Arch. Min. Sci. **65** (2020), 4, 787-801

Electronic version (in color) of this paper is available: http://mining.archives.pl

DOI 10.24425/ams.2020.134147

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CERCHAR ABRASIVITY INDEX PREDICTION USING MULTI-PROXY DATA. A CASE STUDY FROM THE SAGDERE FORMATION (DENIZLI MOLASSE BASIN, TURKEY)

The prediction of rock cuttability to produce the lignite deposits in underground mining is important in excavation. Moreover, the certain geographic locations of rock masses for cuttability tests are also significant to apply and compare the rock cuttability parameters. In this study, sediment samples of two boreholes (Hole-1 and Hole-2) from the Sagdere Formation (Denizli Molasse Basin) were applied to find out the cerchar abrasivity index (CAI), rock quality designations (RQD), uniaxial compressive strengths, Brazilian tensile strengths and Shore hardnesses. The Sagdere Formation deposited in the terrestrial to shallow marine conditions consists mainly of conglomerates, sandstones, shales, lignites as well as reefal limestones coarse to fine grained. A dataset from the fine grained sediments (a part of the Sagdere Formation) have been created using rock parameters mentioned in the study. Dataset obtained were utilized to construct the best fitted statistical model for predicting CAI on the basis of multiple regression technique. Additionally, the relationships among the rock parameters were evaluated by fuzzy logic inference system whether the rock parameters used in the study can be correlated or not. When comparing the two statistical techniques, multiple regression method is more accurate and reliable than fuzzy logic inference method for the dataset in this study. Furthermore, CAI can be predicted by using UCS, BTS, SH and RQD values based on this study.

Keywords: cerchar abrasivity index, fuzzy inference system, denizli molasse sagdere formation, multiple regression

1. Introduction

To characterize the rock samples, uniaxial compressive strength (UCS) and Brazilian tensile strengths (BTS) are mostly used for predicting the cutting behavior of rocks. Also, for UCS and BTS correlation, cerchar abrasivity index can be utilized. The Cerchar abrasivity test is utilized

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for abrasivity evaluation of intact rocks and wear prediction. Comparable and reliable testings are available due to the variations of test results. Some other testing methods such as LCPC (Laboratoire Central des Ponts et Chaussees) abrasivity test and AVS (abrasion value cutter steel) test have become more common for soil and rock investigations in world wide. Thuro and his friends have studied LCPC abrasivity coefficients and Cerchar abrasivity index (CAI) using Cerchar classification in 2007 (Thuro et al., 2007; Cerchar, 1986). The same technique has already been utilized with good results in practice (Kasling & Thuro, 2010). On the other hand, rock quality designation (RQD) can also give us the strength and discontinious situations of the formations. Deere proposed rock quality designation (RQD) in 1964 as a measurement technique of the borehole core quality (Deere, 1964). The total amount of sound core pieces with percentile ration is 0.1 m (4 inch) or more to the length of borehole core measurement is called RQD. In addition to the direct methods used to determine RQD from coring, some other direct methods are also utilized to assess RQD.

In rock mechanics and the design of geotechnical structures, uniaxial compressive strength (UCS) is very important for problem solving in this subject (Armaghani et al., 2015; Ersoy & Kanik, 2012; Armaghani et al., 2016; Torok & Vasarhelyi, 2010). UCS is used for the determination of the mechanical strength of rocks. This process is important for assessing the suitability and durability of the rocks against weathering agents. In addition, UCS value is directly associated with the level of cohesion occurring in grains of rocks and reveals the state of rock fabric and especially the pore system. Usually, UCS is utilized for making an estimation for the maximum value of stress attained before failure.

The tensile strength is also important for the determination of the load bearing capacity, deformation, damage, fracturing and crushing and some other properties of the rock. For that reason, tensile strength is used to determine the usability and stability of rock structures (Dan et al., 2013). Brazilian tensile strength test, semi-circular bending tests, flatten Brazilian disc and ring tests are some of the analysis methods to calculate the tensile strength (Hondros, 1959; Wang et al., 2004; Coviello et al., 2005; Wisetsaen et al., 2015). Due to its easy application, sample preparation and the Brazilian tensile strength test are commonly used in rock engineering and uniaxial compression test machines are commonly used (Dan et al., 2013).

In this study, rock mechanic tests such as cerchar abrasivity index, uniaxial compressive strength (UCS), Brazilian tensile strength (BTS), Shore hardness and rock quality designations of the sediments from two drillings of the Sagdere Formation (Denizli molasse Basin) have been analyzed. Additionally, obtained data have been analysed and compared with using fuzzy logic and multiple regression statistic technique.

2. Geological setting

The Oligocene molasse basins are spread from southwest to northeast, as the Kale-Tavas, Denizli, Çardak-Tokça and Burdur (Fig. 1a). Many studies were carried out on the geological and paleontological aspects of these basins (Sozbilir, 1997, 2005; Akgun & Sozbilir, 2001; Hakyemez, 1989; Akkiraz & Akgun, 2005; İslamoglu et al., 2005, 2006, 2007; Karayigit et al., 2017). The Denizli Molasse Basin is located about 30 km northeast of Denizli (Fig. 1a). A detailed geological map of the area was prepared by Sözbilir and Akgün (Fig. 1b) (Sozbilir, 1997, 2005; Akgun & Sozbilir, 2001). An uncomformably overlain from late Miocene to Pliocene Belevi group and a transgressive sequence unbending on pre-oligocene basement is displayed in basin (Fig. 1c).

As it can be seen in figure 1c, fan deposits with alluvians at the base are included in sequence. The sequence also grades upward into fan delta-shallow marine deposits with lignite and patch reefs in figure 1c. The Çaykavustu Formation forms the basal part of the sequence and comprises reddish-brownish conglomerate intercalated with lithic sandstones. It is overlained by the Sagdere formation including a thick deltaic shallow marine sequence with lenses of reefal limestones and lignite. It also contains massive to cross-bedded conglomerates, wave rippled and planar cross bedded sandstones, fossiliferous and bioturbated mudstones, lignite-bearing mudshales, sandstone-mudstone alternations and lenses of reef limestones (Akgun & Sozbilir, 2001). According to palaeontological data, the age of the Sagdere Formation was suggested as the Late Oligocene-Early Miocene.

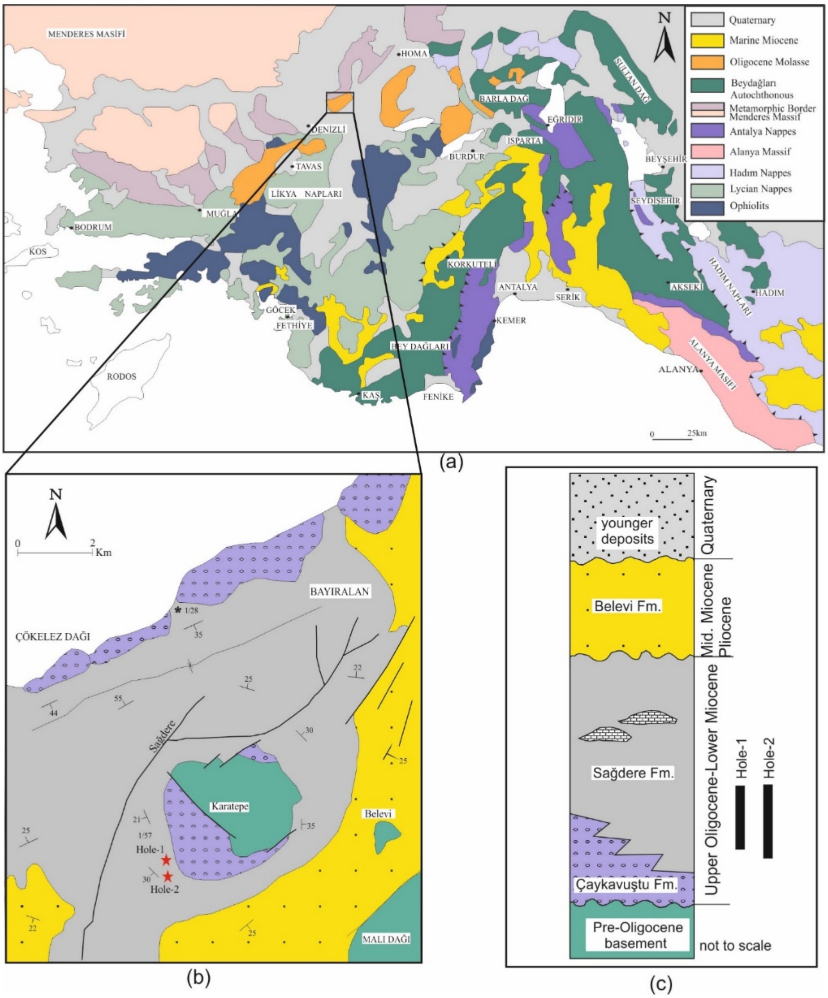
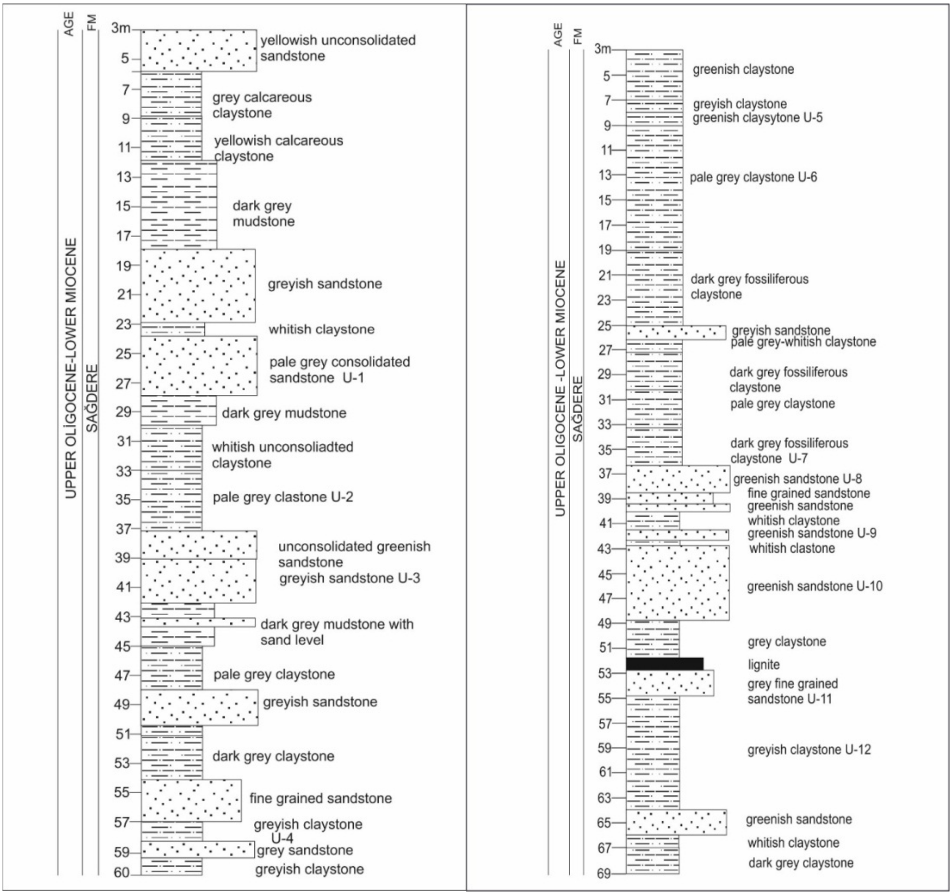


Fig. 1. (a) generalized geological map showing the molasse basins of southwestern part of Turkey, (b) detailed geological map of Denizli molasse basin, (c) generalized columnar section indicating the studied wells of the Denizli molasse basin (coordinates:702914/4196470 for Hole-1;702757/4196887 for Hole-2)

In this paper, a part of the Sagdere Formation from the Denizli Molasse Basin (Hole-1 and Hole-2) has been studied with respect to multiproxy approaches. Hole-1 attaining about 60 total thickness consist mainly of moderate to fine grained deposits such as sandstones and claystones (Fig. 2a). Through the surface, calcalreous claystones are common. The thickness of Hole-2 is about 69 meters (Fig. 2b). It contains sandstone claystone alternation in different thickness (Fig. 2). Fossilliferous level (between 22 and 25 meters) occurs at some parts of the sequence. This profile also includes thin lignite level (between 52,5 and 53 meters).



