CIVIL ENGINEERING JOURNAL

Article no. 26

THE CIVIL ENGINEERING JOURNAL 2-2022

APPLYING BIOGEOGRAPHY-BASED MULTI-LAYER PERCEPTRON NEURAL NETWORK TO PREDICT CALIFORNIA BEARING RATIO STABILIZED POND ASH'S VALUE WITH LIME SLUDGE AND LIME

Jiaman Li[1], Jundong Wu[2] and Wei Hu[3]

1. *Shaanxi College of Communication Technology, Xi'an, Shaanxi, 710000, China; Jiamanli126163@gmail.com*
2. *China Airport Construction Group Co., Ltd. Northwest Branch, Xi'an, Shaanxi, 710000, China; (corresponding author) lixiaojiaman@126.com*
3. *Shaanxi provincial transport planning design and research institute, Xi'an, Shaanxi, 710000, China; weihucivil126@gmail.com*

ABSTRACT

The California Bearing ratio (CBR) value of pond ash stabilized with lime and lime sludge was predicted in this research using a hybrid biogeography-based multi-layer perceptron neural network (BBO-MLP) with varying numbers of hidden layers (one up to three). In order to do this, the model used five inputs—the maximum dry density, ideal moisture content, lime percentage, lime sludge percentage, and curing period. The best BBO-MLP network, BBO-MLP1, has R^2 values of 0.9977, $RMSE$ values of 0.7397, MAE values of 0.476, and PI values of 0.0104. The predicted CBR values in all three of the created systems show a tolerable level of agreement with empirical findings, demonstrating the viability of the suggested models for very accurate CBR value prediction. Comparisons between the three created models show that BBO-MLP1 performs better than the others. BBO-MLP1 might be identified as the suggested model as a result.

KEYWORDS

California bearing ratio, Pond ash stabilized, Lime, Lime sludge, Hybrid biogeography-based multi-layer Pprceptron neural network

INTRODUCTION

It takes a large area to dispose of fly ash from thermal power plants, which leads to environmental issues, including leaching and dusting. Thermal power plants create three forms of ash [l] 1. Fly ash: this is made of electrostatic precipitators**.** 2. Bottom ash: this is mixed with water to make a sludge, which is subsequently disposed of as 3 . Pond ash in ash ponds [2]. ASTM categorizes coal ash as Class F and Class C ash [3]. Class C ash includes extreme concentrations of calcium and reacts with water without a binder [4].

Class F ash has less calcium and is produced by most of the world's thermal power plants [5]. Class F ash lacks the vital strength for use as a construction material. Numerous studies [6–9] were done to enhance the lime-stabilized Class F fly ash's engineering qualities. Cement and gypsum Lime sludge (LS) is an extra byproduct.

About 4.5 million tons of LS are produced yearly by these sectors in India [10], and their disposal is challenging [11–13]. As LS comprises calcium carbonate [14], researchers have proposed employing it in a range of applications [15-17].

CBR is among the most critical metrics to assess the subgrade of elastic and stiff pavements [18]. The CBR validation may be accomplished in the site construction or a laboratory. In the laboratory, it is often examined on compressed soil models, but on the site, it is performed on the ground surface. In addition to being complicated and time-consuming, the CBR test occasionally yields erroneous results owing to sample disruption and inadequate laboratory testing conditions. So, constructing prediction models could benefit and serve as a foundation for analysis.

An artificial neural network (ANN) is a simplified human brain simulation [19]. It is widely recognized for collecting and expressing abstruse inputs and outputs [20]. Unlike most traditional empirical and statistical methodologies [21], our method does not require such knowledge. Therefore, ANNs are suitable for simulating the complicated behavior of the vast majority of geotechnical engineering materials, which are highly variable [21]. ANNs are superior to most traditional procedures [21] due to their modeling capability and capacity to learn from experience. Recently, ANN has been successfully implemented in virtually every field of geotechnical engineering, including the compressive strength and Young's modulus of frozen sand [21-31].

Despite the wealth of literature on ANN applications, some research has been performed to anticipate the soils' CBR values. Yildirim and Gunaydin [32] created statistical models and an artificial neural network (ANN) using CBR data gathered from various sites along Turkey's public highways. In terms of predicting CBR values, the ANN model outperforms statistical approaches. Sabat [33] generated ANN and MR models for assessing the CBR value. The CBR was accurately predicted by the MR and ANN models; however, the ANN model performed significantly better. The M5P and Random forest RF model tree modeling methodology simulate the pond ash's soaking CBR value. LI and LS were utilized to stabilize pond ash. Utilized CBR data collected by experimental software. Model performance was tested to utilize conventional statistical parameters. Although the performance of both models in forecasting the CBR value is excellent, it is evident from the statistical characteristics that the RF technique performs better than the M5P model [34].

