3rd Nordic Rock Mechanics Symposium
October 11-12, 2017, Helsinki, Finland
Johansson & Raasakka (eds)
ISBN 978-951-758-622-1
ISSN 0356-9403

DEFORMATION MODULUS (Em) OF ROCK MASSES: RECENT DEVELOPMENTS

Candan Gokceoglu (cgokce@hacettepe.edu.tr)
Hacettepe University
Turkey

ABSTRACT

Direct determination of the deformation modulus of rock mass needs sophisticated testing equipment, time-consuming processes and experienced technical staff. However, this modulus has a crucial importance for all rock engineering project to be constructed on or in a rock mass. For this reason, indirect determination of deformation modulus of rock mass has been attractive subject for rock engineers and engineering geologists. For this reason, during the last two decades, several empirical equations based on statistical analysis and several other soft computing algorithms for indirect determination of deformation modulus of rock masses have been proposed. In the present study, a critical review on these approaches is performed and a summary is given. For the purpose of the study, an extensive literature survey is carried out and the approaches suggested are discussed.

KEYWORDS

Rock mass, deformation modulus, empirical equation, soft computing

INTRODUCTION

Depending on the increase in World population, new human needs such as high buildings, transportation and energy also increase. As a result of these needs, new infrastructures such as roads, railroads, tunnels, viaducts, dams, ports etch have been constructed and will be constructed. During the project and construction stages of these infrastructures, the deformation modulus of rock mass is necessary. However, field tests to determine this parameter directly are time consuming, expensive and the reliability of the results of these tests is sometimes questionable (Hoek and Diederichs, 2006). For this reason, indirect determination methods can be preferred if the other rock mass and intact rock properties are known well. Considering this reason, during the last two decades, several researchers have suggested empirical equations based on statistical analysis and soft computing algorithms for indirect determination of deformation modulus of rock masses. The main purpose of the present study discusses the approaches suggested for estimation of deformation modulus of rock masses.

The static modulus of deformation is among the parameters that best represent the mechanical behaviour of a rock and of a rock mass, in particular when it comes to underground excavations. The deformation modulus is, therefore, a cornerstone of many geomechanical analyses (Palmstorm and Singh, 2001). The deformation modulus is the most representative parameter describing the pre-failure mechanical behavior of any engineering material (Jiang et al., 2009). However, deformation modulus of a rock mass is affected by various rock mass and intact rock properties as well as environmental conditions. Although its crucial importance, generally, the mechanical properties of rock masses are not clear-cut, and most of the times are associated with uncertainties due to their complex and inhomogeneous nature (Bashari et., 2011). Kavur et al. (2015) applied two in-situ tests such as plate jacking (PJT) and large flat jack tests (LFJ) on the same area. The comparison between the PJT and LFJ test results has shown significant differences.The PJT moduli obtained from displacements measured at extensometer points in depth are much higher than the LFJ moduli but fortunately they can be correlated with reliable LFJ results (Kavur et al., 2015). This example shows that the results of the in-situ tests for determination of deformation modulus of rock mass are also open to discussion because of complex nature of rock mass and difficult test conditions. Recently, a review on the evaluation of rock mass deformability using empirical methods has been published by Zhang (2017). According to Zhang (2017), a large number of empirical methods are available for determining the Em of rock masses. It is hard or impossible to decide which method is the most accurate. Due to this complex nature and high uncertainties, several authors (Shen et al., 2012; Aksoy et al., 2012; Panthee et al., 2017) tried to compare the existing empirical relationships. Normally, the different results are obtained depending on rock type, rock mass quality, test conditions etc. In recent years, some researchers (Kayabasi et al., 2003; Gokceoglu et al., 2004; Sonmez et al., 2006; Majdi and Beiki, 2010; Beiki et al., 2010;

3rd Nordic Rock Mechanics Symposium
October 11-12, 2017, Helsinki, Finland
Johansson & Raasakka (eds)
ISBN 978-951-758-622-1
ISSN 0356-9403

Bashari et al., 2011; Martins and Miranda, 2012; Nejati et al., 2014; Asrari et al., 2015; Feng and Jimenez, 2015; Alemdag et al., 2016; Fattahi, 2016) have attempted to use various soft computing methods to minimize the uncertainties when determining Em of rock masses.

The study contains two main parts such as empirical equations and soft computing algorithms proposed for estimation of Em.

