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Prediction of soil-bearing capacity on forest roads by statistical approaches

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Abstract The soil-bearing capacity is one of the important criteria in dimensioning the superstructure. In Turkey, predictability of California Bearing Ratio values, which may be used in the planning and dimensioning of forest roads, of which about 26% lacks the superstructure, by using soil mechanical properties (cost and time efficient parameters that are easier to determine) is investigated. Simple linear regression, multiple linear regression, artificial neural networks and adaptive network–based fuzzy inference system methods were utilized. Two hundred sixty-four California Bearing Ratio values obtained from the project carried out on the forest roads of Bartin Forest Operation Directorate were used in both the production of training-test data and the creation of models. Statistical performance of the models was assessed by means of parameters such as root-mean-square error, mean absolute error and R^2. The obtained results show that the bearing capacity values predicted by artificial neural networks and adaptive network based fuzzy inference system models display significantly better performance than the simple linear regression and multiple linear regression models. While the highest prediction capacity belongs to adaptive network based fuzzy inference system (0.969–0.991), it is followed by artificial neural networks ($R^2=0.796$–0.974), multiple linear regression ($R^2=0.796$) and simple linear regression ($R^2=0.554$). What makes the algorithms superior than the traditional statistical models is the fact that they have many processing neurons, each with local connections, and thus have higher error tolerance. On the other hand, for the forest and rural roads, which play an important role in rural development of the forest peasants, to be able to operate all-seasons, superstructure should be immediately built in order to minimize the wear on the roads.

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Keywords Forest road · California Bearing Ratio · Atterberg limits · Artificial neural network · Network-based fuzzy inference systems

Introduction

Considering the developments in contemporary forest management in Turkey, approximately 77% of the need for forest roads, which was designated to be 201,810 km (GDF, 1984), was completed by 2018, and approximately 26% of the completed part currently lacks the superstructure (GDF, 2018). In order for the forest roads, which have the functions of transporting material and personnel as well as forest products, carrying out silvicultural activities, ensuring protection, providing access to forest villages and supporting rural development, to operate all-seasons, superstructures must be immediately built on these roads. For this reason, it is critical to perform the superstructure dimensioning of forest roads faster and more economically. California Bearing Ratio (CBR) is one of the various experimental methods used for dimensioning the superstructure for this purpose. The related dimensioning is performed by dynamic CBR test (ASTM, 1883) applied to surfaces in soil examinations and is an integral part of dimensioning the elastic soils (Talukdar, 2014). In fact, CBR is a proxy measure that indicates the shear force, which can be borne by the soil at a given density and moisture content, in percentages. CBR data are of great importance for geotechnical engineering, and soil structures such as soil dams, bridge abutments and fillings behind supporting walls (Yildirim & Gunaydin, 2011). Some difficulties are encountered in designating CBR as optimum, considering the facts that the CBR test results are not very sensitive on soils with medium and weak bearing capacity, that it generally gives high values for the sands and that it is difficult and time consuming (Roy et al., 2010). For this reason, it may be of great use to develop some prediction models by means of various parameters (Kin, 2006). Numerous studies have been conducted in order to see the effects of soil types and properties on CBR. The study, which was on the compression properties of soils and conducted by Jumikis (1958), was one of the first studies on this subject. In this study, while the correlation between the optimum moisture content, plasticity index and CBR were examined, a classification index was developed in order to determine the compaction density for different McRae (1959) soil types. Ring (1962) found a correlation between Atterberg limits (liquid limit-LL and plasticity index-PI), optimum moisture content (OMC) and maximum dry density (MDD). De Graft-Johnson et al. (1969) tried to find the CBR values by means of the conformity index, which they determined by using Atterberg limits, and the amount of the soil sieved through a standard 2.4-mm sieve.

In the prediction of CBR values, generally simple linear regression analysis (SLRA), multiple linear regression analysis (MLRA), multi-layer regression analysis (MRA) and artificial neural networks (ANNs) are used. Agarwal and Ghanekar (1970) presented an equation in which the CBR values could be determined by using OMC and LL. Doshi et al. (1983) tried to determine the CBR values by using the variables of average particle size, granulometric modulus and size factor and found that the best correlation was provided by the distribution of particle size. In prediction of CBR values, Wang and Huang (1984) used a regression analysis that tested and graded the significance of each parameter. Livneh (1989) examined the correlation between the penetration test and CBR in order to point to the changes in CBR values according to geographical regions. Karunaprema (2002) and Nwaiwu et al. (2006) carried out some researches on the prediction of CBR through the penetration and plasticity modulus. Srinivasa Rao (2004) developed a relationship between CBR and group index. ANN is an alternative statistical method which is successfully applied in modelling soil behaviour, especially in geotechnical engineering problems (Das & Basudhar, 2008; Ibrahim, 2017; Shahin et al., 2008). Gunaydin et al. (2010) tried to predict the soil index properties and CBR values by using the artificial neural networks. While Sabat (2013) emphasized that both MRA and ANN could accurately predict CBR values, he also stated that the performance of the ANN model was relatively better. ANN (Baziar et al., 2015; Chao et al., 2018; Hasanipanah et al., 2016; Koopialipoor et al., 2019; Suthar & Aggarwal, 2018; Tizpa et al., 2015), which has been widely used in geotechnical engineering in recent years, is also used in other disciplines (agriculture, transportation, finance, education, etc.) (Talukdar, 2014).