This study's primary purpose was to identify and evaluate the precision of several intelligent techniques [35]. So, a hybrid biogeography-based multi-layer perceptron neural network (BBO-MLP) with varying hidden layers' numbers is constructed to predict CBR values in lime and sludge pond ash. CBR was the starting variable for the model. The input variables for the model were optimal moisture content (OMC), maximum dry density (MDD), the curing period (CP), lime sludge percentage (LS), and lime percentage (LI). Four performance metrics were used to assess the model's accuracy.

DATASET AND METHODOLOGIES

The data set's description

In order to study the influence of lime sludge and lime on the value of CBR, 51 experimental data records were selected from the published document (Table 1) [36] to create a data set. Five unique variables that may affect the CBR's value were investigated. These factors are shown in Table 2**.**

Tab. 1 - The results of CBR and Seventeen mix designs

Mix No.	Lime percentage (LI)	Lime Sludge percentage (LS)	The maximum dry density (MDD(g/cc))	The optimum moisture content (OMC(%))	CBR		
					7.0	28	45
1	0.0	0.0	1.1750	26.80	2.20	3.40	4.30
2	2.0	0.0	1.1940	25.30	10.10	13.40	15.40
3	2.0	5.0	1.2270	25.00	14.60	26.30	29.50
4	2.0	10.0	1.2300	24.80	20.60	33.60	38.50
5	2.0	15.0	1.2380	24.30	24.70	39.50	46.30
6	4.0	0.0	1.2070	24.50	16.20	27.70	31.50
7	4.0	5.0	1.2370	23.80	22.50	32.30	40.50
8	4.0	10.0	1.2510	23.30	28.10	39.40	46.10
9	4.0	15.0	1.2530	23.10	32.40	45.90	52.30
10	6.0	0.0	1.2270	24.20	26.10	42.30	50.60
11	6.0	5.0	1.2590	23.00	33.10	52.60	63.80
12	6.0	10.0	1.2370	23.20	30.40	44.80	54.90
13	6.0	15.0	1.2420	24.00	32.30	47.70	57.40
14	8.0	0.0	1.2560	23.00	29.90	44.80	53.40
15	8.0	5.0	1.2400	22.80	34.20	52.90	61.10
16	8.0	10.0	1.2460	24.70	31.20	46.10	56.30
17	8.0	15.0	1.2410	24.10	32.10	48.90	57.60

Tab. 2: Input and output variable statistical values

VARIABLE	Min	Max	Average	St. deviation
LI	0.00	8.00	4.7060	2.4680
LS	0.00	15.00	7.0590	5.7030
MDD	1.1750	1.2590	1.2330	0.0220
OMC	22.800	26.800	24.1120	1.0080
CP	7.000	45.000	26.6670	15.5420
CBR	2.200	63.800	35.7220	15.4380

Biogeography-based optimization (BBO)

The BBO methodology is Simon's developed meta-heuristic optimization approach [37]. This technique presupposes a restricted number of habitat categories within an ecosystem. Food, water, temperature, and other factors are suitability index variables (SIVs).

The habitat suitability index quantifies the quality of each environment (HSI). When a habitat has a high HIS or is saturated, organisms incline to move and immigrate to environments with a low HIS. Each habitat was a possible solution to the problem, with its appropriateness indices acting as selection criteria (DVs).

Results with minor target values have greater HSI values in the minimization technique. This strategy utilizes the "migration" and "mutation" operators. The HS-sized habitats are ranked according to their respective cost functions. The following equation determines the appropriateness ($\mathrm{HSI_i}$): (1)

$$\mathrm{HSI_i} = -\mathrm{i} + \mathrm{HS} + 1 \tag{1}$$

In Equations. (2)-(3) μ_i indicates the emigration and λ_i is the immigration values which are computed as below:

$$\mu_\mathrm{i} = \frac{\mathrm{HSI_i}}{\mathrm{HS}} \tag{2}$$

$$\lambda_\mathrm{i} = 1 - \frac{\mathrm{HSI_i}}{\mathrm{HS}} \tag{3}$$

The BBO method's migration curve is seen in Figure 1. The transition from the j-th determinant of the r-th habitat to the i-th determinant of the r-th habitat is expressed by equation (4).

