Predicting Maximum Dry Density, Optimum Moisture Content and California Bearing Ratio (CBR) Through Soil Index using Ordinary Least Squares (OLS) and Artificial Neural Networks (ANNS)

Ajalloeian Rassoul, Kiani Mojtaba

Abstract* - Soil compaction and California bearing Ratio (CBR) tests are the common methods in determining the bearing capacity of linear construction like roads, railroads and airfield pavement in designing the different layers of their select fill. Rapid access to the results of these tests contributes to the project management with respect to implementation, time and savings. Attempt is made here to estimate the maximum value of dry density (MDD), optimum moisture Content (OMC), soaked CBR (CBR_S), un soaked CBR (CBR_U) and swelling percentage through OLS and Multi-layer Perception network (MLP) of ANNS with respect to more common and simple tests which include percentage of organic content (OC), liquid limit (LL), plastic limit (PL), Percentage Passing No. 200 and No. 4 sieves. Also results obtained from the processed data indicate that the ANN method not only performs better than OLS but also provides acceptable and reliable outcomes with respect to the predicted objectives' materialization.

Keyword: ANN, CBR, Maximum Dry Density, Optimum Moisture Content.

I. INTRODUCTION

Compaction, in general, is the densification of soil by removal of air with consume of mechanical energy. The degree of compaction is measured in terms of its density. Water is added to the soil during compaction has a lubricant role. The soil particles slip over each other and is made a new fabric with more density. The dry density of soil increase with a certain moisture content that is named optimum moisture content (OMC) and dry density in this point is named maximum dry density (MMD) [1],[2]. The California Bearing Ratio Test (CBR) was introduced by the California HWY Department in 1929 in order to evaluate bearing ratio of the soil supporting road, highways, railroad, airfield runways and other pavement systems. This test applied for determining composite soil stiffness and is used to evaluate the suitability of sub grade and the materials used in sub base and base of pavements. Compaction and CBR are usually accompanied with the grain-size distribution, LL, PL and OC tests. These tests provide the results regarding properties of materials involved, and indicate the tested materials' behavior.

According to this principle, and the innate correlation among these results, by applying data-mining process the available unknown correlations among these specifications can be extracted. In general, presenting a comprehensive model in this respect by having in mind that many variables are effective in soil and aggregate materials is not an easy task, but by adopting the ANN and Statistical Analysis with respect to the advances made in information technology achieving such objectives could be accomplished. Ch. Sudha Rani, Phani Kumar et al (2013); Mohammad, A, Shahin et al(2009); Sathawara Jigar K et al (2013) ; Ramasubbarao, G.V and Siva Sankar, G (2013); A. Ashrafi Fashi et al(2010) and others have conducted many studies in this field. These studies have revealed soil and aggregates behavior in geotechnical activities, where as the material strength can be evaluated through the above mentioned methods. In this study the results obtained from the bigger statistical population (386 cases) are evaluated through the Multi Layer Perception (MLP) from artificial neural networks (ANN) and the approach equation through the Ordinary Least Squares (OLS) method in order to predict the MDD, OMC, soaked CBR (CBR_s) and swelling percentage and to predict the un soaked CBR (CBR_U) tests conducted on 247 cases. To obtain the CBR_s value of a soil sample the specimen prepared is soaked for 4 days under water after which the penetration test is conducted.

II. A REVIEW OF ANN

The ANN is one of the computing methods copied from the animal neuron network system which tries to identify the innate correlation among the data and provide a network between the input spaces (input layer/s) and the desired space (output layer/s) through the processor named neuron. This network is composed of at least three: input, hidden and

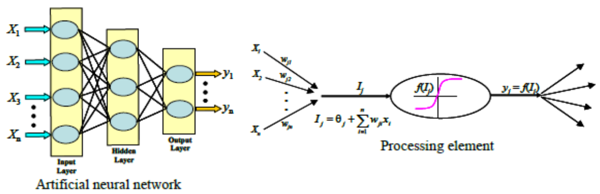

Fig. 1: Structure of ANN [Mohammad A et al, 2009]

Revised Version Manuscript Received on July 17, 2015.

Dr. Ajalloeian Rassoul, Department of Geology, The University of Isfahan, Geology, Isfahan, Iran.

Kiani Mojtaba, Department of Geology, The University of Isfahan, Geology, Isfahan, Iran.

output layers. The hidden layers receives the data from the input layer and delivers them to the output layer after training. Training is a process that ends in learning. The network learning occurs when the communicational weights among the layers change in a manner where the difference between predicted and computed values are at the acceptance level. By obtaining these conditions, the learning process is materialized. These weights express the memory and the knowledge of the network. The trained neuron network can be applied in predicting the outcomes fit to the new data collection (Fig. 1)

III. RESEARCH AND ASSESMENT

In present study with respect to the objectives and accomplishing the desired comprehensive outcomes, the data are obtained from different depths, geological and geographical areas on random bases. In this study, an average real specific gravity of 2.6 is applied. These data are modeled in the following three sections by using Excel, Minitab and MATLAB software.

1) A Matrix with 386*5 dimensions with the inputs of the Organic content(OC), Liquid Limit(LL), Plastic Limit(PL), Percentage Passing No. 4(#4) , Percentage Passing No. 200(#200) to approach MDD and OMC
2) A matrix with 386*7 dimensions with the inputs of the OC, LL, PL, #4 ,#200 OMC and MDD to approach the CBR_s and swelling percentage after 4 days
3) A matrix with 247*7 dimensions with the inputs of CBR_s approach to obtain the CBR_U approach

A. Statistical data analysis

The regression equations are developed for studied parameters using EXCEL 7 software (Table 1 and 2). In these tables the high correlation coefficient among CBR_s and CBR_U (CBR_s=0.826*$CBR_u^{0.967}$) with correlation coefficient of 0.9(Fig.2),OMC and MDD (*MDD*= 0/0450OMC + 2/504) with correlation coefficient of 0.81 (Fig.3) and percentage of the material passed through # 200 and MDD (MDD= 2E-05#200^2 - 0.005#200 + 2.253) with correlation coefficient of 0.69 (Fig.4) are outstanding.

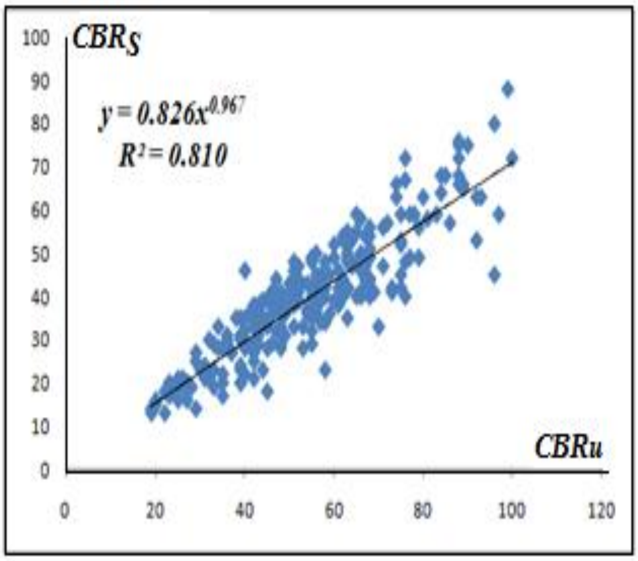

Fig. 2: Corrolation between CBR_s and CBR_U

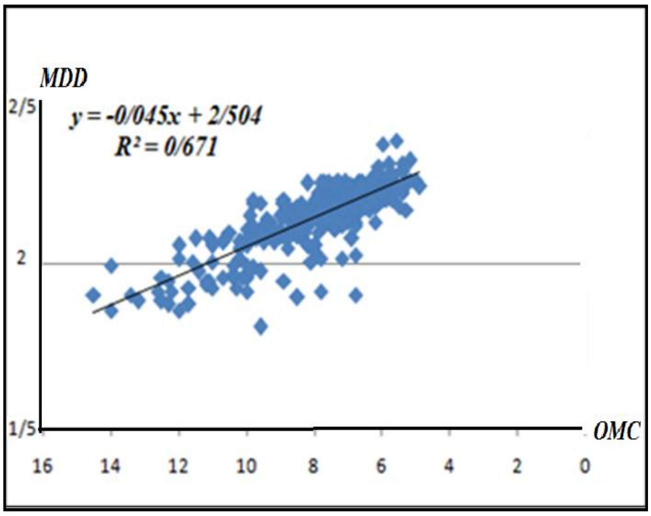

Fig. 3: Corrolation between MDD and OMC

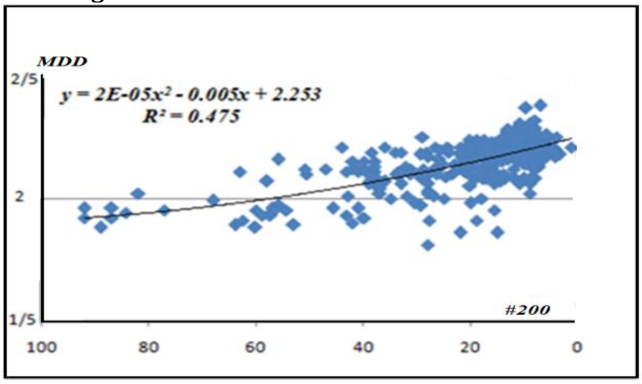

Fig. 4: Corrolation between MDD and Percentage passing 200 sieve

Table1: Models Developed from Regression Analysis between Inputs(x) and Outputs(CBR_s , CBR_U)

Variables		model	R^2
y	x		
SOAKED CBR(CBRs)	CBR_U	$y = 0.826x^{0.967}$	0.81
	MDD	$y = 1.945x^{4.254}$	0.237
	OMC	y = 111.7e-0.10x	0.217
	# 4	y = 56.06e-0.01x	0.147
	# 200	$y = 65.16e^{-0.01x}$	0.098
	PL	$y = -0.015x^2 + 1.444x + 27.70$	0.234
	LL	$y = 65.35e^{-0.01x}$	0.288
	OC	y = -0.323x2 + 3.765x + 52.47	0.004
UN SOAKED CBE(CBR_U)	MDD	$y = 0.141x^{7.074}$	0.318
	OMC	$y = 0.298x^2 - 10.29x + 98.05$	0.235
	# 4	$y = 0.016x^2 - 1.134x + 42.35$	0.125
	# 200	$y = 0.004x^2 - 0.686x + 51.03$	0.137
	PL	y = -0.004x2 + 0.157x + 46.08	0.191
	LL	$y = 114.2x^{-0.46}$	0.295
	OC	$y = 33.96x^{0.053}$	0.005

After that, to predict the objectives of this study the data are analyzed through Minitab and the following Eqs. are obtained.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

The maximum correlation coefficient is of the MDD of o.73 and the minimum correlation coefficient(R) is of the CBR_U of 0.5. According to Table 3 and Fig 4, the findings of this study there exists a proportional agreement with the ANN approach regarding the correlation coefficient but their values are less than that of the ANN. In this regard, following equations are presented through OLS method.

1) MDD = 2.35 - 0.00127 OC - 0.00108 LL - 0.000466 PL - 0.00210 #200 - 0.00186 #4 with R-Sq = 53/2%
2) OMC = 4.80 - 0.101 OC + 0.0150 LL + 0.0216 LP + 0.0368 #200 + 0.0266 #4 with R-Sq = 47.3%
3) CBR_S = 61.4 - 1.17 OC - 0.246 LL - 0.146 LP - 0.0003 #200 - 0.309 #4 - 1.82 OMC + 8.22 MDD with R-Sq = 34.1%
4) Swelling = 0.167 - 0.0624 OC + 0.00298 LL - 0.00061 PL + 0.00708 #200- 0.000069 #4 + 0.00602 OMC - 0.105MDD with R-Sq = 49%
5) CBR_U = 98.8 + 3.54 OC + 0.059 LL - 0.335 PL + 0.0055 #200 - 0.347 #4- 2.63 OMC - 2.46 MDD with R-Sq = 26/6%

Table 2: Models Developed from Regression Analysis between Inputs(x) and Outputs (MDD and OMC)

Variables y	Variables x	model	R^2
MDD	OMC	$y = -0.045x + 2.504$	0.671
	# 4	$y = -4E\text{-}05x^2 + 0.002x + 2.172$	0.374
	# 200	$y = 2E\text{-}05x^2 - 0.005x + 2.253$	0.475
	PL	$y = 6E\text{-}05x^2 - 0.006x + 2.187$	0.188
	LL	$y = -3E\text{-}05x^2 - 0.000x + 2.200$	0.151
	OC	$y = 2.164x^{0.005}$	0.008
OMC	# 4	$y = 0.000x^2 - 0.031x + 7.146$	0.275
	# 200	$y = -0.000x^2 + 0.105x + 5.998$	0.425
	PL	$y = -0.001x^2 + 0.115x + 7.127$	0.221
	LL	$y = 0.000x^2 + 0.016x + 6.888$	0.171
	OC	$y = 0.407x^2 - 1.301x + 8.241$	0.02

Table 3: OLS and MLP models

Row	Targets	ANN R-SQUARE (R^2)	OLS R-SQUARE (R^2)
1	Maximum dry density	0.79	0.53
2	Optimum moisture content	0.71	0.47
3	Soaked CBR	0.67	0.34
4	Swelling after 4 days	0.86	0.49
5	Unsoaked CBR	0.52	0.26

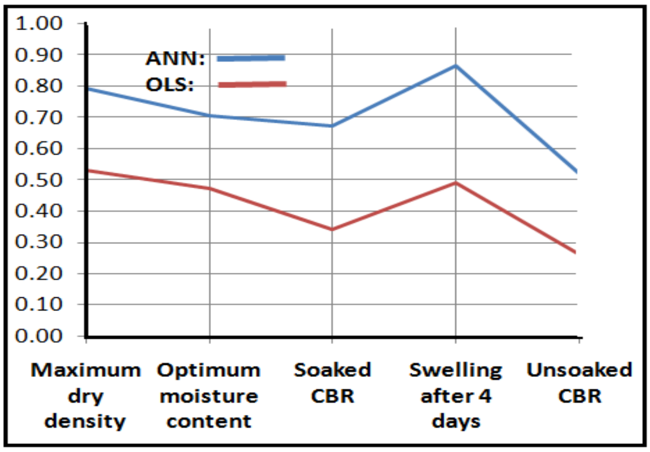

Fig. 5: Comprasion between OLS and MLP models

B. ANN Architecture

The ANN model selected for this study is of the Multi Layer Perception (MLP) following the Feed Forward Back Propagation Network (BP) regulation, Lutenbrg - Marquardt algorithm, Sigmoid Impulse Function for the hidden layer, the linear function for the output layer, Mean Square Error (MSE) function in the three input layers, hidden layer with the hidden neuron numbers and one output layer type which is modeled by MATLAB software.

C. Description of the models

1) To model the MDD prediction an input layer with 5 parameters of *OC*,LL,PL,#200,#4; one hidden layer consisting of 14 Neurons and one output layer with 1 MDD parameter are applied
2) To model the OMC production an input layer with 5 parameters of OC, *LL*, PL, #200 , #4*;* one hidden layer consisting of 14 Neurons and one output layer with 1 OMC parameter are applied
3) To model the CBR_s prediction one input layer with 7 parameters of *OC*, LL,PL,#200, #4,OMC and MDD; 1 hidden layer consisting of 14 Neurons and one output layer of CBR_s parameter are applied
4) To model the CBR_U prediction one input layer with 7 parameters of *OC*, LL,PL,#200,#4,OMC and MDD; 1 hidden layer consisting of 14 Neurons and one output layer with 1 CBR_U parameter are applied
5) To model of the swelling percentage after 4 days of soaked condition, all parameters of 3 in addition to the swelling percentage after 4 days are used.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Table 4: Training, Validation and Testing data

Row	Targets	Total of data	Training		Validation		Testing	
			Percentage	Total	Percentage	Total	Percentage	Total
1	MDD	386	80%	308	10%	39	10%	39
2	OMC	386	80%	308	10%	39	10%	39
3	CBR_s	386	80%	308	10%	39	10%	39
4	Swelling	386	80%	308	10%	39	10%	39
5	CBR_U	247	80%	173	10%	37	10%	37

Table 5: Data test results obtained from ANN

Row	Targets	Regression Equation	R	Reference
1	OMC	Predicted =0.59* Observed +2.8	0.84	Figure 6
2	CBR_s	Predicted =0.52* Observed +17	0.82	Figure 7
3	CBR_u	Predicted =1.1* Observed -11	0.72	Figure 8
4	Swelling	Predicted =0.68* Observed +0.051	0.93	Figure 9
5	MDD	Predicted=0.69*Observed+0.65	0.89	Figure 10

The sum of the data in three groups of Training, Validation and Testing are analyzed and applied through MATLAB normalization function according to Table 4.The results obtained from ANN modeling with respect to the experimental and the results obtained from the models (test data) are presented in Table 5.

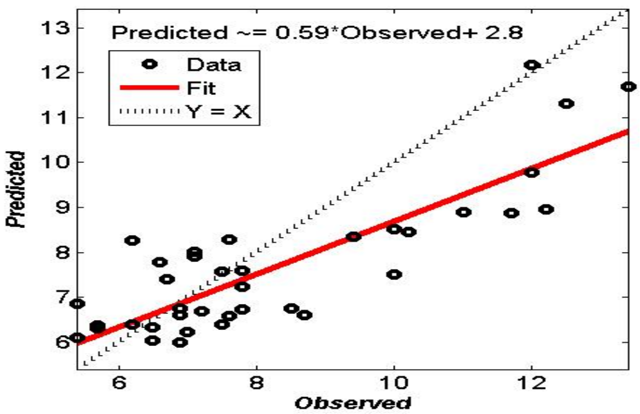

Fig . 6 : *OMC Test Data : R=0.83987*

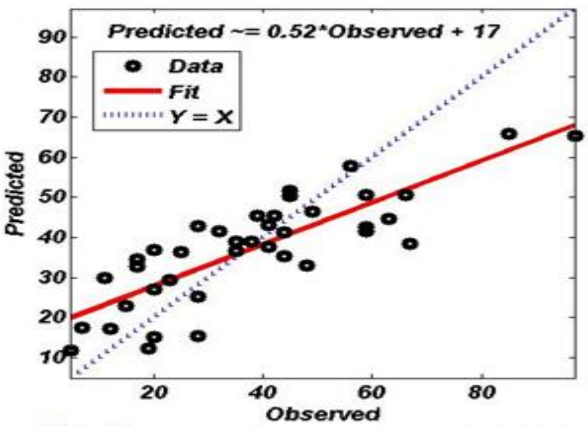

Fig . 7: Soaked CBR Test Data: R=0.82333

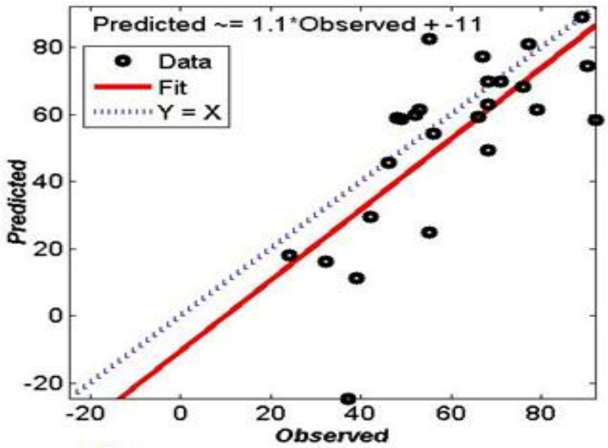

Fig . 8: *Unsoaked Test Data: R=0.72847*

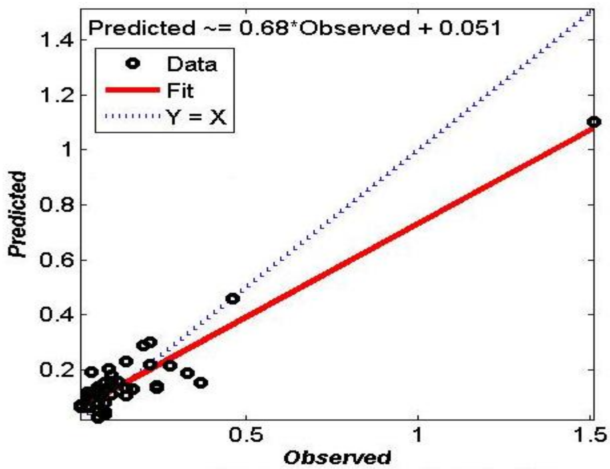

Fig. 9 : *SWELLING Test Data:R=0.93936*

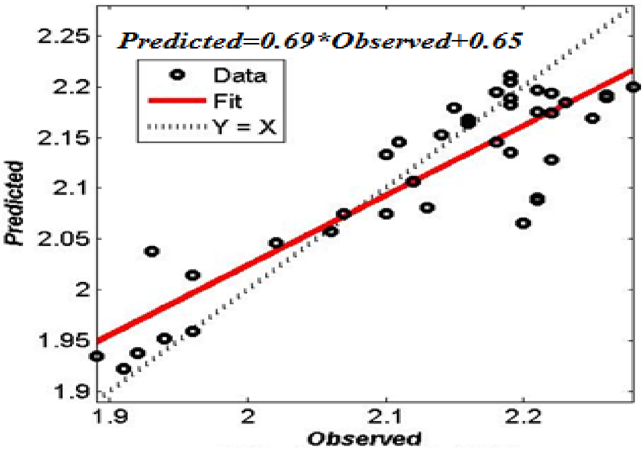

Fig. 10 : MDD Test Data : R=0.89139

IV. CONCLUSION

In civil project management, the linear construction in specific, access to soil test results for determining the bearing capacity is of vital importance. The attempt is made here to apply the OLS and MLP methods in predicting the test results from CBR, MDD and OMC through simple tests like grain-size distribution, liquid and plastic limits and then compare the results obtained by the OLS and MLP methods. The results obtained from the predictions here are:

1) The *OC*,LL,PL,#200,#4 tests are conducted with their corresponding correlation of about 0.73 for MDD and 0.69 for OMC by OLS, and 0.89 for MDD and 0.84 for OMC by ANN.
2) The *OC*, LL, PL, #200,#4 ,MDD , OMC tests are conducted with their corresponding correlation of about 0.58 for CBR_s and 0.70 for swelling percentage after 4 days by OLS, and 0.82 for CBR_s and 0.93 for swelling percentage after 4 days by ANN.

According to the analysis made on the laboratory results of the OLS and ANN methods, it is revealed that the ANNs have acceptable accuracy in approaching MDD, OMC, CBR_s, CBR_U, swelling percentage, while OLS has relatively high error percentage in predicting the result approaches. By comparing the obtained results from CBR_U with low number of tests (weaker results) with the same of CBR_s with high number of tests (stronger results) it can be deduced that: The ANN is capable of approaching the study objectives provided that the bigger statistical population would undergo tests.

REFERENCES

1. BRAJA M. DAS, "Principles of Geotechnical Engineering, 7th Edition," Cengage Learning, 2010, Available: www.cengage.com/engineering.
2. AASHTO-T99, "Standard Test Method for Moisture-Density," American Association of state highway and transportation officials (2007).
3. AASHTO-T193(2007), "Standard Test Method for CBR (Californian bearing ratio) laboratory compacted soil," American Association of state highway and transportation officials (2007).
4. Ch. Sudha Rani, Phani Kumar Vaddi,N.V.Vamsi Krishna Togati , "Artificial Neural Networks (ANNS) For -Prediction of Engineering Properties of Soils," International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-3, Issue-1, June 2013
5. M. A. Shahin, M. B. Jaksa, and H. R. Maier, "Recent Advances and Future Challenges for Artificial Neural Systems in Geotechnical Engineering Applications," Hindawi Publishing Corporation Advances in Artificial Neural Systems, Volume 2009, Article ID 308239, 9 pages
6. V.Phani Kumar and Ch. Suda Rani "Prediction of compression index of soils using artificial networks(ANNs) ," International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622, Vol. 1, Issue 4, pp. 1554-1558, 2009
7. Ramasubbarao, G.V. and Siva Sankar, G. "Predicting Soaked CBR Value of Fine Grained Soils Using Index andCompaction Characteristics," Jordan Journal of Civil Engineering, Volume 7, No. 3, 2013
8. Sathawara Jigar K., Prof. A.K.Patel. "COMPARISON BETWEEN SOAKED AND UNSOAKED CBR," International Journal of Advanced Engineering Research and Studies E-ISSN2249–8974, IJAERS/Vol. II/ Issue III/April-June, 2013/132-135
9. A. Ashrafi Fashi1, M. Khodaparast and N. Nariman-Zadeh. "Modeling and Prediction of CBR Values of soils Using Geotechnical Parameters and Evolved GMDH-type Neural Network," The 4th International Conference on Geotechnical Engineering and Soil Mechanics,November 2-3, 2010, Tehran, Iran Paper No. & Code: 283(TMAASH)

AUTHORS PROFILE

Dr. Ajalloeian Rassoul. (Isfahan, Iran, 1959). B.Sc. in Geology, The University of Isfahan, Isfahan, Iran, 1984. M.Sc. in Engineering Geology, Tarbiat Modares University, Tehran, Iran, 1995. Ph.D. in Geotechnic and Soil Mechanics, The University of Newcastle, Newcastle, Australia, 1995. He has published four books (in Persian) including "Applied Engineering Geology of Tunnels", "Principles of Geotechnical Engineering", "Experimental Criteria for Rocks Failure" and "Rock Mass Classification". He also has published more than 15 international journal papers, 14 national journal articles (in Persian), more than 50 international conference papers and more than 90 national conference papers. Some of his works published in international journals include: "Determination of silica sand stiffness" published in "*Engineering Geology*"; "Geochemistry of the Gavkhoni Playa Lake Brine" in "*Carbonates and Evaporites*"; "Investigation on causes of the Siruyeh Landslide, West Semirom (Iran)" in *Lanslides*; "Application of Rock Mass Characterization for Determining the Mechanical Properties of Rock Mass: a Comparative Study" in *Rock Mechanics and Rock Engineering*; "The effect of Scale Direct Shear Tests on The Strength parameters of Clayey Sand in Isfahan city, Iran" in *Journal of Applied Sciences*; "Chamber Studies of the Effects of Pressuremeter Geometry in Test Results in Sand" in *Geotechnique*; "The effect of water content on the mechanical behavior of Fine grained sedimentary rocks" in *Science Journal, Isfahan University*; "Strength anisotropies in mud rocks" in *Bulletin of Engineering Geology and the Environment;* "Rocks mass characterization for an underground encavation support system: the sabzkuh water con" in *Int. J. of Rock mech. & Mining Sciences*; "The provenance of the varzaneh Aeolian sand field regarding to lithology and tenture,Sw Esfahan, Iran" and "Evaluation of damsite groutability using secondary permeability index rock classification (case study)" in *American Journal of applied sciences*. His main research interests are laboratory testing of geomaterials, soil characterization, ground improvement, problematic soils, rock mechanics, tunnel engineering and site investigation and in situ testing. Dr. Ajalloeian is currently Professor in Geological Sciences department of University of Isfahan and member of Iranian Association of Engineering Geology, Geological Society of Iran, Iranian Society for Rock Mechanics, Iranian Earthquake Engineering Association, Editorial Board of the Journal of Geological Society of Iran, Iranian Construction Engineering Organization and International Association for Engineering Geology (IAEG).