In this study, various models were developed with the purpose of determining CBR values without performing laboratory tests. For this purpose, a total of 264 soil classification results belonging to 9 different soil types (A-1-a, A-2–4, A-2–6, A-2–7, A-4, A-5, 6, A-7–5 and A-7–6) taken from the forest roads located within the boundaries of Bartin Forestry Operation Directorate were utilized. The normalized results of the data are given in Fig. 1. First of all, a simple linear regression analysis was performed in order to determine the relationship between CBR data, sieve analysis, Atterberg limits, MDD and OMC. Later on, respectively, a multiple linear regression analysis (MLRA), ANN and ANFIS analysis were applied.

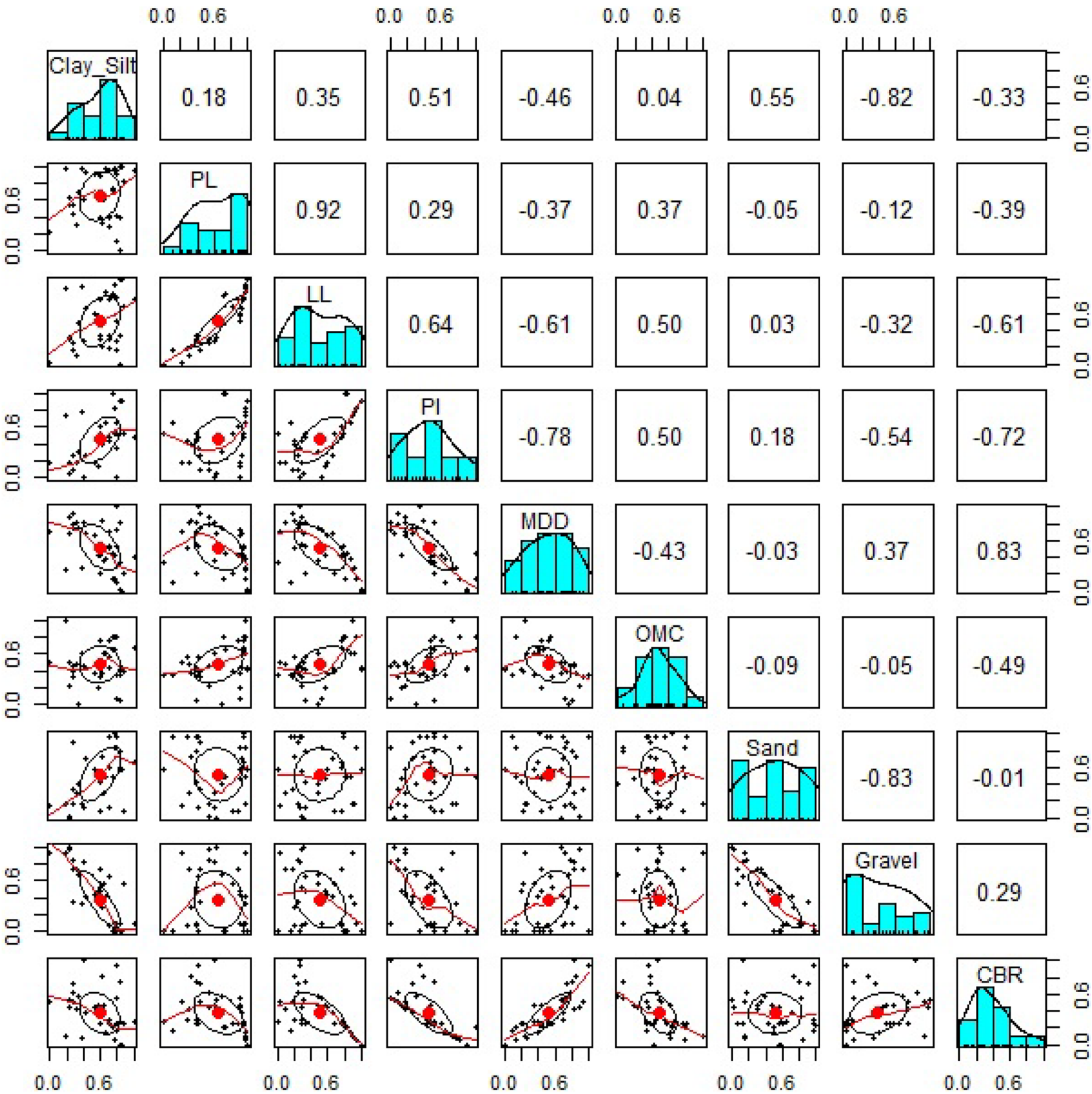

Fig. 1 Normalized sieve analysis, Atterberg limits, MDD and OMC results

Materials and methods

In order to form the models, 264 CBR test data of different groups (9 different soil types) were used. The database consists of soil properties (LL, PL, PI, MDD, OMC, CBR). Descriptive statistics related to the parameters used in modelling are given in Table 1. All four of the analyses described below were performed using R 3.5.3 software program.