$$\mathrm{DV_j^k} = \alpha \mathrm{DV_j^i} + (1-\alpha)\mathrm{DV_j^r} \tag{4}$$

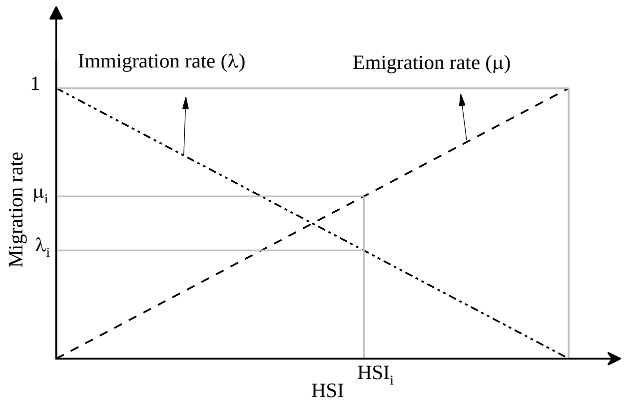


Fig. 1 – The BBO algorithm's migration function

Biogeography-based multi-layer perceptron neural network (BBO-MLP)

A human brain's mathematical process simulation is the basis of an artificial neural network. The key elements of the transfer function, connection pattern, and learning function comprise ANN [38]. These concepts are utilized for training an exclusive network by adjusting its weights according to the structure of the problem [39,40]. Each layer comprises neurons with different mathematical connections; however, neurons number in the output layer through the dataset of interest [41]. The neurons of the unseen layers are essential for distinguishing and recognizing signal properties [42,43].

Although concealed layers' number is studied, each hidden layer is limited to a maximum of 25. Similarly, the BBO approach determines the ideal neurons' number in each hidden layer for models with various numbers of hidden layers. The ANN training phase studied several methods for determining the weights and biases. In order to, the back-propagation strategy for MLP learning [38,39] is utilized based on its previous success. In this technology, input signals are modified and weighted over several layers of neurons to get an acceptable output. Figure 2 depicts the hybrid BBO- MLP process.

