $\bar{W}_i$ is the output of layer 3. Parameters in this layer will be referred to as "consequent parameters".

Layer 5: The single node in this layer is a circle node labeled R that computes the "overall output" as the summation of all incoming signals:

$$Q_i^5 = Overall\ Output = \sum \bar{W}_i f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{5}$$

Also, in this study, FCM is utilized to identify the antecedent MFs.

2.1 Fuzzy c–means clustering method

The FCM is a data clustering algorithm introduced by Bezdek [29] in which each data point belongs to a cluster to a degree specified by a membership grade. FCM partitions a collection of n vector X_i, $i = 1,2,...,n$, into C fuzzy groups, and finds a cluster center in each group such that a cost function of dissimilarity measure is minimized. The stages of FCM algorithm are therefore, first described in brief. At first, the cluster centers c_i, $i = 1,2,...,C$ randomly from the n points $\{X_1, X_2, X_3,..., X_n\}$ is chosen. After that the membership matrix U using the following equation is computed:

$$\mu_{ij} = \frac{1}{\sum\limits_{k=1}^{c} (\frac{d_{ij}}{d_{kj}})^{2/m-1}} \tag{6}$$

where, $d_{ij} = \|c_i - x_j\|$ is the Euclidean distance between i^{th} cluster center and j^{th} data point, and m is the fuzziness index. Then, the cost function according to the following equation is computed. The process is stopped if it is below a certain threshold.

$$J(U, c_1,...,c_2) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \cdot \sum_{j=1}^{n} \mu_{ij}^m d_{ij}^2 \tag{7}$$

In final step, a new c fuzzy cluster centers c_i, $i = 1,2,...,C$ using the following equation is computed:

$$c_i = \frac{\sum_{j=1}^{n} \mu_{ij}^m x_j}{\sum_{j=1}^{n} \mu_{ij}^m} \tag{8}$$

3. INPUT/ OUTPUT DATA SPACE

The main scope of this work is to implement the above methodology in the problem of TBM penetration rate estimation. Dataset applied in this study for determining the relationship among the set of input and output variables are gathered from open source literature [30]. The database composed of actual measured TBM penetration rate and rock properties were established using the data collected from one hard rock TBM tunnel (the Queens Water Tunnel # 3, Stage 2) about 7.5 km long, New York City, USA. Intact rock properties were obtained from laboratory studies conducted at the Earth Mechanics Institute (EMI) in the Colorado School of Mines, CO, USA. In this study, UCS, planes of weakness (DPW), alpha angle (α) and intact rock brittleness (BI) were utilized as the input parameters, while the rate of penetration was the output parameter. Partial dataset used in this study are presents in Table 1. Also, Table 2 shows statistical description of datasets used in this study.

Table 1: Partial dataset used in this study [30]

| Tunnel stations (m) | Input parameters | | | | Output parameter | Type of rock and descriptions |
	UCS (MPa)	BI (kN/mm)	DPW (m)	Alpha angle (degrees)	Penetration rate (m/h)	
929	168.3	58	1.6	41	2.37	Granitoid (felsic) gneiss and orthogneiss
989	174.1	58	2	35	2.34	Mafic-to-mesocratic orthogneiss
1021	177.9	58	0.4	61	2.9	Granitoid (felsic) gneiss and orthogneiss
1027	180.7	57	0.2	55	3.04	Granitoid (felsic) gneiss and orthogneiss
1045	184.1	57	0.4	49	3.07	Granitoid (felsic) gneiss and orthogneiss

Table 2**:** Statistical description of dataset utilized for construction of models

Parameter	Min	Max	Average
UCS (MPa)	118.3	199.7	149.89
BI (kN/mm)	25	58	34.64
DPW (m)	0.05	2	1.02
Alpha angle (degrees)	2	89	44.57
Penetration rate (m/h)	1.27	3.07	2.05