SLRA

Simple linear regression is a statistical method that summarizes and examines the relationships between two continuous (quantitative) variables: A variable represented by *X* is considered to be a prediction, an explanatory or an independent variable. The other variable represented by *Y* is considered to be a response, result or a dependent variable (Rencher & Schaalje, 2008).

Table 1 Descriptive statistics (Varol, 2002)

Descriptive statistics	MDD	OMC (%)	LL	PL	PI	Gravel (G) (%)	Sand (S) (%)	Clay/Silt (C/Si) (%)
Minimum	1.336	5.300	16	10	1	0	3	10
Maximum	1.837	21.800	72	52	24	84	61	68
Median	1.633	15.700	37	27	10	30	35	36
Mean	1.623	15.013	36.649	26.162	10.486	30.703	33.324	36.243
Standard error of mean	0.022	0.607	1.824	1.407	0.908	4.641	2.995	2.755
Variance	0.018	13.646	123.123	73.306	30.534	797.159	331.947	280.856
Standard deviation	0.133	3.694	11.096	8.562	5.529	28.234	18.219	16.759
Example	264	264	264	264	264	264	264	264

MLRA

The general purpose of multiple linear regression analysis (MLRA), which was first used by Pearson in 1908, is to learn more about the relationship between several independent or prediction variables and a dependent or criterion variable (Yilmaz & Yuksek, 2008).

ANN

The researches examining the complex engineering problems within the last decade have begun to use artificial neural networks (ANNs), a simplified model of the biological structure of the human brain (Ibrahim, 2017; Yildirim & Gunaydin, 2011). ANN mainly consists of input layer, hidden layer (one or more) and output layer (Fig. 2). The input sent in order to predict an output is subtracted from each vector stored in hidden layers. The last output of the network is obtained from the output layer where normalization is performed. The normalized output is calculated by dividing the weighted sum value of hidden layer outputs by the value in the addition layer. With the purpose of finding the most suitable ANN model for predicting the CBR value, a multilayer network and a hidden layer with different number of transfer functions were tried. The architecture of one of the models used for this purpose is shown in Fig. 2. In the creation of these models, 250 out of 264 data points were used for training and the remaining 14 for testing.

ANFIS

In terms of structure, the adaptive network–based fuzzy inference system (ANFIS) is an adaptive network with a training architecture that is equivalent to Takagi–Sugeno first degree fuzzy inference system (FIS). A mixed learning algorithm is used to describe the Sugeno-type fuzzy inference system (Kakar et al.,

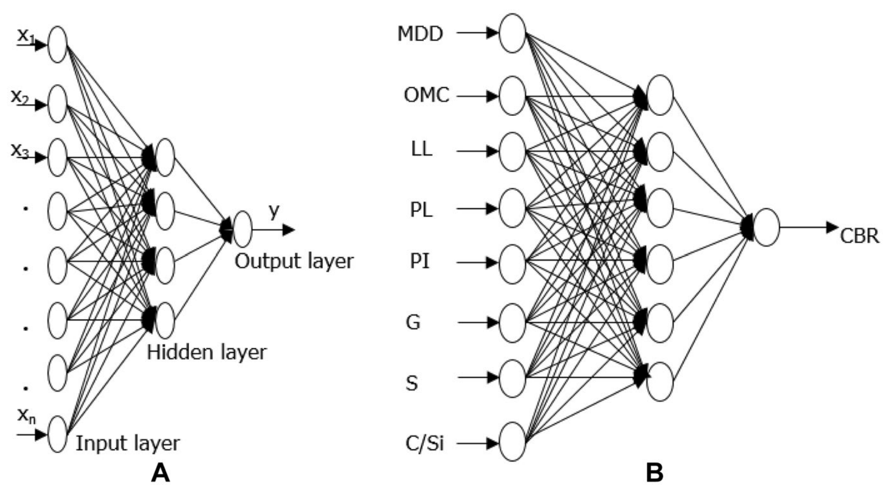

Fig. 2 A multilayer ANN (**a**) and the ANN architecture of Model I (**b**)

2005). ANFIS uses the back-propagation algorithm or the hybrid (combination of back propagation algorithm and least-squares method) optimization algorithm for the function of learning the training data (Sugeno & Kang, 1988). An example of ANFIS structure is given in Fig. 3. The operation of the layers within the ANFIS structure is as follows, respectively: input and fuzzyfication, inference, normalization, purification and collection function (Kumar et al., 2018).

The grid partitioning method was used in the generation of ANFIS. As in ANN, the models to generate the best predictions were tried to be determined by using the training and test set data. The model performances were compared using RMSE values.