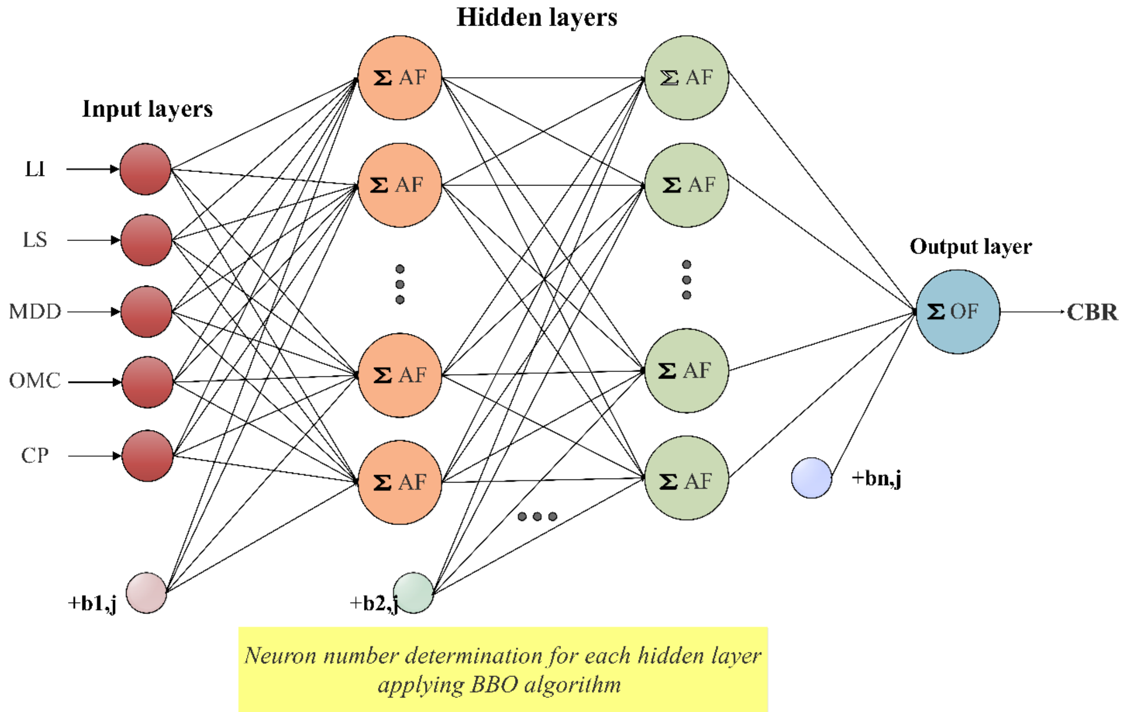


Fig. 2 – BBO-MLP hybridization procedure

Performance evaluators

Various statistical assessors were employed to evaluate the efficacy of hybrid models developed for CS forecasting. As for accuracy measures, R^2, MAE, RMSE, and PI were used (Eqs. (5)-(8)):

$$R^2 = \left(\frac{\sum_{p=1}^{P}(t_P - \bar{t})(y_P - \bar{y})}{\sqrt{\left[\sum_{p=1}^{P}(t_P - \bar{t})^2\right]\left[\sum_{p=1}^{P}(y_P - \bar{y})^2\right]}} \right)^2 \tag{5}$$

$$MAE = \frac{1}{P}\sum_{p=1}^{P}\left|y_p - t_p\right| \tag{6}$$

$$RMSE = \sqrt{\frac{1}{P}\sum_{p=1}^{P}(y_p - t_p)^2} \tag{7}$$

$$PI = \frac{1}{|\bar{t}|}\frac{RMSE}{\sqrt{R^2}+1}$$

R^2 : The determination's coefficient (8)

RMSE : Root mean squared error

MAE : Mean absolute error,

PI : Performance index

y_P : The predicted values of P^{th} pattern

t_P : The target values P^{th} pattern

$\bar{t}$: The averages of target values

$\bar{y}$: The averages of predicted values

RESULTS

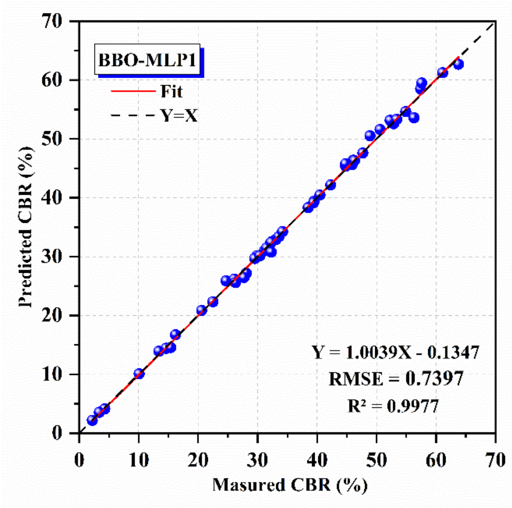
Below are the findings built to forecast the pond ash's CBR value stabilized with sludge and lime. Figure 3 compares experimentally collected data with results calculated by the BBO-MLP1, BBO-MLP2, and BBO-MLP3 models. Observably, the generated models' R^2 values that exceed 0.99620. It suggests that the relationship between the experimental and forecasted values emanated from the integrated models is about identical, thereby displaying the highest level of accuracy. In addition, a score-based technique is established by using statistical indicators to compare the productivity of the used models, like R^2, RMSE, MAE, and PI. Table 3 contains the consequences.

The BBO-MLP1 model has the maximum score (12), with R^2 of 0.99770, RMSE of 0.73970, MAE of 0.4760, and PI of 0.01040. All indices decrease as the hidden layers' number increases. The RMSE rises from 0.73970 to 0.99040 as the hidden layers' number increases. BBO-MLP1 performs better than BBO-MLP2 and BBO-MLP3 (R^2=0.9970, RMSE=0.87550, and PI=0.01230). The performance of the non-BB optimization method for calculating the neurons' number in each hidden layer is satisfactory overall.