4. DATA PROCESSING

To start the training, inputs and output data should be normalized for increasing the efficiency of networks in recognition of the relationships between inputs and output data. Normalization is also really helpful in increasing the accuracy of prediction and scaling the data to minimize the biasing of the networks. Data normalization can also reduce the consuming time of training. It is especially useful for modeling those applications where input data are in different scales [31, 32]. There are many normalization techniques conventionally used to scale up the data including Z–Score normalization, Min–Max normalization, sigmoid normalization, statistical column normalization, etc. However, for the purpose of this study, Min–Max normalization method was used. This was due to the capability of Min–Max normalization in maintaining the variation of each feature after normalization. Beside, this normalization method can preserve all of the relationships in the data [32]. Min–Max normalization equation is expressed as below:

$$x_M = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

(9)

where x is the original value of the dataset, x_M is the mapped value, and x_{max} (x_{min}) denotes the maximum (minimum) raw input values, respectively.

In addition to the normalization, mean square error (MSE) and coefficient of determination (R^2) are two conventional criteria considered to assess the efficiency of the networks. The MSE is calculated using the following equation:

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

(10)

where t_k be the actual value and $\hat{t}_k$ be the predicted value of the kth observation and n is the number of samples used for training or testing the network. MSE is routinely used as a criterion to show the discrepancy between the measured and estimated values of the network. Coefficient of determination, R^2, is also calculated as

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

(11)

R^2 is widely used as a representation of the initial uncertainty of the model. The best network model which is unlikely to build, would have MSE=0 and R^2 =1.

5. RESULTS AND DISCUSSION

In a conventional fuzzy inference system, the number of rules is decided by an expert who is familiar with the target system to be modeled. In ANFIS simulation, however, no expert is available and the number of membership functions (MFs) assigned to each input variable is chosen empirically, that is, by plotting the data sets and examining them visually, or simply by trial and error. For data sets with more than three inputs, visualization techniques are not very effective and most of the time it must be relied on trial and error. Generally, it becomes very difficult to describe the rules manually in order to reach the precision needed with the minimized number of membership functions (MFs), when the number of rules are larger than 3. Therefore, an automatic model identification method becomes a must, which is often realized by means of a training set of input–output pairs (Jang 1993; Jang et al. 1997; [33, 34]).

In this study, ANFIS–FCM model was utilized to build a prediction model for the estimation of TBM penetration rate from available data, using MATLAB environment. Fig. 1 shows the fuzzy architecture of ANFIS–FCM model for the estimation of TBM performance. A dataset that includes 153 data points was employed in current study, while 122 data points (80%) were utilized for constructing the model and the remainder data points (31 data points) were utilized for model performance evaluation. The specifications of the ANFIS–FCM model are illustrated in Table 3.
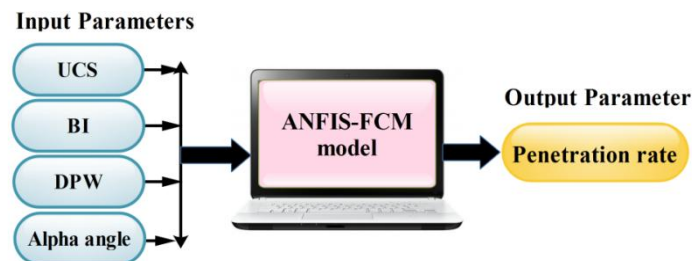

Figure 1. The architecture of ANFIS–FCM model

Table 3: Specifications of the ANFIS–FCM model

Parameter	Description
Membership function type	Gaussian
Output membership function	Linear
Number of nodes	57
Number of linear parameters	25
Number of nonlinear parameters	40
Total number of parameters	65
Number of training data pairs	122
Number of testing data pairs	31
Number of fuzzy rules	5

Fig. 2 shows the membership functions of the input parameters for ANFIS–FCM model. The numbers of rules achieved for the ANFIS–FCM model are 5.
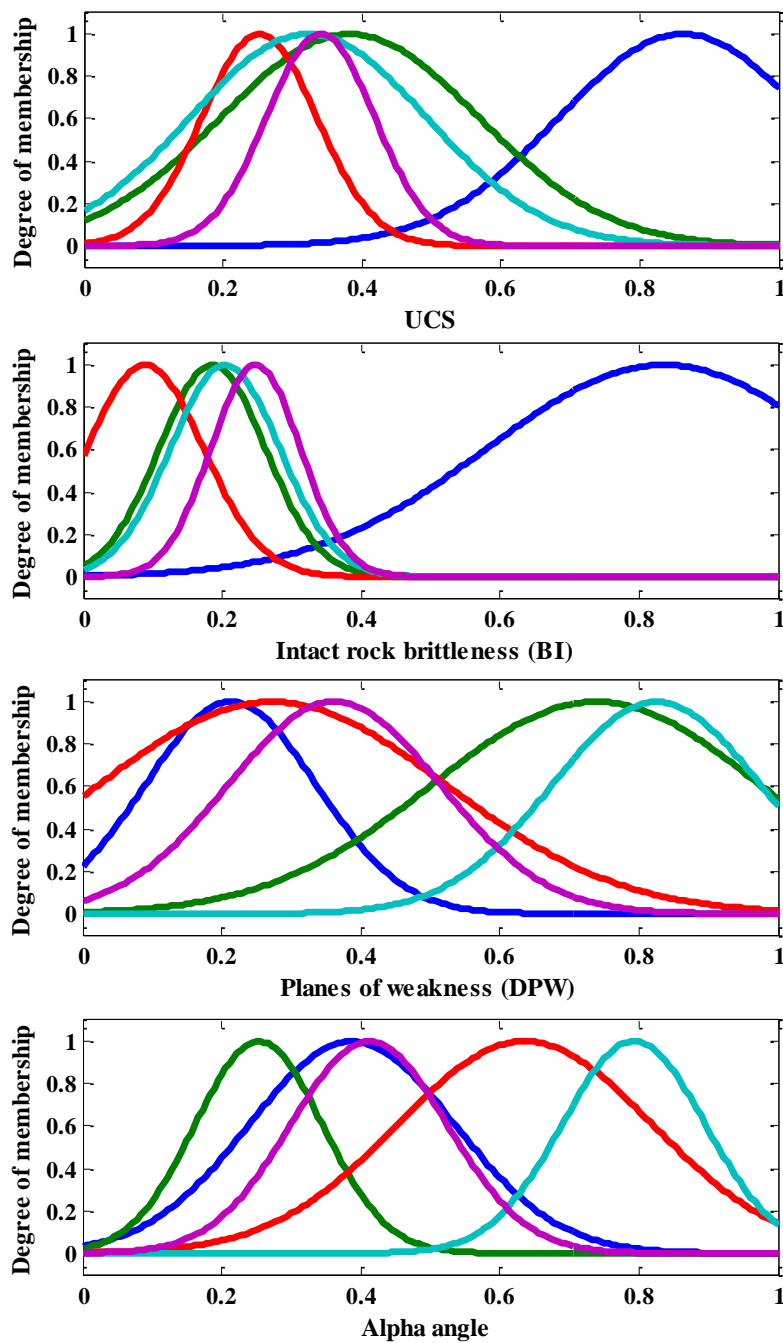
Figure 2. Membership functions of the ANFIS–FCM model

A comparison between estimated values of penetration rate by the ANFIS–FCM model and measured values for 153 data sets at training and testing phases is shown in Fig. 3. As shown in Fig. 3, the results of the ANFIS–FCM model in comparison with actual data show a good precision of the ANFIS–FCM model.
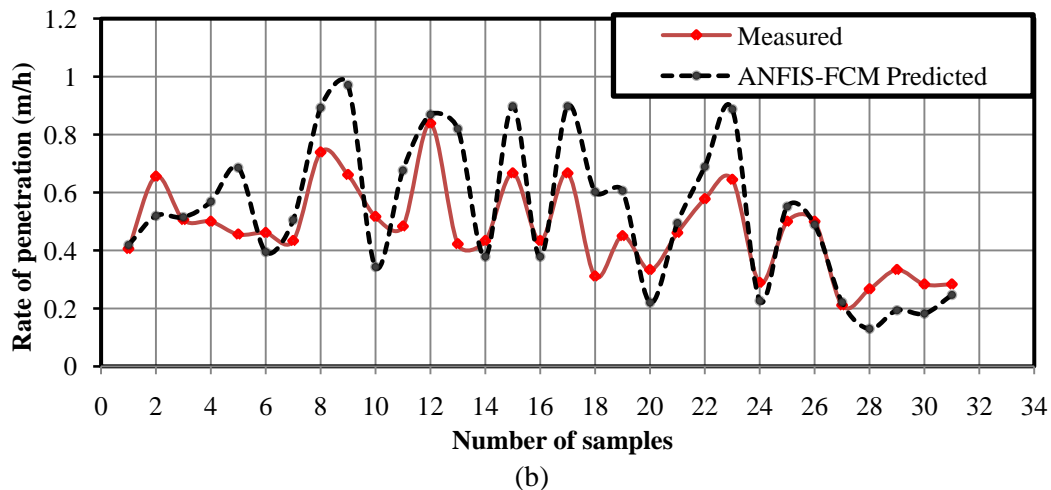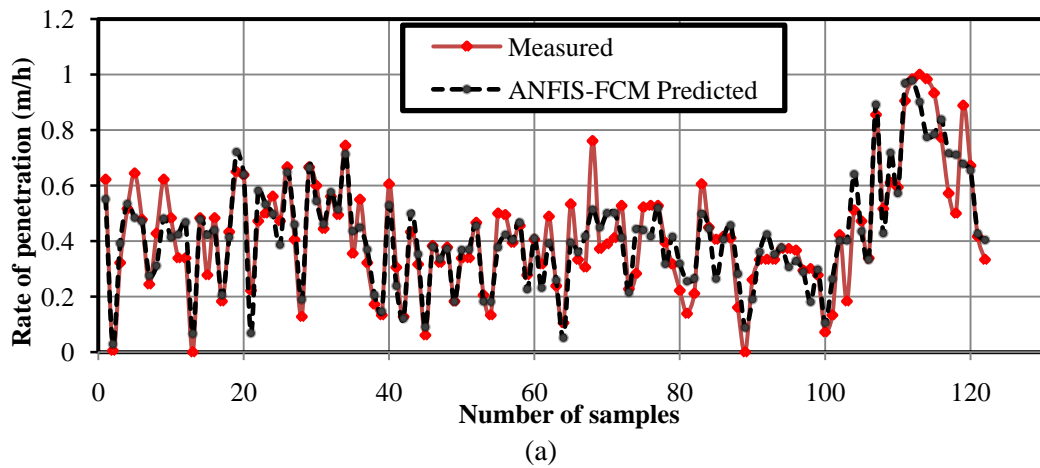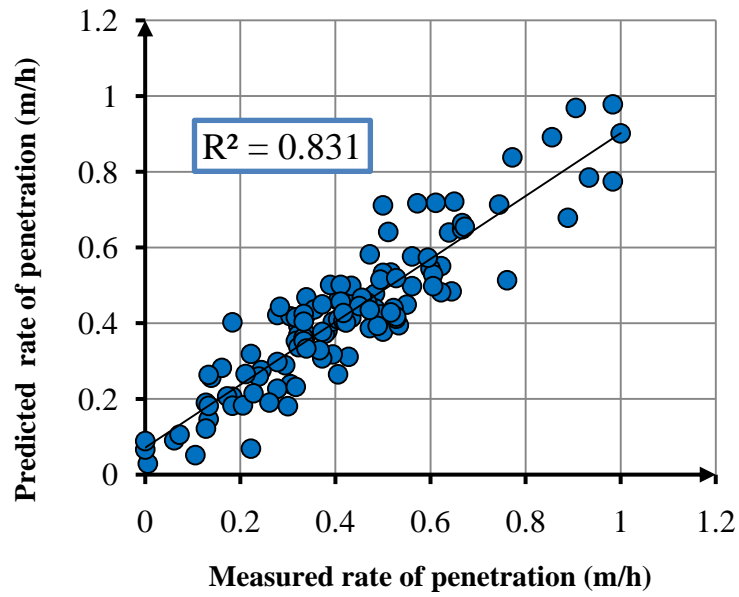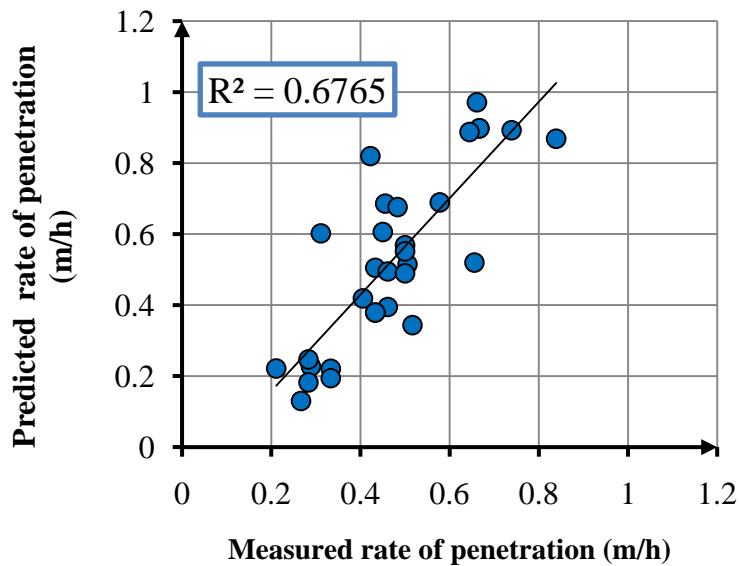
(a)

(b)

Figure 3. Comparison between measured and estimated penetration rate for a) training datasets,
b) testing datasets

Furthermore, a correlation between estimated values of penetration rate by the ANFIS–FCM model and measured values for 153 data sets at training and testing phases is shown in Fig. 4.

Also, performance analysis of the ANFIS–FCM model for predicting penetration rate is shown in Table 4. The performance indices obtained in Table 4 indicate the high performance of the ANFIS-FCM model that can be used successfully to the estimation of the penetration rate.

(a)

(b)

Figure 4. Correlation between measured and estimated rate of penetration for a) training datasets, b) testing datasets

Table 4: Performance analysis of the ANFIS–FCM model for predicting penetration rate

Description		R^2	MSE
ANFIS–FCM model	Training	0.8310	0.0073
	Testing	0.6765	0.0257

Eventually, relative error (error percentage) for data point (training and testing samples) is assessed and revealed in Fig. 5. Relative error for most data points is located in range of [-15% 15%], which is an acceptable value.
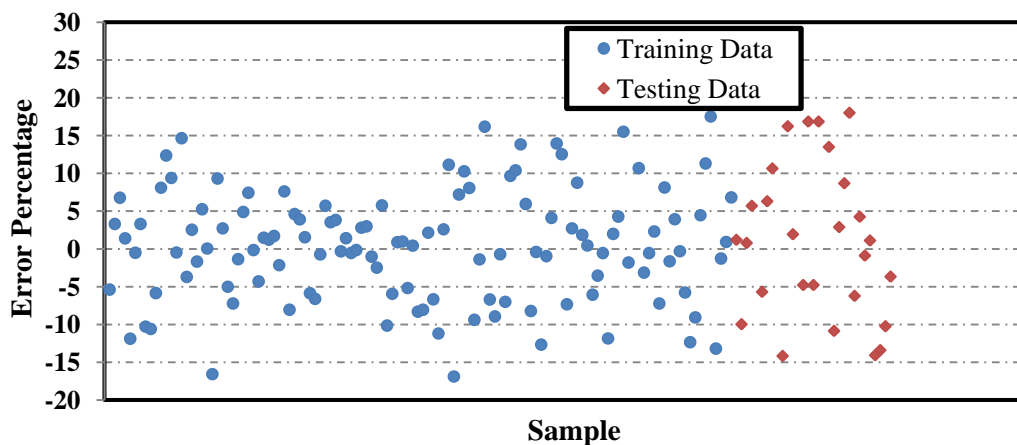

Figure 5. Relative error (error percentage) of ANFIS-FCM model in estimating the penetration rate

6. CONCLUSION

In this study, the ANFIS–FCM technique has been used for estimating the hard rock TBM penetration rate. It is observed that intact and mass rock properties including the UCS, BI, DPW and alpha angle have major effect on the TBM penetration. So, the model was generated based on relevant properties. The following conclusions can be drawn:

- The ANFIS–FCM with R^2= 0.6765 and MSE= 0.0257 is a reliable system modeling technique for predicting penetration rate with highly acceptable degree of accuracy and robustness.
- This study shows that the ANFIS–FCM approach can be applied as a powerful tool for modeling of some problems involved in tunnel engineering.

REFERENCES

1. Bilgin N, Balci C, Acaroglu O, Tuncdemir H, Eskikaya S, Akgul M, et al. The performance prediction of a TBM in tuzla-dragos sewerage tunnel, *World Tunnel Congress* 1999; 817-22.
2. Ribacchi R, Fazio AL. Influence of rock mass parameters on the performance of a TBM in a gneissic formation (Varzo Tunnel), *Rock Mech Rock Eng* 2005; **38**: 105-27.
3. Torabi S, Shirazi H, Hajali H, Monjezi M. Study of the influence of geotechnical parameters on the TBM performance in Tehran - Shomal highway project using ANN and SPSS, *Arabian J Geosci* 2013; **6**: 1215-27.

4. Aeberli U, Wanner H. On the influence of geologic conditions at the application of tunnel boring machines, *3rd International Conferenec International Association of Engineering Geology* 1978*, Madrid*; **2**: pp. 7-14.
5. McFeat-Smith I, Tarkoy PJ. Assessment of tunnel boring machine performance, *Tunnels Tunnell Int* 1979; **11**: 33-7.
6. Cassinelli F, Cina S, Innaurato N. Power consumption and metal wear in tunnel-boring machines: analysis of tunnel-boring operation in hard rock: In: Tunneling 82, *Proceedings of the 3rd International Symposium* 1982, Brighton, 7-11 June, pp. 73-81. Publ London: IMM, 1982. *Int J Rock Mech Mining Sci Geomech Abs* 1983, Pergamon, p. A25.
7. Nelson P. Tunnel boring machine performance in sedimentary rock, 1983.
8. Sanio H. Prediction of the performance of disc cutters in anisotropic rock, *Int J Rock Mech Mining Sci Geomech Abs* 1985, Elsevier, 153-61.
9. Tarkoy P. Practical geotechnical and engineering properties for tunnel-boring machine performance analysis and prediction transportation research record 1087, *Transportation Research Board National Research Council* 1987; pp. 62-78.
10. Barton N. TBM performance estimation in rock using QTBM, *Tunnels & Tunnelling International* 1999; **31**: 41-8.
11. Barton NR. TBM tunnelling in jointed and faulted rock, CRC Press, 2000.
12. Lislerud A. Hard rock tunnel boring: prognosis and costs, *Tunnell Underground Space Technol* 1988; **3**: 9-17.
13. Bruland A. Hard rock tunnel boring advance rate and cutter wear, Norwegian Institute of Technology, Trondheim, Norway, 1999.
14. Norwegian Institute of Technology. Hard Rock Tunnel Boring, Trondheim, Norway, 1995. pp. 1-94.
15. Rostami J, Ozdemir L. A new model for performance prediction of hard rock TBMs, *Proceedings of the Rapid Excavation and Tunneling Conference: Society for Mining*, Metallogy & Exploration, INC, 1993. pp. 793-798.
16. Rostami J, Ozdemir L. Computer modeling for cutterhead design and layout of mechanical excavators, *Proceedings of Institute of Shaft Drilling Technology (ISDT) Annual Technical Meeting* 1993, pp. 2-6.
17. Yagiz S, Ozdemir L. Geotechnical parameters influencing the TBM performance in various rocks, Program with abstracts 44th Annual Meeting of Association of Engineering Geologists Technical Session, 2001.
18. Yagiz S. Development of rock fracture and brittleness indices to quantify the effects of rock mass features and toughness in the CSM Model basic penetration for hard rock tunneling machines [PhD thesis], USA, Colorado School of Mines, 2002.
19. Moradi MR, Farsangi MAE. Application of the risk matrix method for geotechnical risk analysis and prediction of the advance rate in rock TBM tunneling, *Rock Mech Rock Eng* 2014; **47**: 1951-60.
20. Grima MA, Bruines P, Verhoef P. Modeling tunnel boring machine performance by neuro-fuzzy methods, *Tunnell Underground Space Technol* 2000; **15**: 259-69.
21. Benardos A, Kaliampakos D. A methodology for assessing geotechnical hazards for TBM tunnelling - illustrated by the Athens Metro, Greece, *Int J Rock Mech Mining Sci Geomech Abs* 2004; **41**: 987-99.

22. Benardos A, Kaliampakos D. Modelling TBM performance with artificial neural networks, *Tunnell Underground Space Technol* 2004; **19**: 597-605.
23. Zhao Z, Gong Q, Zhang Y, Zhao J. Prediction model of tunnel boring machine performance by ensemble neural networks, *Geomech Geoeng: Int J* 2007; **2**: 123-8.
24. Acaroglu O, Ozdemir L, Asbury B. A fuzzy logic model to predict specific energy requirement for TBM performance prediction, *Tunnelling Tunnell Underground Space Technol* 2008; **23**: 600-8.
25. Yagiz S. Assessment of brittleness using rock strength and density with punch penetration test, *Tunnell Underground Space Technol* 2009; **24**: 66-74.
26. Yagiz S, Karahan H. Prediction of hard rock TBM penetration rate using particle swarm optimization, *Int J Rock Mech Mining Sci Geomech Abs* 2011; **48**: 427-33.
27. Lin CT, Lee CSG. Neural-network-based fuzzy logic control and decision system, *IEEE Trans Comput*1991; **40**: 1320-36.
28. Jang JSR. ANFIS: Adaptive-network-based fuzzy inference system, *IEEE Trans Syst, Man Cybernet* 1993; **23**: 665-85.
29. Bezdek JC. Fuzzy mathematics in pattern classification [Ph.D. Thesis], Ithaca, Cornell university, 1973.
30. Yagiz S. Utilizing rock mass properties for predicting TBM performance in hard rock condition, *Tunnell Underground Space Technol* 2008; **23**: 326-39.
31. Gholami R, Moradzadeh A, Maleki S, Amiri S, Hanachi J. Applications of artificial intelligence methods in prediction of permeability in hydrocarbon reservoirs, *J Petrol Sci Eng* 2014; **122**: 643-56.
32. Jayalakshmi T, Santhakumaran A. Statistical normalization and back propagation for classification, *Int J Comput Theory Eng* 2011; **3**: 1793-8201.
33. Chopra S, Mitra R, Kumar V. Reduction of fuzzy rules and membership functions and its application to fuzzy PI and PD type controllers, *Int J Control, Automat Syst* 2006; **4**: 438-447.
34. Ming-bao P, Xin-ping Z. Traffic flow prediction of chaos time series by using subtractive clustering for fuzzy neural network modeling, , *IITA'08 Second International Symposium on:* Intelligent Information Technology Application *IEEE* 2008. pp. 23-27.