Results

Results of SLRA

The data, of which normalized results are given in Fig. 1, were analysed using the least-squares regression method. In the analysis, approaches for determining the linear, logarithmic and exponential trend lines were tried for each variable, and the equations with the highest correlation value were identified. The highest one among the R^2 values ranging from 0.012 to 0.554 for 8 variables belonged to the MDD independent variable defined by exponential function.

$$\mathrm{CBR} = 0.282\mathrm{MDD}^{5.654} \quad R^2 = 0.554 \tag{1}$$

The other parameters (OMC, LL, PL, PI, G, C/Si and S) could not reach this correlation level. Also in the study conducted by Shirur and Hiremath (2014), the highest R^2 value was obtained for MDD in the prediction of CBR values. It was found by NCHRP (2001) that 84% of CBR values could be explained by one of the independent variables (sieve analysis) with the exponential function obtained. The SLRA equations obtained in several studies have R^2 values varying between 0.002 and 0.979 (Datta & Chottopadhyay, 2011; Gregory & Cross, 2007; Patel & Desai, 2010; Ramasubbarao & Sankar, 2013; Shirur & Hiremath, 2014; Talukdar, 2014; Vinod & Reena, 2008; Yildirim & Gunaydin, 2011). After MDD, the highest relationships were found for OMC, G and LL (Katte et al., 2019).

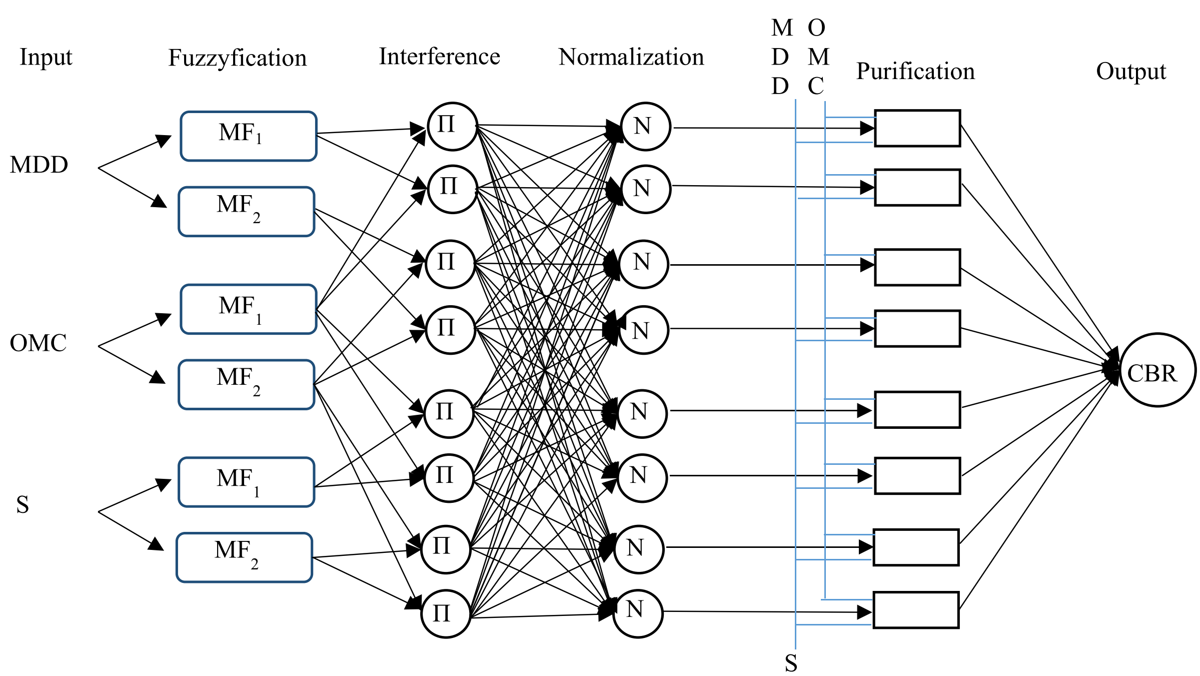

Fig. 3 ANFIS architecture

Table 2 Statistical results of selected MLRA model

Variables	Standard error (%)	R^2	*F* value	*t* value	Significance
MDD	1.537	0.796	36.1	5.62	$3.27\ 10^{-6}$***
OMC	0.053			−6.188	$6.31\ 10^{-7}$***
S	0.011			−1.860	0.072
C/Si	0.013			−3.345	0.002**

Significance code: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '.'1

Results of MLRA

CBR model derived with MLRA analysis:

$$\begin{aligned} CBR = {} & 8.636MDD - 0.329OMC - 0.021S \\ & - 0.043C/Si - 1.989 \quad R^2 = 0.796 \end{aligned} \tag{2}$$

Validation of the model was performed using correlation coefficient, *t* and *F* tests. The statistical results of the model are given in Table 2. The *t* values tabulated for CBR at 95% confidence level were found to be greater than the *t* table value of ± 2.776. According to these data, it was understood that the best predictions could be made, when MDD, OMC and C/Si were used as independent variables. Since the *F* value computed for Eq. 2 was greater than *F*-table value, it was concluded that the model was valid.

Results of ANN

Two examples of ANN architecture used in the prediction of CBR values, which are experimentally observed by means of ANN models using training and test data sets, are shown in Fig. 4. Four models, in which the input variable ranged from 8 to 1 and the output was the CBR value, were analysed (Table 3).