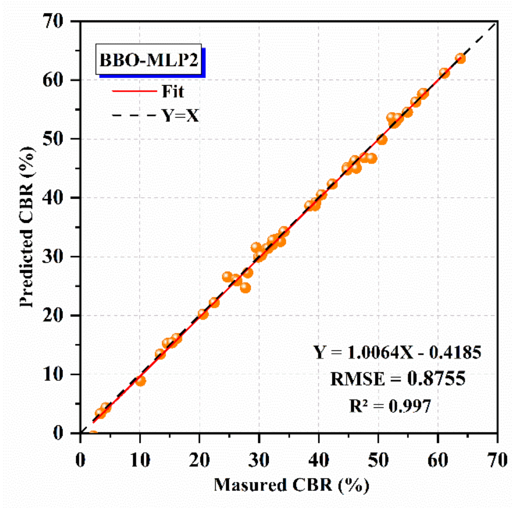
The time series plots in Figs. 4 demonstrate an adequate match between the measured and anticipated CBR. The calculated CBR values for all applicable models are remarkably near experimental data.

Tab. 3 - The outcome of creating GWMLP models for CBR prediction

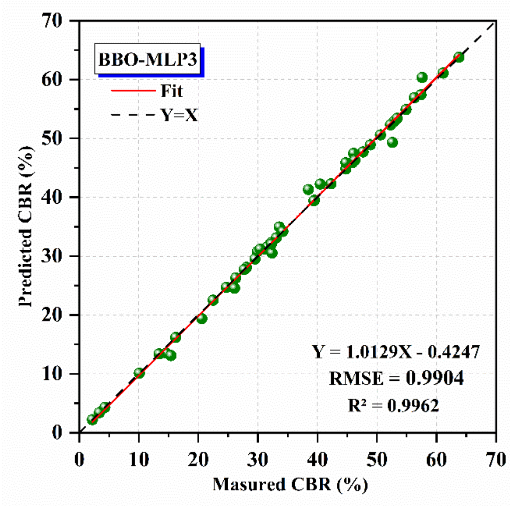
Models			*BBO-MLP1*	*BBO-MLP2*	*BBO-MLP3*
Number(s) of hidden layer			*1*	*2*	*3*
Number of Hidden layers of neurons			*[6]*	*[4, 4]*	*[6,11,5]*
Results of network	*All data*	*RMSE*	*0.73970 (3)*	*0.87550 (2)*	*0.99040 (1)*
		R2	*0.99770 (3)*	*0.9970 (2)*	*0.99620 (1)*
		MAE	*0.4760 (3)*	*0.51030 (1)*	*0.48980 (2)*
		PI	*0.01040 (3)*	*0.01230 (2)*	*0.01390 (1)*
TRS			*12.0*	*7.0*	*5.0*
Rank			*1.0*	*2.0*	*3.0*



(1A)

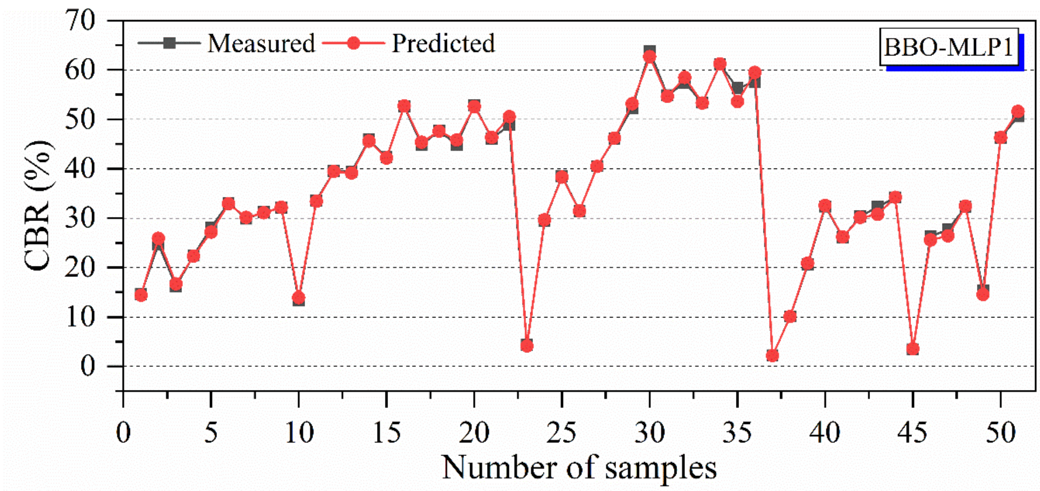


(2B)



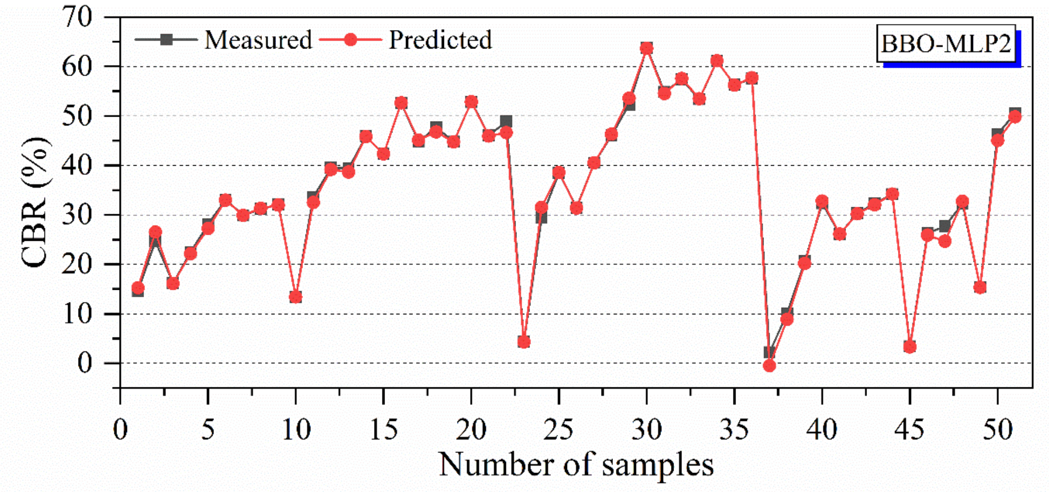
(3C)

Fig. 3 – (1A) BBO-MLP1, (2B) BBO-MLP2, (3 C) BBO-MLP3

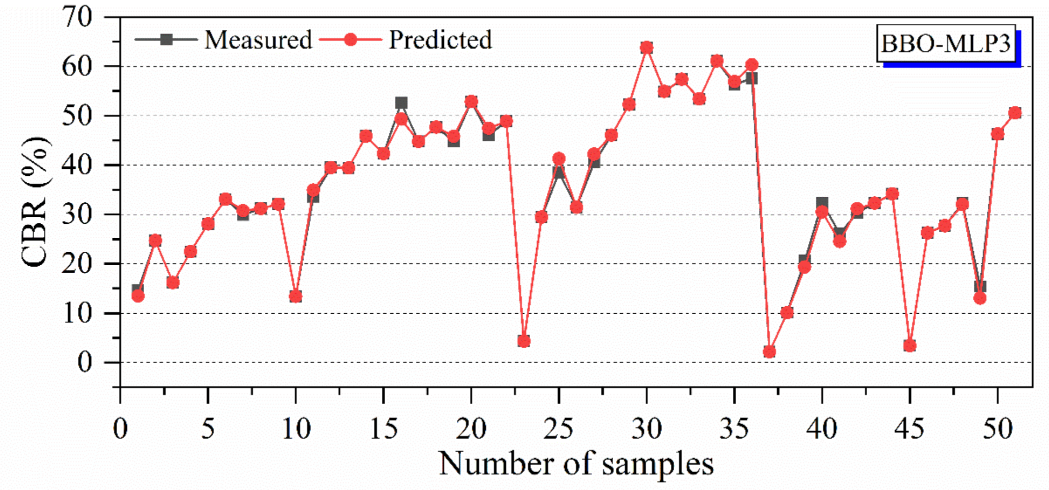


(1) BBO-MLP1 CBR prediction using models

DOI 10.14311/CEJ.2022.02.0026



(2)



(3)

Fig. 4 – (1) BBO-MLP1, (2) BBO-MLP2, (3) BBO-MLP3; CBR prediction using models

SENSITIVITY ANALYSIS

The hybrid models were analyzed to discover the most significant input elements for computing the CBR. The data was generated by eliminating a single input parameter. Here R^2 Moreover, RMSE were statistical performance metrics. Statistical performance criteria are used to choose the suitable model for sensitivity analysis. The BBO-MLP1 model is chosen for this study because of its remarkable performance. According to Table 4, the CP is the most relevant metric. From this viewpoint, additional inputs have minimal impact on the model's performance. It is important to remember that removing the input parameters can result in a modest reduction in model performance. However, where the analysis was through trial measurements to specify the impressions of stabilized materials, removing variables might reduce the model's generalizability. Since the multicollinearity issue has little effect on the model's fit and, in general, has little effect on forecasts, the current research does not propose removing any variables.

Tab. 4: Analysis of sensitivity with the tree-based Random Forest model

Inputs	Removed parameter	R^2	RMSE	Ranking
MDD, OMC, LI, LS, and CP	-	0.99770	0.73970	-
	MDD	0.99580	1.00950	5.0
	OMC	0.99560	1.030	4.0
	LI	0.99360	1.25120	3.0
	LS	0.99360	1.27840	2.0
	CP	0.66480	7.94610	1.0

CONCLUSION

A hybrid biogeography-based multi-layer perceptron neural network (BBO-MLP) with hidden layers' varying numbers was developed to predict California bearing ratio (CBR) values in lime and lime sludge pond ash. CBR was the starting variable for the model. The model included extreme dry density, optimal humidity, lime sludge percentage, cure duration, and CBR as output variables as input factors.

With R^2 of 0.99770, RMSE of 0.73970, MAE of 0.4760, and PI of 0.01040, BBO-MLP1 gives the greatest performance among the BBO-MLP models. All metrics deteriorate as the number of buried layers is decreased. BBO-MLP1 performs better than BBO-MLP2 and BBO-MLP3 (R^2=0.9970, RMSE=0.87550, and PI=0.01230). In each created model, the predicted CBR values accord satisfactorily with investigated data, proving the validity of the proposed models for properly predicting CBR values. Three generated models are compared, and BBO-MLP1 demonstrates superior performance. Consequently, BBO-MLP1 may be known as the planned model.

This study's main aim and contribution were to develop hybrid multi-layer perceptron neural networks to predict the California bearing ratio of stabilized pond ash. These models could be used in practical applications and in order to decrease the time and cost of experimental efforts. The referred citation was used to select the dataset. However, this article used laborious and cost-needed efforts that can be reduced using prediction models with the same accuracy.

REFERENCES

[1]. Esmaeili-Falak, M., Sarkhani Benemaran, R. and Seifi, R. (2020a), "Improvement of the mechanical and durability parameters of construction concrete of the Qotursuyi Spa", Concrete Res., 13(2), 81-90.

[2]. Bera AK, Ghosh A, Ghosh A (2007) Compaction characteristics of pond ash. J Mater Civ Eng 19(4):349–357

[3]. Suthar M, Aggarwal P (2017) Analysis of heavy metals in pond ash samples from Haryana. In Proceedings of 29th research world international conference, Las Vegas, USA, 16–17 March 2017, ISBN: 978-93-86291-88-2

[4]. Parsa J, Munson-McGee SH, Steiner R (1996) Stabilization/ solidification of hazardous wastes using fly ash. J Environ Eng 122(10):935–940

[5]. Ghosh A, Subbarao C (2006) Tensile strength bearing ratio and slake durability of class F fly ash stabilized with lime and gypsum. J Mater Civ Eng 18(1):18–27

[6]. Ghosh A (1996) Environmental and engineering characteristics of stabilized low lime fly ash. PhD dissertation, Indian Institute of Technology, Kharagpur, India

[7]. Ghosh A, Subbarao C (2007) Strength characteristics of class F fly ash modified with lime and gypsum. J Geotech Geoenviron Eng 1337:757–766

[8]. Pandian NS (2004) Fly ash characterization with reference to geotechnical applications. J Indian Inst Sci 184:189–216

[9]. Suthar M, Aggarwal P (2015) Class-F pond ash a potential highway construction material—a review. Ind Highways IRC 43(8):23–32

[10]. Sahu V, Gayathri V (2014) The use of fly ash and lime sludge as partial replacement of cement in mortar. Int J Eng Technol Innov 4(1):30–37
[11]. Battaglia A, Calace N, Nardi E, Petronio BM, Pietroletti M (2007) Reduction of Pb and Zn bioavailable forms in metal polluted soils due to paper mill sludge addition. Effects on Pb
and Zn transferability to barley. Biores Technol 98:2993–2999
[12]. Calacea N, Campisib T, Iacondinib A, Leonia M, Petronioa BM, Pietroletti M (2005) Metal-contaminated soil remediation by means of paper mill sludges addition: chemical and ecotoxicological evaluation. Environ Poll 136:485–492
[13]. Mahmood T, Elliot A (2006) A review of secondary sludge reduction technology for the pulp and paper industry. Water Res 40(11):2093–2112
[14]. Medhi UJ, