Prediction of California Bearing Ratio of Subgrade Soils Using Artificial Neural Network Principles

T. V. Nagaraju, R. Gobinath, Paul Awoyera, and Mohd Abbas H. Abdy Sayyed

Abstract In soil mechanics, prediction of soil properties is necessary due to the large-scale construction activities and time-consuming testing. California Bearing Ratio (CBR) is one of the soul parameters used as strength and stiffness indicator for subgrade soil. However, for investigating soil subgrade in the field, there is a need of more soil samples to be tested; it may be time-consuming and cumbersome task. Moreover, certain issues like lack of funding, unavailability of skilled labour and poor laboratory infrastructure to handle large number of samples put thrust on development of models to predict strength with reference to certain amount of data. Nowadays, the potentiality of prediction models has been gaining importance in every discipline. Numerous tools and techniques were evolved focusing on model development; which will be able to perform iteration-based techniques. In this study, CBR values of subgrade along a proposed road are collected. Nearly, 480 samples were collected in which 15 samples were used for comparison (control value). The results revealed that the artificial neural networks (ANN) prediction models were significant promising tool for predicting CBR of subgrade soil by using index properties as input parameters.

Keywords California Bearing Ratio (CBR) · Artificial neural networks (ANN) · Backpropagation · Pavements

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1 Introduction

Recent years, rapid increase in urbanization leads to increase in the potential of new pavements to each and every nook for sustainable development. Moreover, the main parameter that affects the pavement design and construction is subgrade soil. The properties of soils are varied with place to place and layer to layer from surface. In India, most of the regions covered with the expansive soil, and it possesses variation in swell-shrink behaviour in the field [1, 2]. Further, the distresses caused by the subsoil exposed with moisture content effects the pavements, embankments, and houses. Many researchers are come up with promising findings to counteract the swelling and shrinkage behaviour of expansive clays such as mechanical alteration, chemical alteration and hydraulic modifications [3–6].

Engineering construction of modern highways and transportation modes requires high strength subgrades due to the intensity of loading pattern which is highly demanding. The subgrades that are provided should have sufficient strength, durability, bearing capacity settlement and swelling characteristics [7–9]. Hence, for assessing and investigating the strength and stiffness of the subgrades for new pavements, suitable testing and quality control are needed. Many experimental procedures were available to test the strength of subsoil in which CBR is widely regarded as preferable test which is used frequently throughout the world [10, 11]. It is recommended test for pavement analysis in terms of strength and stiffness. In California Bearing Ratio (CBR) test, the soil strength (penetration resistance) is compared with the penetration resistance of standard crushed rock.

CBR is the ratio between penetration resistance offered by soil to a piston which is travelling at a velocity of 1.27 mm/min and the resistance offered by standard crushed rock for the same penetration depth. CBR of soil subgrades was influenced by various parameters in the field such as moisture content, compaction characteristics, type of soil and method of construction. The presence of excess moisture content not only reduces the maximum density of the soil but also leads to transferring structure of flocculated expansive grains into the dispersed structures [12]. Moreover, subgrade CBR was influenced or altered by chemical alteration of soils using fly ash, rice husk ash, lime and cement. Most of the existing chemical additives such as lime and cement as a stabilizer are not enough sound in the field for higher performance. So, geosynthetics are polymeric materials gaining potential usage in the field of highways, and they can serve as a separator, filter and reinforcement member [13, 14].

On the other hand, few studies show that there will be changes in the experimental values which are caused due to the geographical area all over the world [15]. Despite the reason that it is widely used test, engineers often face issues in obtaining CBR values for longer length of a section due to funding and other related issues, but these values are required for design purpose. Also, concerned with laboratory testing of CBR, it is found that many times the data obtained become inaccurate due to the no control over the soil sampling especially in case of undisturbed sample. CBR can be obtained by other methods, tools and techniques too; researchers had studied CBR by using conic penetrometer experiment, by correlating the soil index with calculated

CBR values and also by using statistical analysis and ANN [16, 17]. Hence, there occurs a need for prediction models utilization in obtaining CBR values which can be validated against real-time data [16, 18]. Research works were undertaken for developing prediction models, since CBR of soil will be affected by index properties in a variety of ways. Most of the models tried to correlate between CBR and the grain size distribution of soils as well as plastic characteristics. Agarwal and Ghanekar [19] made an attempt to correlate CBR with plasticity index (PI), but they failed to obtain convergent correlation. They found that there exists correlation between compaction characteristics and plasticity characteristics instead and they suggested a correlation of sufficient accuracy that can be employed for preliminary identification of material. Even though models are designed to be accurate, reliable and effective, not all models that are available are providing satisfactory results. Stephens [20] reported the models using the single and multi-variable forms for estimating the CBR values based on the soil classification. He found that the estimation models were not convergent. Recent advances arrived in the field of artificial intelligence (AI), techniques such as ANN, support vector machine, natural language processing and algorithms which are gaining potentiality in soil parameters prediction. Moreover, there are not so many research works related to application of soft computing approaches for successful estimation of CBR. Some attempts were made to develop models to predict CBR but most of the models are related to statistical correlations which produce unsatisfactory results. Some attempts of such prediction model development were found in the literature. Many researchers have been attempted for developing prediction models, but reliable models were not developed. Most of the reports, prediction models on CBR of soils, were based on the traditional single and multi-variable regression analysis. Besides, many studies only considered two or three variables to estimate CBR value. For example, compaction characteristics alone do not have significant influence on subgrade CBR value. In similar fashion, plasticity characteristics or soil classification alone do not have profound significance over prediction models [18]. Prediction of CBR of fine-grained soils using artificial intelligence methods was emerging [18, 21]. Recent decade seen splurge in the research works dedicated to the usage of artificial neural networks (ANNs) concerned with the application of geotechnical engineering and allied disciplines; this is used particularly for prediction of critical parameters in soil mechanics [22–24].

For overcoming these problems, implementation of soft computing methods is used, many researchers have studied the behaviour of the soil and they done the experiments on soft computing methods such as artificial neuron networks (ANN), adaptive neuro-fuzzy interface systems (ANFIS) and support vector machine (SVM), and also traditional mathematical regression analysis is in vogue. Patel and Desai [25] reported the convergent correlations between CBR values and soil properties. His research also found that the compaction characteristics and index properties have significant effect on CBR values of soils. Taskiran [18] suggested that AI approaches such as ANN and gene expression programming (GEP) results show best estimation of CBR values.

Trivedi et al. [26] reported that the subgrade soils altered with fly ash can be assessed or predicted using genetic algorithm. Katte et al. [27] reported the estimation models of CBR value using multiple linear regression analysis based on the input variables as OMC and MDD. Especially in construction materials, not only soils but there are also more uncertainties in the concrete composition, which influences strength properties [28]. So, using AI tools gives validate results for predicting the concrete behaviour [29]. This paper presents the prediction of California Bearing Ratio (CBR) of subgrade soil using artificial neural networks (ANN). The predicted model equations have been developed, use five input parameters namely particle sizes (gravel, sand and fines) contents, liquid limit (LL), plastic limit (PL), optimum moisture content (OMC) and maximum dry density (MDD). The paper also focuses on the potentiality of ANN models for predicting soil properties.

2 Materials

Obtaining California Bearing Ratio (soaked or unsoaked) in tandem with other soil characteristics requires considerable effort, resources and time to make a preliminary assessment for the soil suitability for a particular project. In this scenario, implementing prediction models will be suitable considering the reason that they are easy to perform, take less time and also cost-effective comparing the cost required to obtain index and engineering properties of soils. In this research, an attempt is made to use ANN to predict the CBR values of soil with various input parameters.

Considering the neural network usage of relatively less influential parameters in tandem with strong parameters will be definitely beneficial and not like generic statistical procedures which will end up in unpredictable and not so favourable results. Mostly, very weak parameters that are related to the output parameters alone need to be avoided for ANN [30]. Studies suggest that usage of less influential parameters will lead to better prediction of CBR values in case of clays and silts [30]. Their results found that ANN models have significant ability to predict CBR values with very less input variables than the multiple regression analysis.

The soil samples were collected from the road network of S-Yanam to Cheer-aYanam, Andhra Pradesh, India, at a depth of 0.5 m for every 250 m longitudinal interval of proposal road stretch. Moreover, for any road or pavement design, only soil parameters can decide the road thickness. The strength and stiffness of the road can be assessed by the CBR value, which further affects by the index properties of soils.

2.1 Particle Sizes

In general, soils consist of fine-grained (silts and clays) and coarse-grained particles (gravels and sand). Fine-grained particles are dominant in surface forces and coarse-grained particles are higher in gravity forces, which further affect the compaction characteristics such as OMC and MDD. Moreover, based on the local availability of sources and conditions, the composition of sand may vary certainly. But, silica in the form of quartz is the most general constituent of sand followed by calcium carbonate.

Fines are the smaller-sized particles. These finer particles are used for binding the soil materials. Fines are the first particles move on the surface of the earth when erosion takes place. Finer particles are smaller than 0.0075 mm such as silt and clay.

2.2 Plasticity Characteristics

The amount of water required to transfer soil from plastic state to liquid state is known as liquid limit. It also defined as a soil sample cut into two parts in a cup by a groove of standard dimension of 1 cm deep should join by ½ inches fewer than 25 blows of using the mechanical liquid limit device. Plastic limit is the stage of the soil at which the soils start crumbling when it is rolled into 3 mm diameter threads under the palm of the hand.

2.3 Compaction Characteristics

Compaction characteristics such as optimum moisture content and maximum dry density influence the stiffness of the subgrade soil. The maximum dry density can be achieved by the proper gradation of soil and the compaction effort, which results in the reduction of air voids and strength improvement.

2.4 California Bearing Ratio (CBR)

California Bearing Ratio is a parameter for evaluating the mechanical strength characteristics of ground beneath pavement construction. The standard test is done by penetrating the plunger of fixed area and measure the pressure generated. Measuring load-bearing capacity is the crucial part while constructing roads. CBR can be used for evaluating the strength and the stiffness of both low and heavy-volume roads.

3 Artificial Neuron Network

ANN is brought into usage in 1958 which is the outcome of a fundamental research carried out to develop them such as Hopfields work in 1982 and McClelland and Rumelhart in 1986 considered to be the most important studies. Artificial neuron network model is a computational model which is based on the structure and functions of biological neural networks [18]. They are most reliable of learning complexity in the data and also capture convergent relationships with the given data sets [33, 34].

ANN methods are mostly adopted when direct mathematical formulae do not exist and obtaining the results may take more time for accurate results. Modern research works done in the last two decades had shown that artificial neural networks (ANN) have powerful pattern classification and pattern recognition capabilities too. Since they are biological system inspired, it will learn generally from experience and more iteration produce better results. Standard algorithm used mostly in ANNS includes backpropagation algorithms that will be employed to find the optimal choices for training a model, and the network will comprise of three layers: input, hidden and output layers [35, 36]. Compared with generic statistical methods, the effectiveness and flexibility of ANNs are more, and they are nonlinear in nature. One of the major applications they are used is in forecasting [37]. ANN models were the best tools for both researchers and engineering in the field owing to several features which are efficient and effective. Even though forecasting is a domain of linear statistics, ANNs that are nonlinear perform well [38]. They are capable of performing nonlinear modelling without any knowledge about the input and output variable relationship. But ANNs can often generalize since they are learning from the data that is presented to them; if the data contains noisy information, they can see the unseen part of a population. Also, they are universal functional approximators; they can approximate any continuous function focusing on obtaining desired accuracy.

The results obtained from the models developed using the ANN and MR were compared with the field results or experimental results. By comparison, ANN models were very efficient and effective based on the performance indices than the MR. In spite of the reason that ANN has many advantages such as easiness in applying, robustness, the main disadvantage being it is a black-box model in which no explicit relationship between input and output variables can be obtained, and hence, the results are difficult to interpret sometimes [39].

The typical structure of a feed-forward artificial neural network is sown in Fig. 1. The train program allows the user to determine the number of iterations [17]. The complexity of any problem depends on the hidden layer neurons, the connection between the neurons to their adjacent layer and the weights [23, 40–42]. Once if the system is trained, the trained file is called into the main program. In this process, there are seven input layers, ten hidden layers and one output layer.

ANN forecasting model of single hidden layer was constructed with the training and learning functions. The output of ANN model was calculated as:

$$Y = f_2(W_2 f_1(W_1 X + b_1) + b_2)$$

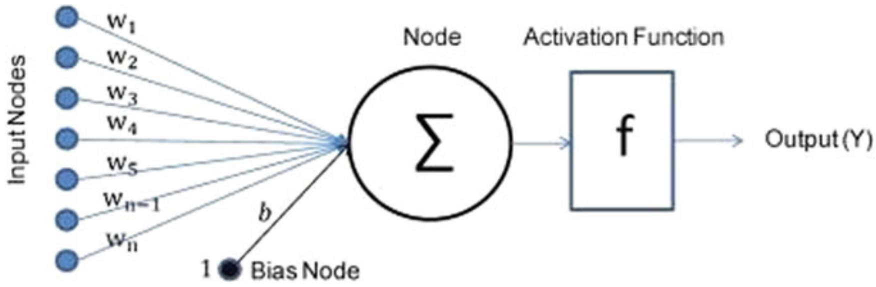

Fig. 1 Schematic representation of an artificial neuron

where y is the output. X is the input vector; f_1 and f_2 are transfer functions of the hidden and output layer, respectively; b_1 and b_2 are biases of the hidden and output layer, respectively; w_1 and w_2 are weights of the input and hidden layer, respectively.

4 Results and Discussion

In this study, for prediction of CBR value, a data set of 90 soil samples was preferred. All the 90 samples were tested for various geotechnical properties, in which 68 sample data was used for training and the remaining 22 sample data utilized for testing the ANN model. Prediction models were generated using the ANN tool from MATLAB software. Hidden layers and input layers are one and five, respectively, and preferred hyperbolic tangent sigmoid for activating layers of input, output and hidden.

Artificial neural network technique has been applied to develop a better predictive model to find California Bearing Ratio (CBR) of soil samples. Several soil samples consisting gravel, fines and sand in varying proportions were prepared to find the CBR values. The statistics such as minimum, maximum, average and standard deviation of the soil samples are listed in Table 1.

The experimental data was used for training the network, and it was divided as 70% for training, 15% for testing and 15% for validation. Various data learning techniques are available in artificial neural networks; within that, Levenberg Marquardt

Table 1 Statistics of soil data used for training the network

	Gravel (%)	Sand (%)	Fines (%)	Liquid limit	Plastic limit	OMC (%)	MDD (g/cc)	CBR (%)
Min	0	4	1	0	0	1.92	1	0.5
Max	86	99	96	60	26	24.5	6.8	35
Average	18.293	47.298	34.191	28.214	17.731	11.761	1.928	10.986
Standard deviation	17.61	16.583	19.288	9.359	5.822	2.838	0.278	7.997

algorithm was chosen based on previous studies which portraits its high accuracy of predicting targets. The input parameters considered for this study are gravel, sand and fines, LL, PL, OMC and MDD; and the output layer is having one node, California Bearing Ratio (CBR). Several iterations were conducted by retraining as well as by changing the number of hidden layers to get the best-fitting model. The final architecture selected for this network is 7–101, and it was taken by considering least mean squared error (MSE). The developed model will be considered best for prediction only if the R^2 value is more and MSE is less.

Figure 2 represents regression plot for the trained model. The linear plots clearly indicate the valid prediction plots as well as deviating plots. The regression value was found to be 0.90943 for training data, 0.92681 for validation data and 0.94597 for testing data. Overall R^2 value for the network was 0.91906 which is very close to unity

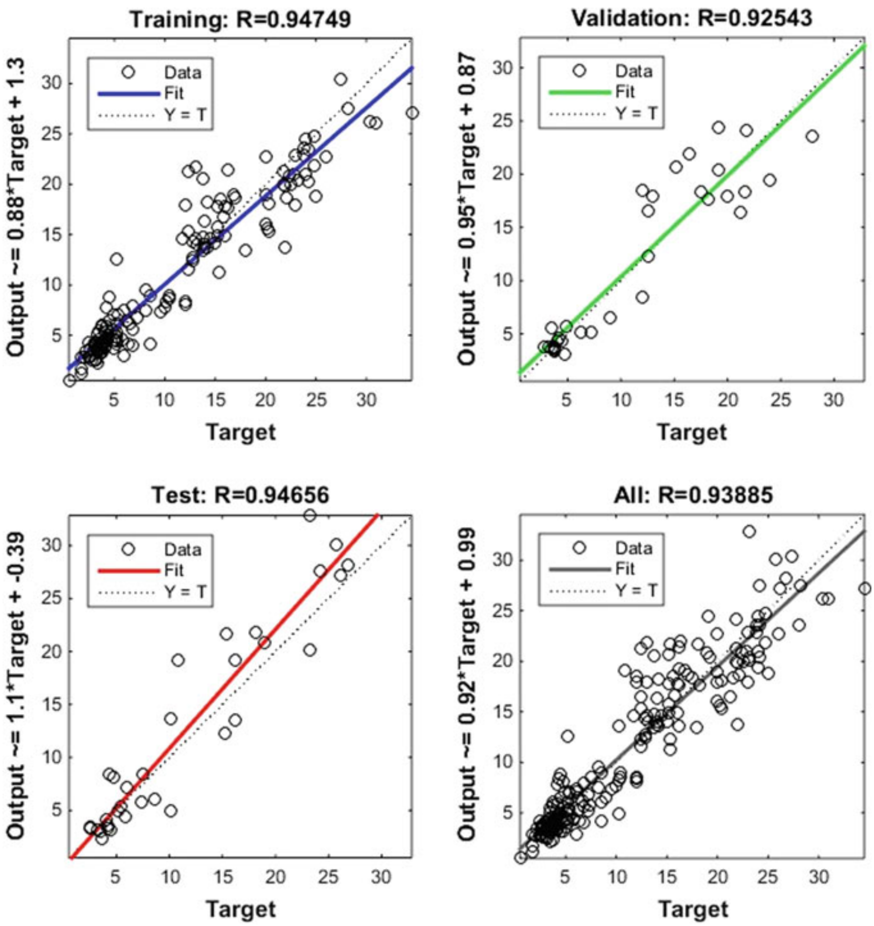

Fig. 2 Data correlations: actual and predicted values

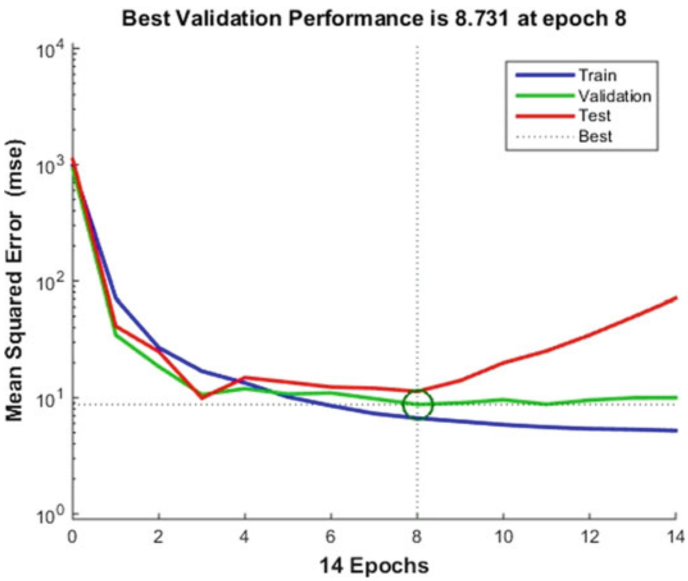

Fig. 3 Performance plot for finding CBR

indicating high accuracy. R^2 values obtained in the four cases were quite different; it implies that input data aforementioned was sensitive to choose for prediction. Best performance was observed as 9.0352 at epoch 10 and it was shown in Fig. 3. Also, the error histogram and gradient plots were shown in Figs. 4 and 5, respectively.

After training the network with 480 soil experimental data sets, 15 samples were used for testing the generated model's accuracy. The experimental data used for this is shown in Table 2. The predictions from generated neural network model are precisely matching with the actual results obtained in the laboratory. The comparison between actual and predicted CBR is shown in Fig. 6. By comparing predicted and experimental results of soil data, it is clearly evident that the best performance was occurred. Even though predicted CBR values have variation with the experimental laboratory results, it does not make any sense, because the maximum error percentage is 15%. In general, CBR values were soul parameters for pavement or road construction. This study is evident that index properties of soils such as gravel, sand and fines, LL, PL, OMC and MDD influence the subgrade CBR value. CBR prediction models using ANN can be ideal for estimating CBR values in the field.

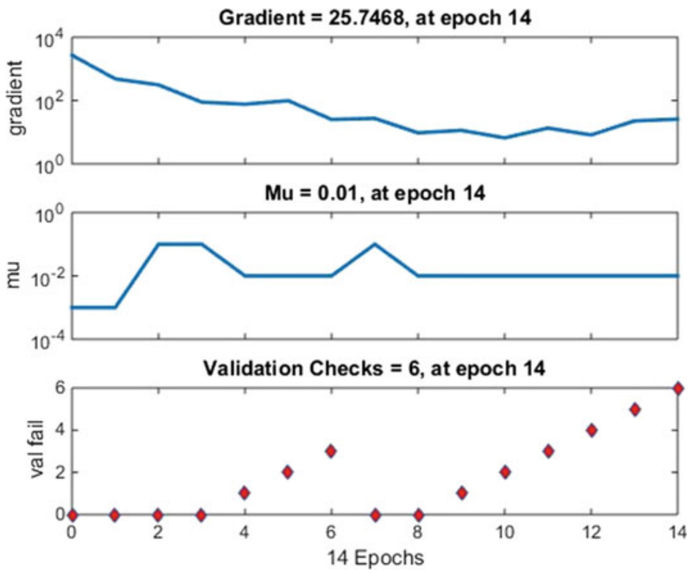

Fig. 4 Gradient plot for Soil CBR

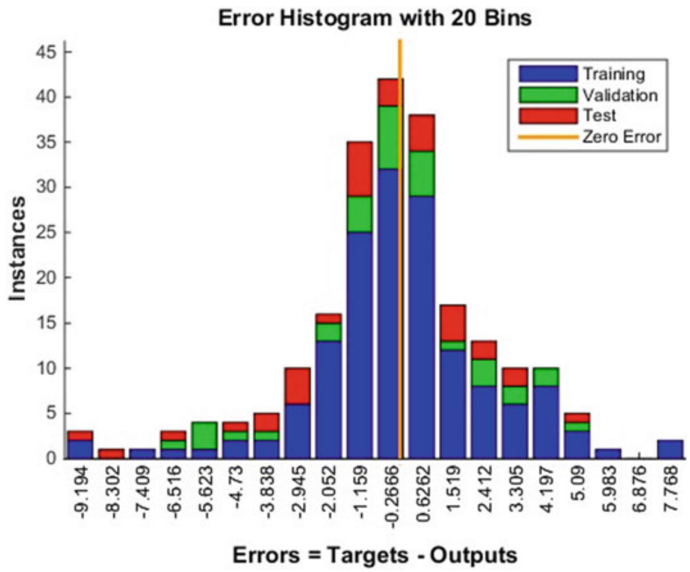

Fig. 5 Error histogram of soil samples

Table 2 Data used for testing the ANN model

S. No	Gravel (%)	Sand (%)	Fines (%)	Liquid limit	Plastic limit	OMC (%)	MDD (g/cc)	Actual CBR (%)	Predicted CBR (%)
1	20	44	36	37	20	15.2	1.9	8	8.462
2	7	60	33	26	19	11	1.98	4	6.14
3	14	53	33	36	21	15	1.86	5.3	5.363
4	25	44	31	27	19	10.5	2.04	14	13.68
5	7	35	58	42	23	18	1.76	3.6	3.299
6	25	50	25	25	18	11.2	1.93	12.8	12.72
7	0	55	45	26	19	11.8	1.81	4.5	4.328
8	19	61	20	27	18	10	2.01	15	14.09
9	20	52	28	23	18	8.3	1.95	5	6.497
10	24	45	31	25	18.5	9	1.96	6	8.016

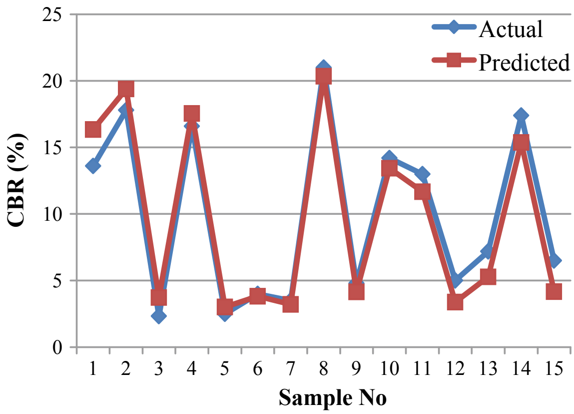

Fig. 6 Comparison between actual and predicted CBR

5 Conclusions

The research mainly focuses on developing prediction models for finding the California Bearing Ratio (CBR) of soil samples by using experimental data. The following conclusions were drawn from the study:

1. The study illustrates the properties of soils such as grain size, plasticity characteristics and compaction characteristics have significant influence on the CBR of subgrade soils.
2. The selected model for the study consists of three input layers, six hidden layers and one output layer.
3. The overall regression value was found to be 0.91906. The high regression value for training, testing and validation represents more accuracy of the network. Best performance of the model is experienced at epoch 10. The high R^2 defines that the inputs and outputs of the model are having strong correlation. Apart from training data, 15 samples were used for prediction of CBR with generated model, and interestingly, they were very close to experimental results.
4. Soft computing techniques were potential and promising tools for the prediction of geotechnical parameters and helpful for practising engineers in the field.

References

1. Chen FH (2012) Foundations on expansive soils, vol 12. Elsevier
2. Nagaraju TV, Satyanarayana PVV (2019) Geotechnical aspects of various constructions along the canal embankment using rice husk ash as stabilizer. In: Ground improvement techniques and geosynthetics. Springer, Singapore, pp 143–150
3. Moseley MP Kirsch K (2004) Ground improvement. CRC Press

4. Yarbaşı N, Kalkan E, Akbulut S (2007) Modification of the geotechnical properties, as influenced by freeze–thaw, of granular soils with waste additives. Cold Reg Sci Technol 48(1):44–54
5. Gobinath R, Ganapathy GP, Akinwumi II (2020a) Stabilisation of natural slopes using natural plant root as reinforcing agent, Materials Today: Proceedings Available online 18 September (2020a) https://doi.org/10.1016/j.matpr.2020.08.227
6. Gobinath R, Raja, G, Prasath E, Shyamala G (2020b) Amelec viloria & noel varela.: studies on strength characteristics of black cotton soil by using novel SiO_2 combination as a stabilizing agent, materials today: proceedings, vol 27, Part 1, pp 657–663
7. Heydinger AG (2003) Evaluation of seasonal effects on subgrade soils. Transp Res Rec 1821(1):47–55
8. Jones D, Jones D (2010) Guidelines for the stabilization of subgrade soils in California. University of California Pavement Research Center
9. Gobinath R, Akinwumi I, Ganapathy GP, Mithuna R (2020c) Compaction and shear strength enhancement of weak soil by copper slag addition. Materials Today: Proceedings
10. Magnan JP, Ndiaye M (2015) Determination and assessment of deformation moduli of compacted lateritic gravels, using soaked CBR tests. Transp Geotechnics 5:50–58
11. Rehman ZU, Khalid U, Farooq K, Mujtaba H (2017) Prediction of CBR value from index properties of different soils. Technical journal university of engineering and technology Taxila, Pakistan 22
12. Phanikumar BR, Nagaraju TV (2018) Engineering behaviour of expansive clays blended with cement and GGBS. Proc Inst Civil Eng Ground Improv 171(3):167–173
13. Koerner RM (1991) Geosynthetics in geotechnical engineering. In: Foundation Engineering Handbook. Springer, Boston, MA, pp 796–813
14. Brandl H (2011) Geosynthetics applications for the mitigation of natural disasters and for environmental protection. Geosynthetics Int 18(6):340–390; Chen FH (2012) Foundations on expansive soils; vol 12. Elsevier (2011)
15. Linveh M (1989) Validation of correlations between a number of penetration tests and in situ California bearing ratio test. Transp Res Rec 1219:56–67
16. Kin MW (2006) California bearing ratio correlation with soil index properties. Faculty of Civil Engineering, University Technology Malaysia, Master degree Project
17. Günaydın O (2009) Estimation of soil compaction parameters by using statistical analyses and artificial neural networks. Environ Geol 57(1):203
18. Taskiran T (2010) Prediction of California bearing ratio (CBR) of fine grained soils by AI methods. Adv Eng Softw 41(6):886–892
19. Agarwal KB, Ghanekar KD (1970) Prediction of CBR from plasticity characteristics of soil. In Proceeding of 2nd south-east Asian conference on soil engineering, Singapore, pp 571–576
20. Stephens DJ (1990) The prediction of the California bearing ratio. Civ Eng Siviele Ingenieurswese 1990(v32i12):523–528
21. Nagaraju TV, Prasad CD, Raju MJ (2020) Prediction of California Bearing Ratio using particle swarm optimization. In: Soft computing for problem solving. Springer, Singapore, pp 795–803
22. Das SK, Basudhar PK (2008) Prediction of residual friction angle of clays using artificial neural network. Eng Geol 100(3–4):142–145
23. Gunaydin O, Gokoglu A, Fener M (2010) Prediction of artificial soil's unconfined compression strength test using statistical analyses and artificial neural networks. Adv Eng Softw 41(9):1115–1123
24. Abdalla JA, Attom MF, Hawileh R (2015) Prediction of minimum factor of safety against slope failure in clayey soils using artificial neural network. Environ Earth Sci 73(9):5463–5477
25. Patel RS, Desai MD (2010) CBR predicted by index properties for alluvial soils of South Gujarat. In Proceedings of the Indian geotechnical conference, Mumbai, pp 79–82
26. Trivedi JS, Nair S, Iyyunni C (2013) Optimum utilization of fly ash for stabilization of sub-grade soil using genetic algorithm. Procedia Eng 51:250–258
27. Katte VY, Mfoyet SM, Manefouet B, Wouatong ASL, Bezeng LA (2019) Correlation of California bearing ratio (CBR) value with soil properties of road subgrade soil. Geotech Geolog Eng 37(1):217–234

28. Kumar S, Murthi P, Awoyera P, Gobinath R, Sathiskumar (2020) Impact resistance and strength development of fly ash based self-compacting concrete. Silicon. https://doi.org/10.1007/s12633-020-00842-2
29. Udaya Banu T, Rajamane NP, Awoyera PO, Gobinath R (2020) Strength characterisation of self cured concrete using AI tools, materials today: proceedings available online (11 November 2020) In Press. https://doi.org/10.1016/j.matpr.2020.10.101
30. Venkatasubramanian C, Dhinakaran G (2011) ANN model for predicting CBR from index properties of soils. Int J Civ Struct Eng 2(2):614620
31. Hopfield JJ (1982) Neural networks and physical systems with emergent collective computational abilities. Proc Nat Acad Sci 79(8):2554–2558
32. Parallel distributed processing (1986) McClelland, J. L., Rumelhart, D. E., & PDP Research Group. Explor Microstruct Cognit 2:216–271
33. Ripley BD (1993) Statistical aspects of neural networks. Networks Chaos—Statist Probab Aspects 50:40–123(1993).
34. Cheng B, Titterington DM (1994) Neural networks: a review from a statistical perspective. Statist Sci 2–30
35. Erzin Y, Turkoz D (2016) Use of neural networks for the prediction of the CBR value of some Aegean sands. Neural Comput Appl 27(5):1415–1426
36. Widrow B, Rumelhart DE, Lehr MA (1994) Neural networks: applications in industry, business and science. Commun ACM 37(3):93–106
37. Sharda R (1994) Neural networks for the MS/OR analyst: an application bibliography. Interfaces 24(2):116–130
38. Hu MJC (1964) Application of the adaline system to weather forecasting Doctoral dissertation Department of Electrical Engineering, Stanford University
39. Tayfur G, Erdem TK, Kırca Ö (2014) Strength prediction of high-strength concrete by fuzzy logic and artificial neural networks. J Mater Civ Eng 26(11):04014079
40. Zhang G, Patuwo BE, Hu MY (1998) Forecasting with artificial neural networks
41. Betaubun P (2018) Engineering of clay soil stabilization with cement and fiber on cbr value for road materials in merauke district. Int J Civ Eng Technol (IJCIET) 9(8):562–567
42. Reddy RA, Sivakrishna A, Gobinath R, Babu DR (2020) A novel method to predict pozzolanic nature of concrete with sintered clay using soft computing techniques. IOP Conf Ser Mater Sci Eng 872(1):012159 (IOP Publishing)