The performance of the four models developed was assessed by using some statistical parameters such as MSE, RMSE, MAE and R^2 (Table 4). Table 4 indicates that ANN models give better results than SLRA and MLRA models in terms of statistical performance. In Model II, it has four input variables (S (sand), C/S (clay/silt), MDD (maximum dry density) and OMC (optimum moisture content)) and has the highest R^2 value of 0.974. Since it is assumed that there is a strong correlation between the predictions and actual data (Faul et al., 2009) if the R^2 values of the suggested models are higher than 0.8, almost all models demonstrate a strong correlation. Taking the learning and test data and validation results into consideration,

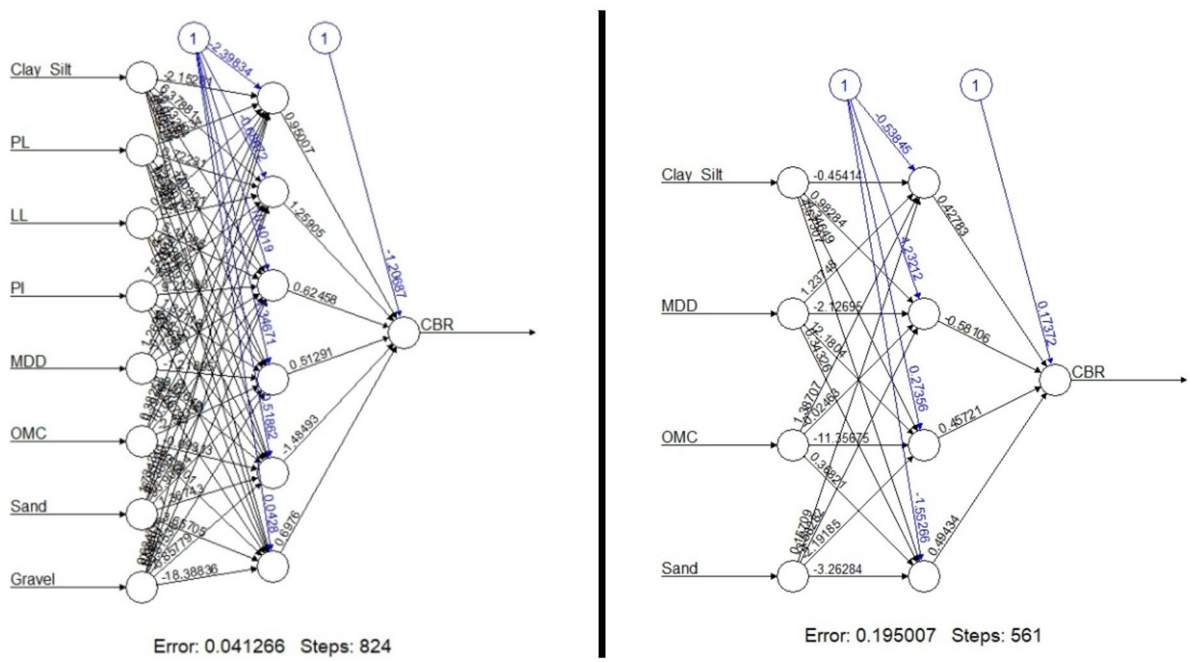

Fig. 4 ANN architecture of Model I and II

Table 3 ANN models used in CBR prediction

Models	Inputs	Structure
I	LL, PL, PI, G, S, C/S, MDD, OMC	8–6-1
II	S-C/S-MDD-OMC	4–4-1
III	C/S-MDD-OMC	3–2-1
IV	MDD	1–1-1

Model II has the best results among the four models. In addition, Fig. 5 shows the comparison of the predicted values with the measured CBR values.

Results of ANFIS

A summary of the best CBR results obtained with the ANFIS approach as a result of modelling and prediction studies is presented in Table 5. As can be seen from the table, for all four models, the combinations, where R^2 was greater than 0.90 and RMSE was minimum, were deemed to be the best ANFIS models. The genfis1 function used here uses the initial conditions for ANFIS training and forms a single output Sugeno-type fuzzy inference system (FIS) by applying the grid partitioning method to the data. Genfis1 function used different number and different input and output functions (MF) for CBR model. It was seen that pimf was successful as the MF type in models, where the number of input variables was small (1 and 3) in terms of model performances, while the positive effect of gauss2mf, gaussmf and gbellmf membership functions increased with increasing number of input variables. In all ANFIS models, the hybrid optimization algorithm performed better as the learning algorithm.

Table 4 Statistical Performance of ANN Models

Model	MSE	RMSE	MAE	R^2	Error	Steps
I	0.031	0.177	0.142	0.883	0.041	824
II	0.001	0.037	0.031	0.974	0.195	561
III	0.004	0.063	0.039	0.850	0.202	1331
IV	0.005	0.073	0.068	0.797	0.299	177

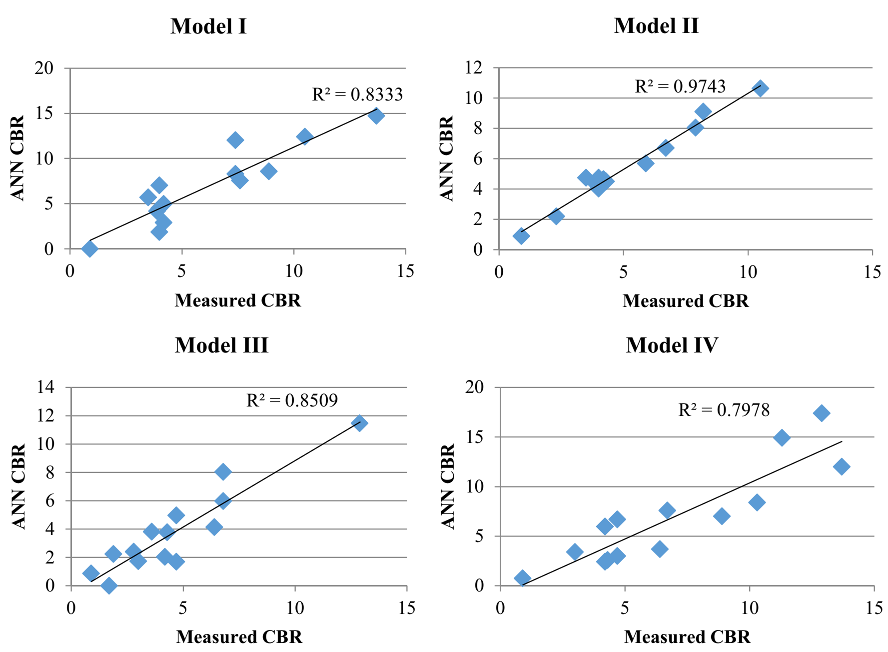

Fig. 5 Comparison of CBR values with ANN models

Table 5 Statistics of ANFIS models

Model	Input	MF type input	MF type output	Number of MF	Training		Test	
					R^2	RMSE	R^2	RMSE
Model I	C/S PL LL PI MDD OMC S G	gauss2mf gauss2mf gaussmf gaussmf gauss2mf gauss2mf gauss2mf gauss2mf	Fixed	2.2.2.2.2.2.2.2	1.000	0.0001	0.969	0.725
Model II	C/S MDD OMC S	gauss2mf gauss2mf gaussmf gbellmf	Fixed	2.2.2.2	0.872	1.114	0.971	0.738
Model III	C/S MDD OMC	pimf pimf pimf	Fixed	3.2.2	0.839	1, 253	0.991	0.805
Model IV	MDD	pimf	Fixed	4	0.702	1.701	0.984	0.478

Discussions

As in SLRA, the relationship between CBR and 8 independent variables has been tried to be explained by Agarwal and Ghanekar (1970), Nwaiwu et al. (2006), Satyanarayana and Pavani (2006), Patel and Desai (2010), Taskiran (2010), Yildirim and Gunaydin (2011), Ramasubbarao and Sankar (2013), Shirur and Hiremath (2014), Talukdar (2014), Jayamali and Nawagamuwa (2015), Ibrahim (2017), Suthar and Aggarwal (2018), Katte et al. (2019), by MLRA equations since 1970s. In these studies, R^2 values of the models obtained by MLRA ranged from 0.80 to 0.96. The common characteristic of the equations obtained is the fact that MDD and OMC variables are included in each model, similar to Eq. 2 found by us. While the models generated by Mak and Gofar (2007), Shirur and Hiremath (2014), Jayamali and Nawagamuwa (2015) and Katte et al. (2019) included only MDD and OMC variables, other studies included LL, PL and PI variables as well as S, C/Si and G variables. However, models with LL, PL and PI variables generally contain all variables together (Ibrahim, 2017; Patel & Desai, 2010; Ramasubbarao & Sankar, 2013; Suthar & Aggarwal, 2018).

When the four ANN models identified are compared with the models used in the prediction of CBR values in the literature, statistically, it is seen that results, which are close 0.84–0.99 R^2 values found by Suthar and Aggarwal (2018), are obtained, and MAE and RMSE values are observed to be even smaller. The R^2 value range of 0.846–0.99 found by Yildirim and Gunaydin (2011), Momeni et al. (2014) and Kuo et al. (2009) indicates similar results as well. Moreover, it is seen that the RMSE results of 00.47 obtained by Pham et al. (2018) from the models used in the prediction of CBR values are similar to Table 4 data.

Since ANN models simultaneously optimized many parameters (number of hidden layers, learning speed, number of hidden layers and nodes, weighted prioritization techniques and transfer functions) during learning (Samui, 2008), they gave better results than MLRA models. Therefore, these results show that ANN models give better results than SLRA and MLRA models. Kanungo et al. (2014) stated that ANN was a promising method for predicting CBR values.

Even though machine learning techniques such as ANN are advanced methods for prediction problems, their performance mainly depends on the quality of the data used (Mair et al., 2000). In geotechnical problems, the use of variables identified from various samples of the same soils may affect the performance of the models used. In this study, four models gave acceptable results in making predictions. However, the results obtained can be improved by providing more data input. Considering that the tests are performed under different test conditions, using different equipment by different practitioners even in the laboratory environment, it becomes more evident how difficult it is to predict soil properties. The fact that the ANN models developed in this study have smaller error rates than the standard deviation values of 0.2521765 (Model I), 0.2478055 (Model II) and 0.2708287 (Model III) indicates the usability of CBR values in prediction.

According to ANN results, only Model II was seen to be more than 90% successful in predicting the measured CBR values, while the four ANFIS models were found to be more than 90% successful in predicting the CBR values (Fig. 6). When the four analyses are compared, R^2 values of 0.984/0.991/0.971 and 0.969 show that ANFIS automated learning algorithm has the highest level of efficiency (Shirzadi et al., 2017). As in ANN models, the RMSE values of ANFIS models were also smaller than the standard errors of the models. Similar results were also obtained by Pham et al. (2018).

Cumulative frequency is used to evaluate the effectiveness of the analyses (Jain et al., 2001). The cumulative frequency indicates the distribution of prediction errors as well as the performance index of the predicted bearing capacity. For x% threshold level, the following equation (Eq. 3) is used:

$$TS_x = \frac{y_x}{n}100 \tag{3}$$

In the equation, y_x refers to the number of bearing capacity from x%, relative error outside the computed total bearing capacity (n). Figure 7 presents the error distributions of four analyses (SLRA, MLRA, ANN and ANFIS). While ANFIS predicts 57.14% of the validation data with less than 5% error, the results are 50.00% for ANN, 28.57% for MLRA and 7.14% for SLRA. These results indicate that ANFIS is more successful in predicting the

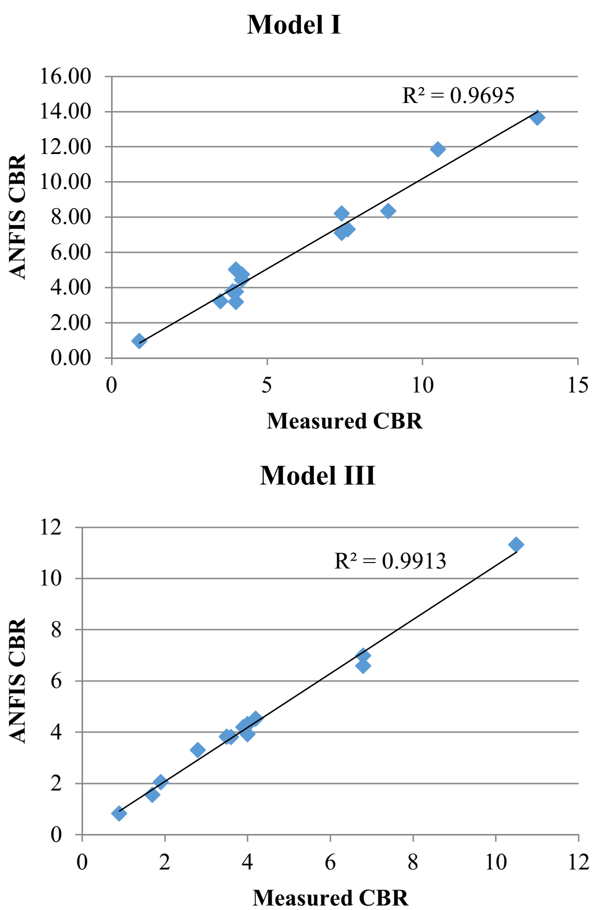

Fig. 6 Comparison of CBR values with ANFIS models

bearing capacity of soil with mechanical properties than other analyses. The use of ANN learning principles by ANFIS in order to derive pre-determined parameters leads to a better performance (Padmini et al., 2008). This is because the ANFIS and ANN analyses differ from the other two analyses by using the training data of learning algorithms. ANN analysis is more successful than MLRA and SLRA in predicting the bearing capacity. While the processing speed of the ANN takes 5 to 10 s depending on the number of inputs, ANFIS can complete the process in 20 s to 1 h. This is due to the fact that the least-squares prediction used by ANFIS requires further calculations (Padmini et al., 2008).

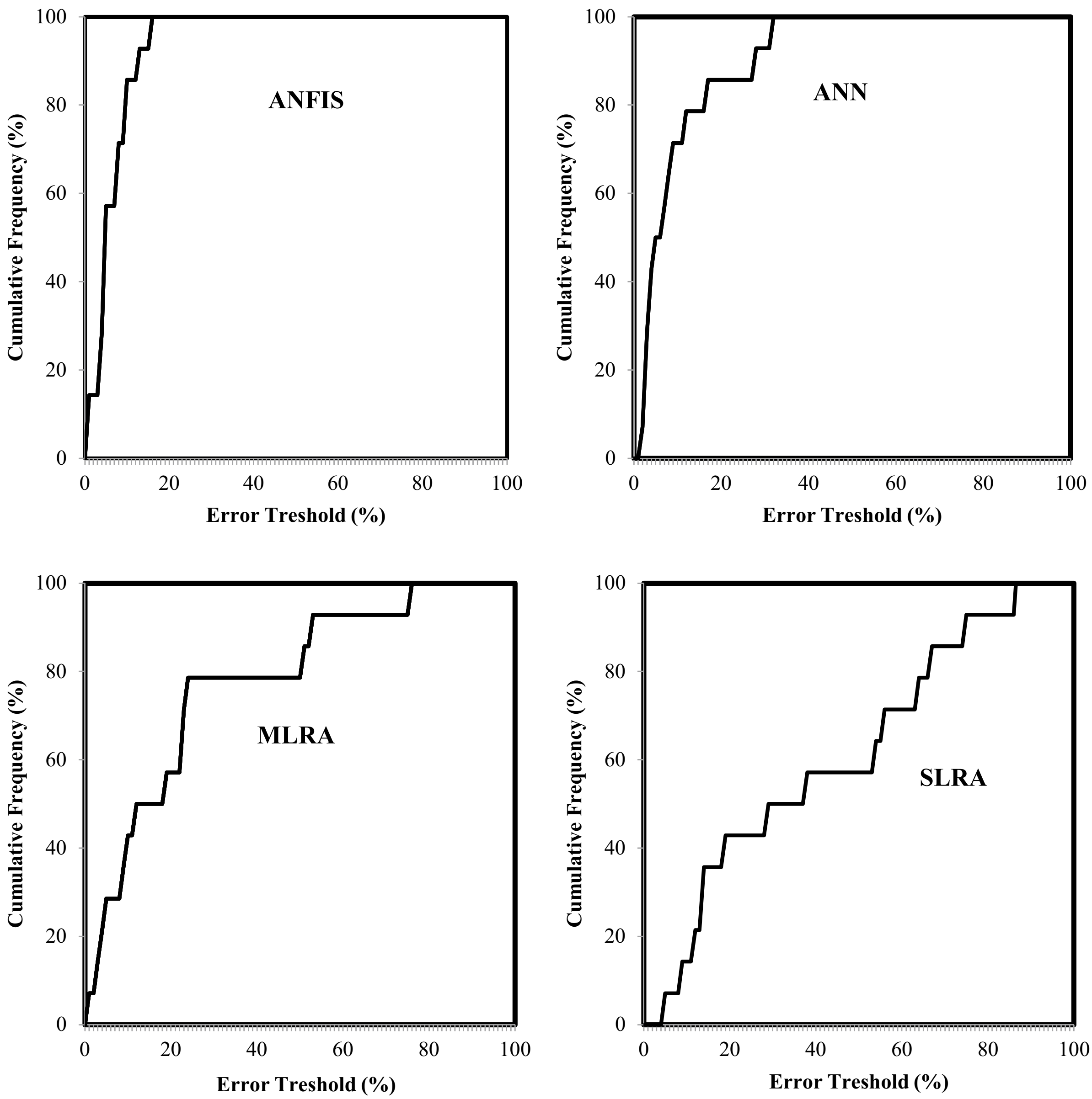

Fig. 7 Distribution of prediction error to different error thresholds

Conclusions

The aim of this study was to identify the models that are able determine CBR values faster and more economically by using the correlation between the measured CBR values and mechanical soil properties. The samples were collected from the forest roads located within the borders of Bartin Forestry Operation Directorate, and 264 samples were gathered from different geological points. Relations were developed with various models in order to predict the CBR values with LL, PL, PI, S, G, C/Si, MDD and OMC. In addition, four different analyses (SLRA, MLRA, ANN and ANFIS), where the models were developed, were compared with each other. Of those four models, the accuracy of ANN and ANFIS analyses was at a similar level. R^2 values obtained for the models were 0.554/0.796/0.833–0.974/0.970–0.991, respectively. When the study was technically evaluated, it was found to be a good tool for minimizing the uncertainty at the determination stage of bearing capacity during the design of forest roads with the statistical comparison of analysis performances and automated learning algorithms.

Therefore, the use of automated learning algorithms may reduce the potential inconsistency of correlations as well as providing new approaches to such problems. What makes the algorithms superior than the traditional statistical models is the fact that they have many processing neurons, each with local connections, and thus have higher error tolerance. On the other hand, for the forest and rural roads, which play an important role in rural development of the forest peasants, to be able to operate all seasons (the roads that were originally built as forest roads and then evolved into the village roads in time), superstructure should be immediately built in order to minimize the wear on the roads.

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Author contribution Tuğrul Varol, as the researcher of the project number TOGTAG 2762, has carried out field studies and took part in the statistical analysis of the article, evaluation and writing of the paper. Mertol Ertuğrul, Halil Barış Özel, Mehmet Cetin, Hakan Sevik and Tuna Emir made statistical analysis of the article, evaluation and writing of the article. Mertol Ertuğrul, Halil Barış Özel, Mehmet Cetin, Hakan Sevik and Tuna Emir contributed to the statistical evaluation and provided literature support. Metin Tunay served as an academic advisor.

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Data availability All data are given in manuscript.

Declarations

Competing interests The authors declare no competing interests.

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