1. THE EXISTING EMPIRICAL EQUATIONS PORPOSED FOR DEFORMATION MODULUS

In the last two decades, several researchers have suggested various empirical equations to predict Em of rock mass. Twenty-eight empirical equations were collected from the literature and were tabulated in Table 1. An important number of these equations use Rock Rass Rating (RMR) (Bieniawski, 1973; Serafim and Pereira, 1983; Nicholson and Bieniawski, 1990; Mitri et al., 1994; Aydan et al., 1997; Read et al., 1999; Palmstrom, 2000; Gokceoglu et al., 2003; Ramamurty, 2004; Galera et al., 2005; Sonmez et al., 2006; Chun et al., 2006; Isık et al., 2008; Mohammadi and Rahmannejad, 2010; Shen et al., 2012; Alemdag et al., 2015). A minor number of equations employ Tunnelling Quality Index (Q) (Grimstad and Barton, 1993; Barton, 2002) and the Geological Strength Index (GSI) (Hoek and Brown, 1997; Hoek and Diederichs, 2006; Beiki et al., 2010; Ghamgosar et al., 2010) and remains considered rock mass properties, such as RQD and weathering degree (Kayabasi et al., 2003; Gokceoglu et al., 2003; Zhang and Einstein, 2004; Sonmez et al., 2006; Alemdag et al., 2016).

Table 1. Summary of empirical equations considered

Author	Empirical Equation	Limitations
Bieniawski (1973)	E_m=2RMR-100	RMR>50
Serafim and Pereira (1983)	$E_m=100^{(RMR-10)/40}$	RMR<50
Nicholson and Bieniawski (1990)	$E_m=E_i$[0,0028RMR2+0.9exp(RMR/22.92)]	
Grimstad and Barton (1993)	E_m=25 log Q	For Q>1
Mitri et al. (1994)	$E_m=E_i$[0,5(1-(Cos(π*RMR/100)))]	
Hoek and Brown (1997)	$E_m=(\sigma_c/100)^{0.5}*10^{(GSI-10)/40}$	σ_c<100(MPa)
Aydan et al. (1997)	$Em=0.1(RMR/10)^3$	
Read et al. (1999)	$E_m=0.1(RMR/10)^3$	
Palmstorm (2000)	$E_m=5.6(RMR)^{0.375}$	
Barton (2002)	$E_m=10(Q\sigma_c/100)^{1/3}$	
Kayabasi et al. (2003)	$E_m=0.135[(E_i(1+RQD/100))WD]^{1.811}$	
Gokceoglu et al. (2003)	$E_m=0.001[((E_i/UCS)(1+RQD/100))/WD]^{1.5528}$	
Gokceoglu et al. (2003)	$E_m=0.0736e^{(0.0755RMR)}$	
Carvalho (2004)	$Em=E_is^{1/4}$ Ei=50 GPa, s=exp((GSI-100)/9)	
Zhang and Einstein (2004)	$E_m=E_i10(^{0.0186RQD-1.91)}$	
Ramamurty (2004)	$E_m=E_ie(^{-0.035(5(100-RMR))}$	
Galera et al. (2005)	$E_m=E_ie^{(RMR-100)/36}$	
Sonmez et al. (2004)	$E_m=E_i(s^{a})^{0.4}$	
Sonmez et al. (2006)	$E_m=E_i$*10[((RMR-100)(100-RMR))/(4000exp(-RMR/100))]	
Hoek and Diederichs (2006)	$E_m=E_i[0.02+(1-(D/2))/(1+e^{((60+15D-GSI)/11)}]$	D=1
Chun et al. (2006)	$E_m=0.003228e^{(0.0495RMR)}$	
Isık et al. (2008)	E_m=(6.7*RMR-103.6)/1000	RMR≥27
Mohammadi and Rahmannejad (2010)	$E_m=0.0003RMR^3-0.0193RMR^2+0.315RMR+3.4065$	
Beiki et al. (2010)	$E_m=\tan(1.56+(\ln(GSI)^2)^{1/2}\sigma^{1/3}$	
Ghamgosar et al. (2010)	$E_m=0.0912e^{0.0866GSI}$	
Shen et al. (2012)	$E_m=1.14E_ie^{-((RMR-116)/41)\wedge 2}$	
Alemdag et al. (2015)	$E_m=0.058e^{0.0785RMR}$	
Alemdag et al. (2016)	$E_m=0.00067RQD^2+0.00067RQD\sigma+(0.00067RQD\sigma+0.00067\sigma^2)$ /(RQD+99.5)	

Depending on the increase in the number of the empirical equations for estimating Em of rock masses, some authors (Gokceoglu et al., 2003; Aksoy et al., 2012; Shen et al., 2012; Panthee et al., 2017; Zhang, 2017) have attempted to check their performances employing their measured data. According to the findings of Gokceoglu et al. (2003), Nicholson and Bieniawski's (1990) empirical equation exhibited high performance considering the data presented in Gokceoglu et al. (2003). The equations proposed by Bieniawski (1973) and Mitri et al. (1994) yielded highly scattered results (Gokceoglu et al., 2003). Hoek and Brown's (1997) equation gave the best results for mainly weak rock masses having a low uniaxial compressive strength (Gokceoglu et al., 2003). Working at 12 hydroelectric plant tunnels and at 3 metro tunnels, having different rock mass conditions, rock mass deformation modulus calculated from different empirical equations were evaluated by Aksoy et al. (2012). According to the results of Aksoy et al. (2012), Em of rock mass obtained from Barton (2002) empirical equation are higher than the others. Em of rock mass calculated through suggested empirical equation by Palmstrom and Singh (2001) gives more realistic results in tunnels which have hard (almost brittle level) and big block sized rock

ISBN 978-951-758-622-1
ISSN 0356-9403

mass (Aksoy et al., 2012). As the other finding obtained from the study of Aksoy et al. (2012), values of Em of rock mass calculated from the equation suggested by Sonmez et al. (2004) are lower in hard and big block-sized rock masses and higher in weak and little block sized rock masses than that suggested by Hoek and Diederichs (2006). Finally, Aksoy et al. (2012) emphasised that performance of the equation suggested by Sonmez et al. (2004) for determining the rock mass deformation modulus in numerical modelling is more realistic.

The most widely used empirical equations for the estimation of Em of rock mass based on the Rock Mass Rating (RMR) and the Geological Strength Index (GSI) classification systems have been reviewed by Shen et al. (2012). Comparison analyses of existing equations show that in the category which does not involve the deformation modulus of intact rock (Ei) the equations proposed by Read et al. (1999) and Hoek and Diederichs (2006) give the best prediction for the RMR and GSI category respectively (Shen et al., 2012). As the other important conclusion drawn by Shen et al. (2012), in the category where the deformation modulus of intact rock is considered, the equations proposed by Sonmez et al. (2006) and Carvalho (2004) performed the best for the RMR and GSI category respectively.

Recently, an extensive research on comparison of Em of rock mass was carried out by Panthee et al. (2017) and some interesting and comprehensible results were obtained. The obtained values from the empirical equations were compared to understand the disparity or similarity emanating from rock mass class and rock types by Panthee et al. (2017). According to the findings of Panthee et al. (2017), a significant pattern of Em depending on rock classes was not observed for all equations, as stated by Kayabasi et al. (2003) previously. A range of differences in Em values obtained from different equations was observed for the same rock class by Panthee et al. (2017). According to the results of Panthee et al. (2017), based on RMR, values of Em of rock mass obtained from Gokceoglu et al. (2003) and Bieniawski (1978), Serafim and Pereira (1983) show a wide range of difference. The equation used by Bieniawski (1978) is in linear function which is less sensitive with the parameters, while the equation used by Gokceoglu et al. (2003) is an exponential function which is very sensitive to the parameters (Panthee et al., 2017). The conclusion drawn by Panthee et al. (2017) is important and correct assessment for this subject. Similar differences were found for the equations suggested by Grimstad and Barton (1993) and Barton (1983) by Panthee et al. (2017).

A comprehensive and recent review on Em of rock mass was published by Zhang (2017). Zhang (2017) discussed the scale effect on rock mass deformability, the effect of confining stress on rock mass deformability, and the anisotropy of rock mass deformability in his study. According to Zhang (2017), it is hard or impossible to decide which method is the most accurate. The estimated Em values from the various empirical methods can be very different. So the evaluation of Em should not rely only on a single empirical method. Instead, various empirical methods should be used to get an idea on the possible range of the Em (Zhang, 2017). The most important and original conclusion drawn by Zhang (2017) is on the scale and anisotropy effects on Em of rock mass. Zhang (2017) stated that rock mass deformability is strongly scale and stress dependent and usually shows strong anisotropy. However, the empirical methods do not consider either the effect of scale and stress on Em or the anisotropy of Em. It is important to specify the corresponding conditions such as orientation of the parameter(s) used in the determination of Em (Zhang, 2017).

As can be seen from the results of the recent studies on the Em of rock mass, the equations proposed by various researches have been under discussion and there is no a consensus on the reliability of an empirical equation due to the complexity of the problem. The behaviour of rock masses against to different stresses is extremely complex and non-linear. In addition, type and size of project to be applied affect directly deformability pattern of rock mass. This complexity results in a serious uncertainty on rock mass deformability characteristics.

2. USE OF SOFT COMPUTING ALGORITHMS TO PREDICT DEFORMATION MODULUS OF ROCK MASS

As stated previously, Em of rock mass is governed by several parameters, environmental conditions, and nature and magnitude of stresses acting to rock mass, and hence this situation creates high complexity and uncertainty. Considering this situation, some researches have attempted to employ some soft computing algorithms to handle the complexity and to minimize the uncertainties.

ISBN 978-951-758-622-1
ISSN 0356-9403

The first attempt to estimate Em of rock mass by Mamdani fuzzy inference system was carried out by Kayabasi et al. (2003). Kayabasi et al. (2003) constructed a fuzzy inference system considering modulus of elasticity of intact rock, RQD and weathering degree of rock mass. According to the results of Kayabasi et al. (2003), the fuzzy inference system provided the more reliable results than the empiricial equations obtained from the simple and multiple regression analyses. As a more powerful algorithm due to its hybrid nature, neuro-fuzzy was first used to predict Em of rock mass by Gokceoglu et al. (2004). When developing this algorithm, Gokceoglu et al. (2004) considered uniaxial compressive strength and modulus of elasticity of intact rock, RQD and weathering degree of rock mass. Gokceoglu et al. (2004) stated that the neuro-fuzzy model exhibits a high performance when compared to the empirical equations based on regression analyses. When using these algorithms and models, rock engineers and engineering geologists have probably encountered some difficulties. For this reason, these models have not been used in practice although their high prediction performances. Additionally, for a long time after publication of these prediction models, new soft computing models to predict Em of rock mass have not been published in the international literature. However, during the last seven years, some serious studies have been published.

Majdi and Beiki (2010) proposed a model to predict Em of rock mass based on neural network and genetic algorithm. They found that uniaxial compressive strength of intact rock, GSI and RQD are the main parameters to predict Em of rock mass. It is evident that these results are controlled by the data at hand. If the database changes, the results also change because these methods are data-driven. However, the results obtained by Majdi and Beiki are plausible. Beiki et al. (2010) used genetic algorithm to develop empirical equation to predict Em of rock mass. The parameters considered by Beiki et al. (2010) for estimation of Em of rock mass are uniaxial compressive strength of intact rock, GSI and RQD. The study published by Beiki et al. (2010) is the first attempt to develop empirical equation based on genetic algorithm to predict Em of rock mass. The equations of Beiki et al. (2010) exhibited very high prediction performances. Bashari et al. (2011) developed a Takagi-Sugeno fuzzy algorithm for estimation of Em of rock mass. As stated previously, Gokceoglu et al. (2003) developed a Mamdani fuzzy algorithm for the same purpose. Takagi-Sugeno fuzzy algorithms is data-driven model while Mamdani fuzzy algorithm can be developed by only expert opinion and knowledge. Consequently, the results obtained by Bashari et al. (2011) are promising although the number of cases are limited. Martins and Miranda (2012) used various data mining algorithms to predict Em of rock mass. These techniques include multiple regression, artificial neural networks, support vector machines, regression trees and k-nearest neighbours. Martins and Miranda (2012) assessed the importance of the parameters on Em of rock masses, and they found that depth, uniaxial compressive strength and joint spacing are the most important parameters. Consequently, employing these parameters, several models were developed by Martins and Miranda (2012). Among the models developed by Martins and Miranda (2012), artificial neural network exhibited best performance. In fact, these models are far from practical use because the models are based on data mining with limited number of cases and without considering the nature of rock mass. However, this study (Martins and Miranda, 2012) can be accepted as a good data mining application in rock mechanics and engineering geology literature.

Nejati et al. (2014) developed an artificial neural network model to predict Em of rock mass. They used basic RMR parameters such as uniaxial compressive strength, RQD, joint spacing, joint condition and groundwater. Nejati et al. (2014) proposed both multiple regression equation and artificial neural network model for estimation of Em of rock mass. When the prediction capacities of both models are compared, it is seen that artificial neural network model exhibited very high prediction capacity. However, the number of cases of Nejati et al. (2014) is limited and the number of free parameters of their model is very high. For this reason, the artificial neural network model developed by Nejati et al. (2012) is a typical overlearned model and hence, it is impossible to use it in engineering applications. Asrari et al. (2015) developed an ANFIS model for prediction of Em of rock mass. In the ANFIS model developed by Asrari et al. (2015), five parameters, including depth, uniaxial compressive strength of intact rock, RQD, spacing of discontinuities, and the condition of discontinuities were considered. Although Asrari et al. (2015) obtained very high performance, the number of free parameters of the model is high and, consequently this model is also overlearned model and it is impossible to use for practical engineering purposes. Feng and Jimenez (2015) proposed an approach, based on model selection criteria such as Akaike information criterion, Bayesian information criterion and deviance information criterion to select the most appropriate model, among a set of four candidate models to estimate Em of rock mass. The study of Feng and Jimenez (2015) can be accepted as an important contribution to reduce prediction uncertainty.

3rd Nordic Rock Mechanics Symposium
October 11-12, 2017, Helsinki, Finland
Johansson & Raasakka (eds)
ISBN 978-951-758-622-1
ISSN 0356-9403

Alemdag et al. (2016) developed some soft computing models such as neural network, neuro fuzzy and genetic programming approaches to estimate Em of stratified rock mass. They used RMR, uniaxial compressive strength and modulus of elasticity of intact rock and RQD as the independent variables while Em of rock mass is dependent variable. Due to the limited number of cases, the number of membership functions and independent variables were considered limited to avoid overlearning. The results obtained by Alemdag et al. (2016) are satisfactory but these models can only be valid for stratified rock masses. Asadizadeh and Hossaini (2016) developed an artificial neural network model for predicting Em of rock mass. Their model includes overburden height, rock quality designation, uniaxial compressive strength, bedding/joint inclination to core axis, joint roughness coefficient and filling thickness of joints as input parameters. The model developed by Asadizadeh and Hossaini (2016) yielded good prediction performance and this model can be used for practical purposes in similar rock mass conditions.

Fattahi (2016) developed some ANFIS models based on grid partitioning, fuzzy c-means clustering and subtractive clustering for estimation of Em of rock mass. When developing models, Fattahi (2016) considered RMR, uniaxial compressive strength and elasticity modulus of intact rock and depth as the input parameters. As can be seen Figure 1, while the trained data sets yielded exceptional high performances, the coefficients of cross-correlation of the testing data sets are rather low. This is another typical example for overlearning problems. Theoretically, excessive training, which is also known as overlearning can result in near-zero error on predicting training data. However, this overlearning may result in loss of the ability of the ANN to generalize from the test data, Figure 2. The increasing point in the error of the test data or the closest point to the training curve is considered to represent the optimal number of cycles for the artificial neural network architecture (Sonmez et al., 2006). Another problem causing overlearning is the unsuitable model structure. Some researchers do not pay attention to the model structure and the number of free parameters. However, the model structure is directly affected by the number cases and the models must be constructed considering the number of cases in the database at hand. These types of misuses prevent the use of the soft computing models in practical purposes.

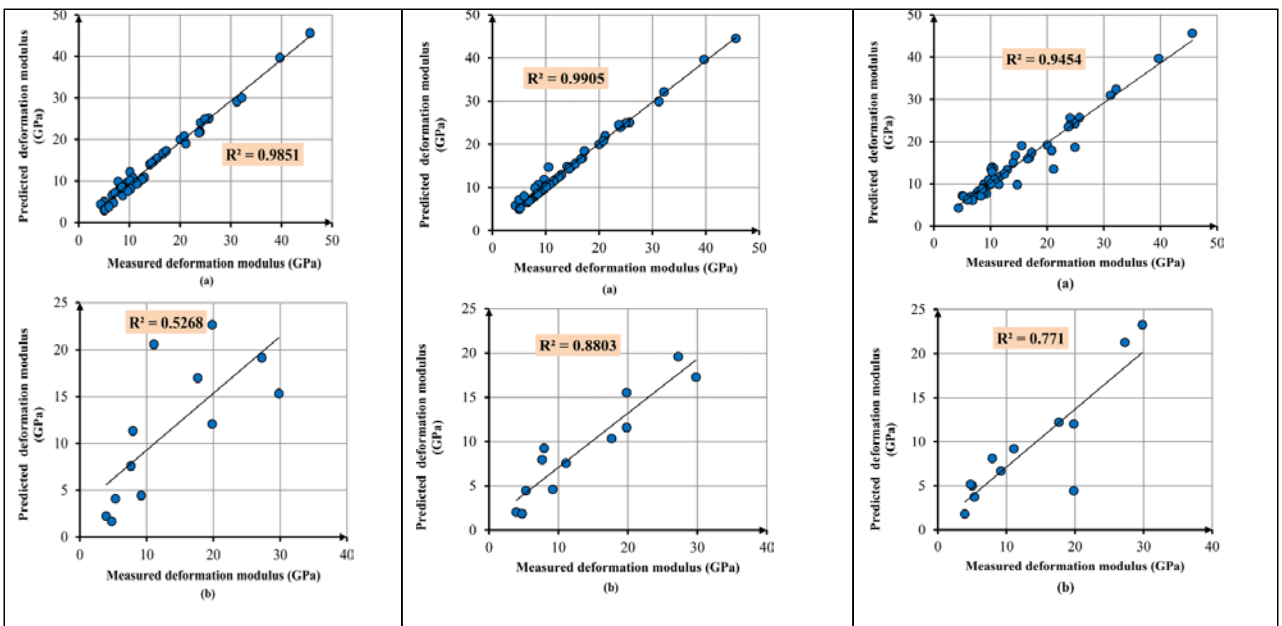

Fig. 6. Correlation between measured and predicted values of deformation modulus by ANFIS-GP model (a) training data, (b) testing data.

Fig. 7. Correlation between measured and predicted values of deformation modulus by ANFIS-SCM model (a) training data, (b) testing data.

Fig. 8. Correlation between measured and predicted values ofdeformation modulus by ANFIS-FCM model (a) training data, (b) testing data.

Figure 1. Cross-correlations of training and testing data sets of the models developed by Fattahi (2016) (Figures and Figure captions are taken directly from Fattahi, 2016).

ISBN 978-951-758-622-1
ISSN 0356-9403

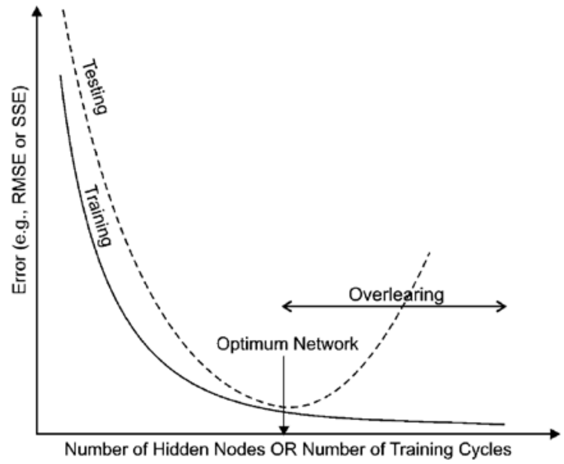

Figure 2. A criteria for termination of training and selection of optimum network architecture (after Basheer and Hajmeer 2000; Figure is taken directly from Sonmez et al., 2006)

3. CONCLUSIONS

In this proceeding paper, the recent developments on estimation of Em of rock mass are summarized and the existing shortcomings on estimation of Em of rock mass are tried to put forth. The following conclusions can be drawn from the review of the literature:

(a) Although technological developments, direct determination of Em of rock mass is still an exhaustive process. For this reason, rock engineers and engineering geologists will continue to use and to develop models for predicting Em of rock mass.
(b) Em of rock mass is controlled by numerous factor; structure of rock mass is highly complex and heteregenous; and deformation reaction of rock mass against to stresses is not linear. For this reason, reliable measurement and/or reliable estimation of Em of rock mass are still very difficult task although its crucial importance for safe and economic design of a rock structure.
(c) The limitations of the existing empirical equation for prediction of Em must be considered when used for engineering purposes. Misuse of these equations results in failure or overdesign. As a consequence of this problem, uneconomical or unreliable rock structures may be constructed.
(d) Recently, several authors proposed soft computing models for prediction of Em of rock mass. However, these models are still far from use of engineering purposes. The main limitation of these models is the required number of data for model construction. Also, use of these models by practionners is still difficult.

REFERENCES

Aksoy, O.C., Genis, M., Aldas, U.C., Ozacar, V., Ozer, C.S., Ozcelik, Y., (2012). *A comparative study of the determination of rock mass deformation modulus by using empirical approaches*. Engineering Geology 131-132, 19–28.

Alemdag, S., Gurocak, Z., Gokceoglu, C., (2015). *A simple regression based approach to estimate deformation modulus of rock masses*. J. Afr. Earth Sci. 110, 75–80.

Alemdag, S., Gurocak, Z., Cevik, A., Cabalar, A.F., Gokceoglu, C., (2016). *Modeling deformation modulus of a stratified sedimentary rock mass using neural network, fuzzy inference and genetic programming*. Eng Geol, 203: 70–82.

Asrari, A.A., Shahriar, K., Ataeepour, M., (2015). *The performance of ANFIS model for prediction of deformation modulus of rock mass*. Arab J Geosci, 8:357–365, DOI 10.1007/s12517-013-1097-9.

Aydan, O., Ulusay, R., and Kawamoto, T., (1997). *Assessment of rock mass strength for underground excavations*. Proceedings of the 36th US rock mechanics symposium, New York, June/July, 777-786.

Barton, N., (1983). *Application of Q system, index tests to estimate shear strength and deformability of rock masses*. In: Proceedings of the international symposium on engineering geology and underground construction, vol I(II), Lisbon, pp. 51–70.

Barton, N., (2002). *Some new Q value correlations to assist in site characterization and tunnel design*. Int J Rock Mech Min Sci 39:185–216.

Bashari, A., Beiki, M., Talebinejad, A., (2011). *Estimation of deformation modulus of rock masses by using fuzzy clustering-based modelling.* Int J Rock Mech Min Sci 48: 1224-1234.

Beiki, M., Bashari, A., Majdi, A., (2010). *Genetic Programming approch for estimating the deformation modulus of rock mass using sensitivity analysis by neural network*. Int J Rock Mech Min Sci, 47, 1091-1103.

Bieniawski, Z., (1973). *Engineering classification of rock masses*. Trans S Afr Inst Civ Eng, 15: 335–344.

Carvalho, J., (2004). Estimation of rock mass modulus. Personal communication by Hoek and Diederichs (2006).

Chun, B., Lee, Y., Seo, D., Lim, B., (2006). *Correlation of deformation modulus by PMT with RMR and rock mass condition*. Tunnelling and Underground Space Technology, 21(3-4), 231-232.

Fattahi, H., (2016). *Indirect estimation of deformation modulus of an in situ rock mass: an ANFIS model based on grid partitioning, fuzzy c-means clustering and subtractive clustering*. Geosciences Journal, 20(5): 681-690.

Feng, X., Jimenez, R., (2015). *Estimation of deformation modulus of rock masses based on Bayesian model selection and Bayesian updating approach*. Eng Geol, 199: 19-27.

Galera, J. M., Alvarez, Z., Bieniawski, Z.T., (2005). *Evaluation of the deformation modulus of rock masses: comparison between pressure meter and dilatometer tests with RMR predictions*. Proc. ISP5-PRESSIO 2005, eds Gambin, Magnen, Mestat and Baguelin. LCPC Publication Paris.

Ghamgosar, M., Fahimifar, A., Rasouli, V., (2010). *Estimation of rock mass deformation modulus from laboratory experiments in Karun dam*. Proceedings of the International Symposium of the International Society for Rock Mechanics (pp. 805-808). Zhao, Laboise, Dudt & Mathier (eds): Taylor & Francis Group.

Gokceoglu, C., Sonmez, H., and Kayabasi, A., (2003). *Predicting the deformation moduli of rock masses*. Int. J. Rock Mech. Min. Sci. 40, 701-710.

Gokceoglu, C., Yesilnacar, E., Sonmez, H., Kayabasi, A., (2004). *A neuro-fuzzy model for modulus of deformation of jointed rock masses*. Computers and Geotechnics 31: 375–383.

Grimstad, E., Barton, N., (1993). *Updating the Q-System for NMT*. In:Proceedings of the International Symposium on Sprayed Concrete-Modern Use of Wet Mix Sprayed Concrete for underground Support, Oslo, Norwegian Concrete Association.

Hoek, E., Brown, E.T., (1997). *Practical estimates of rock mass strength*. Int J Rock Mech Min Sci 34(8):1165–86.

Hoek, E., Diederichs, M., (2006). *Empirical estimation of rock mass modulus*. Int J Rock Mech Min Sci 43:203–215.

ISBN 978-951-758-622-1
ISSN 0356-9403

Isik, N., S., Ulusay, R., Doyuran, V., (2008). *Deformation Modulus of Heavily Jointed-Sheared and Blocky Greywackes by Pressuremeter Tests: Numerical, Experimental and Empirical Assessments*. Eng Geol, 101: 269-282.

Jiang, X-W., Wan, L., Wang, X-S., Wu, X., Zhang, X., (2009). *Estimation of rock mass deformation modulus using variations in transmissivity and RQD with depth*. Int J Rock Mech Min Sci 46:1370–1377.

Kavur, B., Cvitanović, N.S., Hrženjak, P., (2015). *Comparison between plate jacking and large flat jack test results of rock mass deformation modulus*. Int J Rock Mech Min Sci 73: 102-114.

Kayabasi, A., Gokceoglu, C., Ercanoglu, M., (2003). *Estimating the deformation modulus of rock masses: a comparative study*. Int J Rock Mech Min Sci 40: 55-63.

Majdi, A., Beiki, M., (2010). *Evolving neural network using a genetic algorithm for predicting the deformation modulus of rock masses*. Int J Rock Mech Min Sci 47: 246-253.

Martins, F.F., Miranda, T.F.S., (2012). *Estimation of the Rock Deformation Modulus and RMR Based on Data Mining Techniques*. Geotech Geol Eng, 30:787–801.

Mitri, H.S., Edrissi, R., Henning, J., (1994). *Finite element modeling of cable bolted stopes in hard rock ground mines*. Presented at the SME annual meeting, New Mexico, Albuquerque p. 94–116.

Mohammadi, H., Rahmannejad, R., (2010). *The estimation of deformation modulus using regression and artificial neural network analysis*. The Arabian Journal for Science and Engineering, 35: 205-217.

Nejati, H.R., Ghazvinian, A., Moosavi, S.A., Sarfarazi, V., (2014). *On the use of the RMR system for estimation of rock mass deformation modulus*. Bull Eng Geol Environ, 73:531–540, DOI 10.1007/s10064-013-0522-3.

Nicholson, G.A., Bieniawski, Z.T., (1990). *A nonlinear deformation modulus based on rock mass classification*. Int J Min Geol Eng, 8:181–202.

Palmstrom, A., (2000). *Recent developments in rock support estimates by the RMi*. J. Rock Mech.Tunn.Technol 6(1): 1–19.

Palmstrom, A., Singh, R., (2001). *The deformation modulus of rock masses – comparisons between in situ tests and indirect estimates*. Tunnelling and Underground Space Technology 16: 115-131.

Panthee, S., Singh, P.K., Kainthola, A., Das, R., Singh, T.N., (2017). *Comparative study of the deformation modulus of rock mass*. Bull Eng Geol Environ, DOI 10.1007/s10064-016-0974-3.
Ramamurthy, T., (2004). *A geo-engineering classification for rocks and rock masses*. Int J Rock Mech Min Sci, 41, 89-101.

Read, S.A.L., Richards, L.R., Perrin, N.D., (1999). *Applicability of the Hoek–Brown failure criterion to New Zealand greywacke rocks*. In: Vouille G, Berest P, editors. Proceedings of the nineth international congress on rock mechanics, Paris, August 2: 655–60.

Serafim, J.L., Pereira, J.P., (1983). *Considerations on the geomechanical classification of Bieniawski*. In: Proceedings of the Symposium on Engineering Geology and Underground Openings, Lisboa, Portugal, p. 1133–44.

Shen, J., Karakus, M., Xu, C., (2012). *A comparative study for empirical equation in estimating deformation modulus of rock masses*. Tunneling and Underground Space Technology, 32, 245-250.

Sonmez, H., Nefeslioglu, H.A., Gokceoglu, C., Kayabasi, A., (2006). *Estimating of rock modulus: for intact rocks with an artificial neural network and for rock masses with a new empirical equation.* Int J Rock Mech Min Sci, 43: 224-235.

3rd Nordic Rock Mechanics Symposium
October 11-12, 2017, Helsinki, Finland
Johansson & Raasakka (eds)
ISBN 978-951-758-622-1
ISSN 0356-9403

Zhang, L., (2017). *Evaluation of rock mass deformability using empirical methods-A review*. Underground Space, doi: http://dx.doi.org/10.1016/j.undsp.2017.03.003.

Zhang, L., Einstein, H. H., (2004). *Using RQD to estimate the deformation modulus of rock masses*. Int J Rock Mech Min Sci, 41: 337-341.