(a) (b)

Fig. 2. Lithological aspects of the Sagdere Formation from the Hole-1(a) and Hole-2 (b)

3. Cerchar Abrasivity Index

In underground, while permanently being accepted for practices, Cerchar (Centre d'Etudes et Recherches des Charbonages de France) has first introduced the Cerchar abrasivity test in coal bedding rocks in the industry (Alber, 2008; Plinninger et al., 2004). Particular setups are also available for Cerchar testing while testing layout was introduced by Cerchar (Cerchar, 1986). All methods require a vice clutching the sample while a toughened steel stylus with 90 cone tip is scratched over the rock surface under 70 N constant load and the scratch covers 10 mm distance. It is available in different laboratories that the Cerchar test results can not be same due to the test apparatus, measurement types and testing procedures (Rostami et al., 2014).

In this study, the cerchar tests were applied on 12 different rock types from Denizli Molasse basin. The tests were operated in Afyon Kocatepe University, Mining engineering laboratories. HRC 54/56 steel pins were used for the abrasivity measurement based on french standard (Michalakopoulos et al., 2006). The test equipment setup and the steel pins are shown in figure 3.

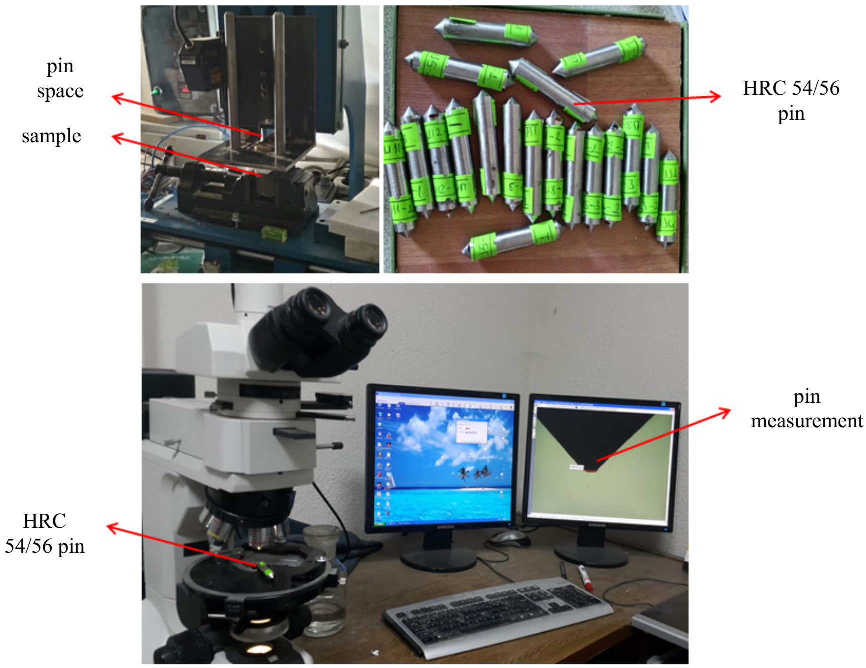


Fig. 3. Cerchar test device and steel pins (HRC 54/56) in Afyon Kocatepe University, Mining Engineering Laboratory

4. Material and Methods

In this study, two borehole logs operated by Arafa Mining Company have been sampled. The depth of the first sounding (Hole-1) bored southwest of Karatepe is about 60 meters. The other hole (Hole-2) was bored about 500 meters southern side of the first one reaching to 69 meters total thickness. Totally 12 samples from the Hole-1 and Hole-2 were collected (Fig. 4). UCS, BTS, shore hardness and RQD tests were carried out at the laboratory of the Mining Engineering Department in Dumlupınar University and the Mining Engineering Department in Middle East Technical University. Furthermore, rock quality designation was determined. The sediment samples are clay-stone and sandstone with different characteristics. The rock mechanical tests were carried out on samples taken in NX standards with a diameter of 54,7 mm and the mean values were calculated. The rock quality designation (RQD) was determined on the obtained cores shown in figure 4.

(a) (b)

Fig. 4. Borehole logs of the Hole-1(a) and Hole-2(b), Sagdere formation

5. Experimental studies

5.1. Rock mechanics test results

The UCS, BTS, Shore hardness, rock quality designation and cerchar abrasivity index (CAI) experiments were conducted on the cores with a diameter of 54,7 mm in NX standard. Totally 12 different sedimentary rock samples were tested in the study. For UCS and BTS, five samples for each were tested and the arithmethical averages were calculated. For CAI, 5 steel pins were used and arithmethical averages were calculated. For Shore hardness, 10 readings were applied at each time and the arithmethical average of 5 of 10 highest values were calculated. The results of the experimental studies are given in table 1. The results obtained can be correlated with each other, and do not indicate nonsense values.

TABLE 1

Rock mechanics test results

Sample Number	Sample Name	UCS (MPa)	BTS (MPa)	SH	RQD (%)	CAI No
U1	Pale grey consolidated sandstone	48.39	7.62	15	12	0.09
U2	Pale grey claystone	64.63	9.8	24	23	0.08
U3	Greyish sandstone	12.73	3.58	30	12	0.09
U4	Greyish claystone	36.76	8.33	18	11	0.09
U5	Greenish claystone	11.78	2.86	13	21	0.02
U6	Pale grey claystone	30.53	2.78	14	28	0.02
U7	Dark grey fossiliferous claystone	22.81	6.68	23	26	0.03
U8	Greenish sandstone	48.8	8.58	17	34	0.03
U9	Whitish claystone	11.76	2.67	12	12	0.05
U10	Greenish sandstone	28.77	7.73	22	35	0.04
U11	Greyish fine grained sandstone	30.85	7.00	20	9.0	0.07
U12	Greyish claystone	50.27	6.96	23	17	0.04

The correlation between the obtained values according to results of the rock mechanic experiments was investigated (Fig. 5). The best result was obtained from the Brazilian tensile strength with uniaxial compressive strength. The correlation between these parameters is above the average and the correlation coefficient R^2 = 0,6549. Moreover, the correlation coefficient R^2 = 0,4541 between cerchar abrasivity index and rock quality designation. The rock quality designation effects the abrasivity index according to the correlation results. The correlation between other rock parameters are not high enough.

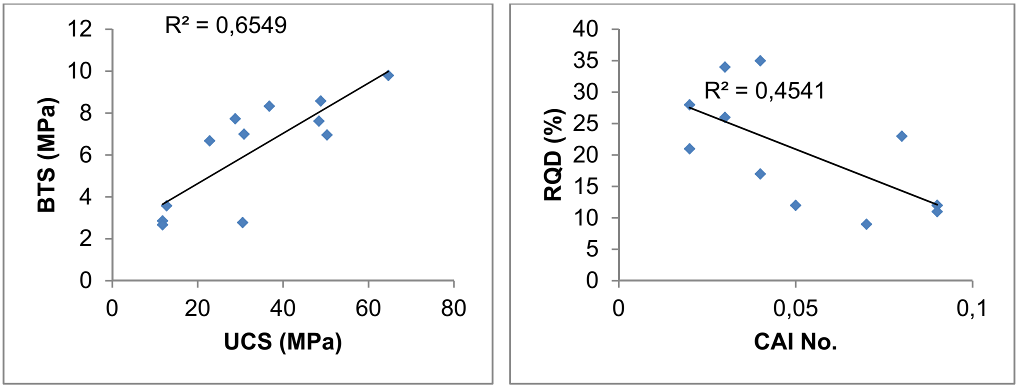


Fig. 5. Correlations between UCS, BTS, CAI and RQD values

One of the main objectives in this study is to determine the relationship between CAI values and other variables including RQD. The RQD value is a method of calculating the ratio of the total sample length over 10 cm of the cores to the total sample length.

5.2. Fuzzy logic inference system

The relationships between CAI values and other parameters are evaluated by using fuzzy logic method. Fuzzy logic inference systems have been recently used increasingly in rock mechanics and engineering geology (Alvarez & Babuska, 1999; Finol et al., 2001; Gokceoglu, 2002; Gokceoglu & Zorlu, 2004; Nefeslioglu et al., 2003; Sonmez et al., 2003; Tutmez & Hatipoglu, 2007). A study on overviewing the algorithm of fuzzy modeling was conducted by Alvarez (Alvarez, 2000). The most commonly used models reported for solving such engineering problems comprise the Mamdani, Tsukamoto,Tagaki-Sugeno-Kang and Singleton fuzzy models. This paper utilized the Mamdani fuzzy algorithm as the Mamdani method is probably the most suitable fuzzy method used in in engineering geological problems (Alvarez, 2000). The UCS and BTS comprise the inputs of the fuzzy logic inference system. In the paper, MATLAB 7.3.0 version was applied for structuring the fuzzy logic inference system (Demuth et al., 2005). Setnes, Babuska, and Verbruggen states that one of the striking properties of fuzzy models is nonlinear multivariable issues in a sensitive way. Moreover, their ability to describe complexity is another statement comparing to the other traditional methods including statistics widely used in geosciences (Setnes et al., 1998). Usually, the fuzzy logic is utilized in geology engineering and rock engineering issues to reduce the uncertainties arising from variations and ignorance

(Gokceoglu, 2002). For main standardization, the variables were set between the values 0 and 1 (Eq. 1) and then the fuzzy sets for the aims of the constructed models were extracted.

$$Xnorm = (X \_ Xmin)/(Xmax \_ Xmin) \tag{1}$$

Fuzzy logic inference system is fast, easy to analyse the results and convenient for complex systems. Moreover, direct user access and experience is also available in the system. Engineering geological parameters including uniaxial compressive strengths, tensile strengths and some others have been analyzed by using fuzzy logic system in the past (Yagiz, 2010). However, there are no more studies analyzing the relationships between chercar abrasivity and rock mechanics parameters with less rock mechanics data. Usually, fuzzy logic system is used to analyze more complex and specific with multiple data. For that reason, fuzzy logic inference system is also used to compare the results with multiple regression method to see the differences between chercar abrasivity and different rock mechanic parameters with less but enough dataset in this study.

Previously, the relationship between brittleness index and some rock mechanical results was determined by using fuzzy logic method (Yagiz, 2010). However, the relationship between cerchar abrasivity index, UCS, BTS, shore hardness and rock quality designation values have not been studied. In this study, standard ISRM and Deere ranges of the mentioned experiments were used, and fuzzy logic analysis was performed using these index ranges (Deere, 1964; ISRM, 1981; Deere & Miller, 1966). As shown in table 2, there are five value ranges for RQD and UCS variables, whereas three value ranges for BTS and SH variables.

TABLE 2

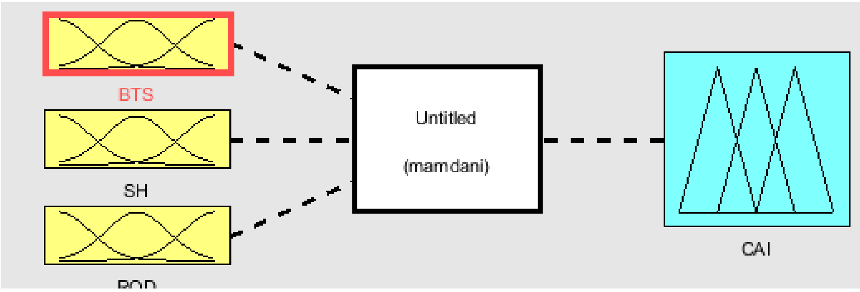
Rock mechanic parameters indexes (Deere, 1964; ISRM, 1981; Deere & Miller, 1966)

RQD (%)	Rock Quality	UCS (Mpa)	Rock Quality	BTS (Mpa)	Rock Quality	SH	Rock Quality
0-25	Very poor	<6	Very low	2-4	Strong	<20	Low
25-50	Poor	6-20	Low	4-10	Very strong	20-60	Medium
50-75	Fair	20-60	Medium	>10	Extremely strong	>60	High
75-90	Good	60-200	High				
90-100	Excellent	>200	Very high				

By applying fuzzy logic analysis, input and output algorithm of variables were firstly created. As it can be seen in figure 6(a), input1, input2 and input3 are BTS, SH and RQD while output1 is CAI values. On the other hand, in figure 6(b), input1, input2 and input3 are UCS, SH and RQD while output1 is CAI. It is possible to observe the relationship between these input and output parameters and the used variables. When these variables are entered to the software, the index ranges were used given in table 2. Therefore, it can be determined how the variables are related to each other in certain ranges.

As it can be seen in figure 7, two different models were created and evaluated based on fuzzy logic inference system. In figure 7(a), CAI values are predicted using BTS, SH and RQD values. Moreover, CAI values are also predicted using UCS, SH and RQD values in figure 7(b).

A model for CAI, UCS, BTS, SH and RQD has been proposed in the paper. In this regard, the study investigates whether CAI is a significant predictor of UCS, BTS, SH and RQD. Therefore, a model was created by comparing multiple regression studies. This model is based on the "IF and THEN" rule used in fuzzy logic analysis.



(a)

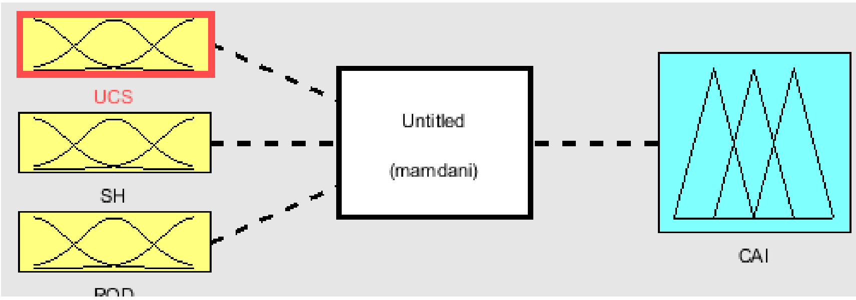


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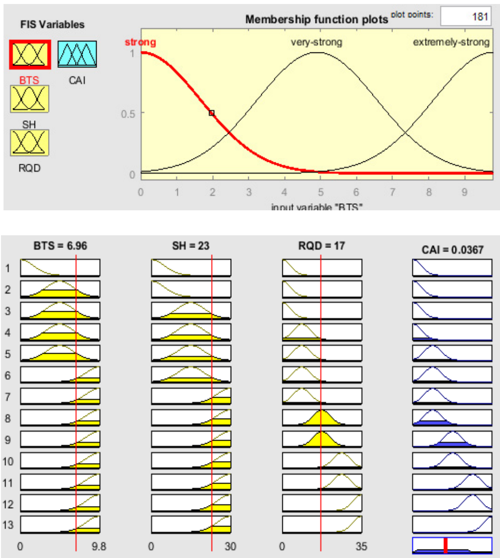
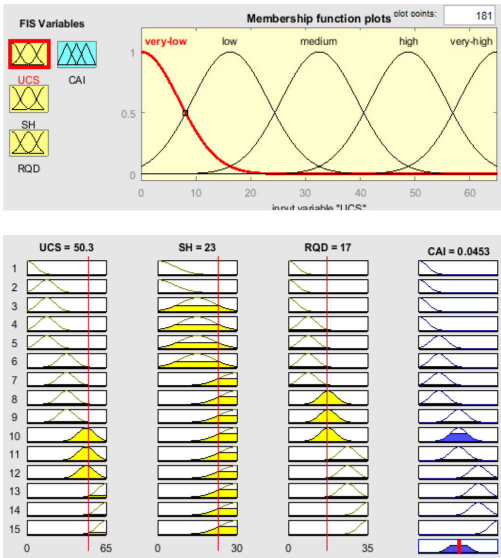
Fig. 6. The alghoritms of the fuzzy logic inference system indicating model1 with BTS, SH, RQD (a) and model2 with UCS, SH, RQD (b)



(a)



(b)

Fig. 7. Fuzzy logic membership function plots and rules with prediction values for model1 (a) and model2 (b)

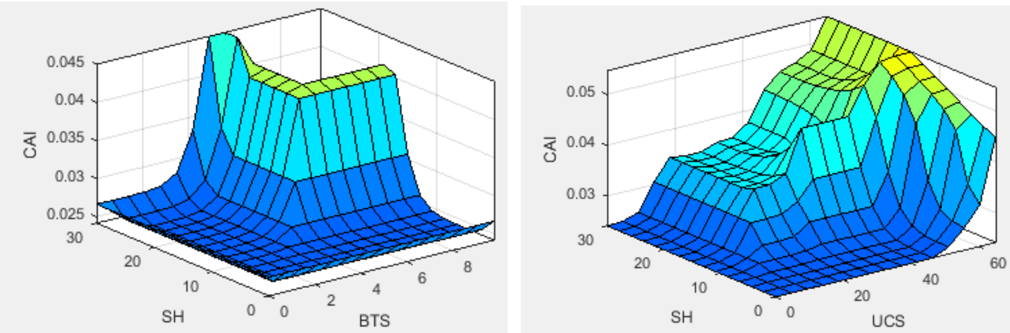


Fig. 8. Fuzzy logic surface views of BTS, SH and CAI versus UCS, SH and CAI values

By processing the input and output values in the fuzzy logic result system, the relation between these values are observed with the surface visuality, as shown in figure 8. The relationship between CAI index versus SH, BTS and RQD, and CAI index versus SH, UCS and RQD are not similar. The correlation between CAI versus and BTS and UCS variables shows a different tendency. There is a system called Fuzzy C-Means for general purposes (Bezdek, 1981). The system was also used by Sugeno and Yasukawa to construct a fuzzy model based on rules of the form below:

$$R' = \text{IF } x \in \text{A' THEN } y \in B' \tag{2}$$

where $x = (x1, x2, \ldots, xn) \in R\ n$ are input variables, A = (A1, A2, …, An) are n fuzzy sets, $y \in R$ is the output variable and B is a fuzzy set for this variable. Sugeno and Yasukawa described the developed fuzzy clustering tool called PreFuRGe (Sugeno & Yasukawa, 1993). Based on this principle, when the obtained rock mechanical results are modified by IF and THEN commands, the following conditions are established.

5.3. Multiple regression analyses

Experimental data were analyzed by correlation and multiple linear regression analyses. Determination as to whether provide the linearity assumptions was carried out, and it was found that there was a non-linear relationship between the CAI and other variables. This relationship was linearized by logarithmic transformation ($\log_y$) and the analysis was continued (Alpar, 2017). Findings for the multiple correlation matrix calculated between variables are presented that shows the correlation between the CAI dependent variable and each of the UCS, BTS, RQD and SH independent variables and the correlation of the independent variables between each other. The high correlation between the independent variables causes the variables to provide similar information, thus making each variable potentially ineffective. Therefore, in order for the results of the regression analysis to be valid, the correlation values should be below 0.80 (Alpar, 2017).

Regression analysis was used for testing inter-variable relationships. Regression analysis is a method for explaining the relationship between a dependent and one or more than one independent variables by a mathematical equation (Buyukozturk, 2011). In this study, a multiple

TABLE 3

Multiple regression matrix for the variables

		CAI	BTS	SH	RQD	UCS
Pearson Correlation	**CAI**	1	0,36	0,371	–0,674	0,249
	BTS	0,36	1	0,324	0,182	0,809
	SH	0,371	0,324	1	–0,007	0,137
	RQD	–0,674	0,182	–0,007	1	0,171
	UCS	0,249	0,809	0,137	0,171	1

regression model was applied, including the analysis of a large number of independent variables would affect a dependent variable. Table 3 shows the pearson correlation matrix which gives us the relationships between the dependent and undependent variables.

The significance of multiple regression analyses is tested by analysis of variance (Aydin, 2014). The results of multiple regression analysis to determine the CAI predicting power of UCS, BTS, SH and RQD are presented in table 4.

TABLE 4

Multiple regression analyses results for CAI prediction

Variable	B	Standard error	β	T	Sig
Constant	6,102	5,831	—	1,046	0,330
UCS	–0,066	0,134	–0,316	–0,497	0,634
BTS	0,256	0,948	0,181	0,270	0,795
SH	–0,030	0,265	–0,044	–0,112	0,914
RQD	0,079	0,145	0,201	0,543	0,604

As it can be seen in table 4, CAI is a significant predictor of UCS, BTS, SH and RQD. Standardized regression coefficients (β) show that the significance ratios of the predictive dimensions in describing CAI are sorted as UCS, BTS, SH and RQD. The t-test results on the significance of the regression coefficients show that UCS, BTS, SH and RQD are significant predictors of CAI.

The parameters used in the multiple regression model are CAI, UCS, BTS, SH and RQD values. CAI values are assigned as dependent variables in the model while others are assigned as independent variables. The resulting models are as follows;

$$CAI = 0.048 + 0.005 \times BTS + 0.001 \times SH - 0.002 \times RQD \quad \text{(Model1)} \tag{3}$$

$$CAI = 0.048 + 0.001 \times UCS + 0.002 \times SH - 0.002 \times RQD \quad \text{(Model2)} \tag{4}$$

where CAI is cerchar abrasivity index number, BTS is brazilian tensile strength (MPa), SH is shore hardness, RQD is rock quality designation as percentage (%) and UCS is uniaxial compressive strength (MPa).

The correlation coefficients between the actual and predicted values of the rock mechanics parameters obtained by BTS, UCS, SH and RQD was found to be high (Fig. 9). The R^2 value is 0.735 for model1 and 0.6149 for model2. The proximity between the real values and the estimated values is quite high. It shows that the independent variables BTS, UCS, SH and RQD values play an important role to determine the CAI index.

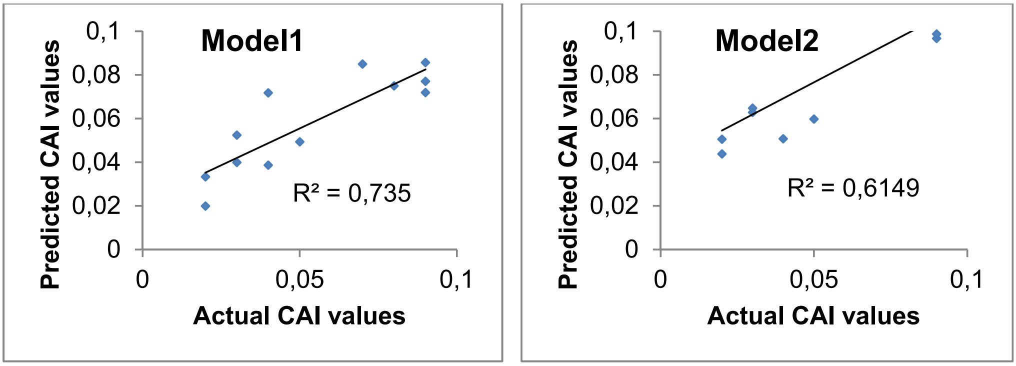


Fig. 9. Predicted CAI values against actual CAI values based on multiple regression technique with model1 and model2

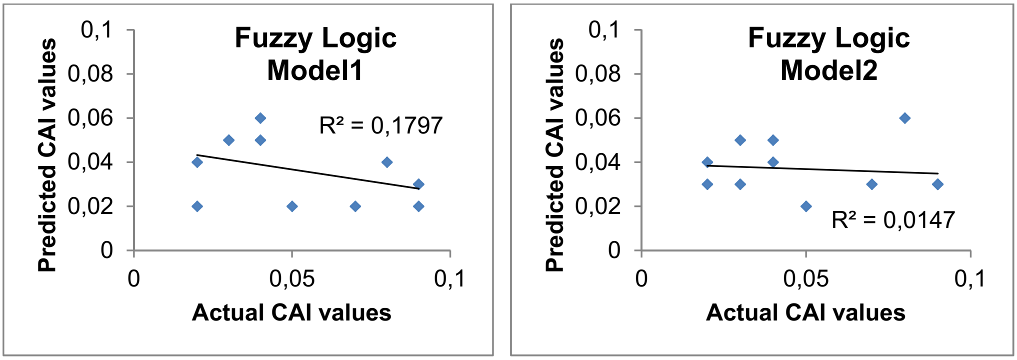


Fig. 10. Predicted CAI values against actual CAI values based on fuzzy logic inference system with model1 and model2

The predicted and actual CAI values based on fuzzy logic inference technique were evaluated and the results were given in figure 10. As it can be seen in figure 10, R^2 values are not as high as multiple regression analyse results. According to figure 9 and figure 10, the multiple regression analyse technique is more accurate and reliable than fuzzy logic inference technique.

6. Conclusion

The prediction of cerchar abrasivity index (CAI) utilizing main prediction tool comprising multiple regression analysis is reliable to obtain the good results of rock parameters. Since, there is no more studies related to predicting the CAI values, UCS, BTS, Shore hardness and rock quality designation tests were introduced and applied to predict CAI values. Utilizing the data collected from two different boreholes in the Sagdere Formation, CAI was estimated based on the multiple regression model. Geological setting of the Sagdere location was also studied and the Hole-1 and Hole-2 were also analysed in this paper. It is concluded that relationships between rock parameters and CAI values can also be displayed using fuzzy logic inference system. As function of measured rock properties, two models were introduced based on obtained performance values. Due to there is no more study related to predicting the CAI values by using rock parameters taken from exact boreholes in situ, this study can be a pioneer to determine the real results. Two statistical models based on multiple regression technique to predict CAI values were implemented to identify the most appropriate fitting models. Fuzzy logic inference system was also used to indicate the relationships between CAI and rock parameters together. After getting the statistical analyse observations, two techniques were compared and contrasted between each other. The intervals of the parameters were determined based on accepted CAI and rock parameters indexes. The input of the predictive multiple regression model includes the rock mass parameters namely UCS, BTS, Shore hardness and RQD. The models are representative for the rock mass parameters and they offer a systematic way to carry out the actual values. Fuzzy logic inference system is usually used with multiple data sets in applications. However, there is no more studies in literature utilizing less but enough data set as analysed in this paper. One of the main purposes in this study was to show that the fuzzy logic inference system can also be used to analyse the rock mechanics results with less but enough data, however it can be more convenient while utilizing regression analyse techniques. As a result of this study, multiple regression technique is %57.77 more accurate and reliable than the fuzzy logic inference system for the dataset used in Denizli, Sagdere formation. Furthermore, CAI index values can also be predicted with using UCS, BTS, SH and RQD values for rock cuttability performances. Furthermore, Mining or different projects can be applied in Denizli region in the future. For that reason, the field studies and the laboratory test results are very significant for this Sagdere formation. Based on tests results in the study, CAI and other rock mechanics parameters can also be useful for further studies in the location.

Acknowledgements

Author is grateful to Arafa Mining Company for their help in the usage of borehole samples that made the lithological correlation possible.

References

Akgun F., Sozbilir H., 2001. *A palynostratigraphic approach to the SW Anatolian molasse basin: Kale-Tavas molasse and Denizli molasses*. Geodynamica Acta **14** (1-3), 71-93.

Akkiraz M.S., Akgun F., 2005. *Palynology and age of the Early Oligocene units in Çardak–Tokça Basin, Southwest Anatolia, Paleoecological implications*. Geobios, **38** (3), 283-299.

Alber M., 2008. *Stress dependency of the Cerchar abrasivity index (CAI) and its effects on wear of selected rock cutting tools*. Tunn Undergr Space Technol **23**, 351-359.

Alpar R., 2017. *Uygulamali cok değişkenli istatistiksel yöntemler*. Detay Yayincilik, Turkey, 840

Alvarez Grima, M., Babuska R., 1999. *Fuzzy model for the prediction of unconfined compressive strength of rock samples*. International Journal of Rock Mechanics and Mining Science **36**, 339-349.

Alvarez Grima M., 2000. *Neuro-Fuzzy Modeling in Engineering Geology*. Rotterdam: A.A. Balkema. 244.

Armaghani D.J., Mohamad E.T., Momeni E., Narayanasamy M.S., Mohd F.M., 2015. *An adaptive neuro-fuzzy inference system for predicting unconfinedcompressive strength and Young's modulus: a study on Main Range granite*. Bull. Eng. Geol. Environ. **74**, 1301-1319.

Armaghani D.J., Mohamad E.T., Momeni E., Monjezi M., Narayanasamy M.S., 2016. *Prediction of the strength and elasticity modulus of granite through an expertartificial neural network*. Arab. J. Geosci. **9** (48), 1-16.

Aydin D., 2014. *Uygulamalı Regresyon Analizi-Kavramlar ve R Hesaplamaları*. Nobel Yayınları, Ankara.

Bezdek J.C., 1981. *Pattern Recognition with Fuzzy Objective Function Algorithm*. Plenum Press, New York.

Buyukozturk S., 2011. *Sosyal bilimler için veri analizi el kitabı*. Ankara: Pegem Akademi.

Cerchar 1986. *Centre d'Etudes et Recherches de Charbonnages de France*. The Cerchar abrasiveness index, Verneuil 12S.

Coviello A., Lagioia R., Nova R., 2005. *On the measurement of the tensile strength of soft rocks*. Rock Mech. Rock Eng. **38** (4), 251-273.

Dan D.Q., Konietzky H., Herbst M., 2013. *Brazilian tensile strength tests on some anisotropic rocks*. Int. J. Rock Mech. Min. Sci. **58**, 1-7.

Deere D.U., 1964. *Technical description of rock cores for engineering purposes*. Rock Mechanics and Engineering Geology **1** (1), 16-22.

Deere D.U., Miller R.P., 1966. *Engineering classification and index properties for intact rock*. technıcal report no. afwl-tr-65-116, University of Illinois, Contract AF 29(601)-6319.

Demuth H., Beale M., Hagan 2005. *MATLAB Version 7.3.0: Fuzzy Logic Toolbox for Use with Matlab*. The Mathworks.

Ersoy H., Kanik D., 2012. *Multicriteria decision-making analysis based methodologyfor predicting carbonate rocks uniaxial compressive strength*. Earth Sci. Res. J.**16** (1), 65-74.

Finol J., Guo Y.K., Jing X.D. 2001. *A rule based fuzzy model for the prediction of petrophysical rock parameters*. Journal of Petroleum Science and Engineering **29**, 97-113.

Gokceoglu, C. 2002. *A fuzzy triangular chart to predict the uniaxial compressive strength of Ankara agglomerates from their petrographic composition*. Engineering Geology **66**, 39-51.

Gokceoglu C., Zorlu K. 2004. *A fuzzy model to predict the uniaxial compressive strength and modulus of elasticity of a problematic rock*. Engineering Application of Artificial Intelligent **17**, 61-72.

Hakyemez H.Y., 1989. *Kale-Kurbalık (Güney Batı Denizli) Bölgesindeki Senozoyik Yaslı Çökel Kayaların Jeolojisi ve Stratigrafisi*. Bull. Min. Res. Expl. Inst. Turkey **109**, 9-21.

Hondros G., 1959. *The evaluation of Poisson's ratio and the modulus of materials of a low tensile resistance by the Brazilian (indirect tensile) test with particular reference to concrete. Aust*. J. Appl. Sci. **10**, 243-268.

Islamoğlu Y., Atay G., Gedik F., Aydın A., Hakyemez A., Babayiğit S., Sarıkaya H., 2005. *Batı Toroslardaki denizel Oligosen-Miyosen biyostratigrafisi (Denizli). Mineral.* Reasearc and Exploration report 10763, 155, Ankara

Islamoğlu Y., Gedik F., Aydın A., Atay G., Hakyemez A., Babayiğit S., 2006. *Foraminifera, Nannoplankton, Coral and Ostrocoda Biostratigraphy of the Oligocene Lagoonar and Marine Deposits in Denizli Region (SW Turkey)*. **59**. Geological Congress of Turkey, March 20-24,The Chamber of Geological Engineers, Congress Center of General Directorate of MTA, 245-249, Ankara.

Islamoğlu Y., Gedik F., Çulha G., 2007. *Mollusc, benthic foraminifer and ostracod faunas of the early Miocene deposits in Denizli region and biostratigraphic pre-results (SW Anatolia, Turkey)*. 16th International Petroleum and Naural Gas Congress & Exhibition of Turkey, 29-31 May 2007, Ankara, 91-93.

ISRM, 1981. *The complete ISRM suggested methods for rock characterization, testing and monitoring*. Standard Book.

Karayigit A.I., Littke R., Querol X., Jones T., Oskay R.G., Christanis K., 2017. *The Miocene coal seams in the Soma Basin (W. Turkey): Insights from coal petrography, mineralogy and geochemistry*. Int. J. Coal Geol. **173**, 110-128.

Kasling H., Thuro K., 2010. *Determining abrasivity of rock and soil in the laboratory*. In: 11th IAEG Congress, Auckland, New Zealand **235**,1973-1980.

Michalakopoulos T., Anagnostou V., Bassanou M., Panagiotou G., 2006. *The influence of steel styli hardness on the Cerchar abrasiveness index value*. Int. J. Rock Mech. Min. Sci. **43**, 321-327.

Nefeslioglu H.A., Gokceoglu C., Sonmez H., 2003. *A Mamdani model to predict the weighted joint density*. Lecture Notes in Artificial Intelligence **2773**, 1052-1057.

Plinninger R., Kasling H., Thuro K., 2004. *Wear prediction in hardrock excavation using the Cerchar Abrasiveness Index (CAI).* In: Proceedings of the Eurock 2004 and 53rd Geomechanic Colloquium, p. 599-604.

Rostami J., Ghasemi A., Gharahbagh E.A., Dogruoz C., Dahl F., 2014. *Study of Dominant Factors Affecting Cerchar Abrasivity Index*. Rock Mech. and Rock Eng. **47**, 1905-1919.

Setnes M., Babuska R., Verbruggen H.B., 1998. *Rule-based modeling: precision and transparency*. IEEE Transactions on Systems Man and Cybernetics, Part C, **28**, 165-169.

Sonmez H., Gokceoglu C., Ulusay R., 2003. *An application of fuzzy sets to the geological strength index (GSI) system used in rock engineering*. Engineering Applications of Artificial Intelligence **16**, 251-269.

Sozbilir H., 1997. *Stratigraphy and sedimentology of the Tertiary sequences in the northeastern Denizli province (southwest Turkey*). PhD Thesis, Dokuz Eylül University, Izmir,

Sozbilir H., 2005. *Oligo-Miocene extension in the Lycian orogen: evidence from the Lycian molasse basin*. SW Turkey. Geodinamica Acta **18**, 255-282

Sugeno M., Yasukawa A., 1993. *A fuzzy-logic based approach to qualitative modelling*. IEEE Trans. Fuzzy Syst. **1**, 7-31.

Thuro K., Singer J., Kasling H., Bauer M., 2007. *Determining abrasivity with the LCPC Test*. Proceedings of the 1st Canada-US rock mechanics symposium, 27.

Torok A., Vasarhelyi B., 2010. *The influence of fabric and water content on selected rock mechanical parameters of travertine, examples from Hungary*. Eng. Geol. **115**, 237-245.

Tutmez B., Hatipoglu Z. 2007. *Spatial estimation model of porosity*. Computers and Geosciences **33**, 465-474.

Wang Q.Z., Jia X.M., Kou S.Q., Zhang Z.X., Lindqvist P.A., 2004. *The flattened Brazilian disc specimen used for testing elastic modulus, tensile strength and fracture toughness of brittle rocks: analytical and numerical results*. Int. J. Rock Mech. Min. Sci. **41** (2), 245-253.

Wisetsaen S., Walsri C., Fuenkajorn K., 2015. *Effects of loading rate and temperature on tensile strength and deformation of rock salt*". Int. J. Rock Mech. Min. Sci. **73**, 10-14.

Yagiz S., 2010. *Application of fuzzy inference system and nonlinear regression models for predicting rock brittleness*. Expert Systems with Applications **37** (3), 2265-2272.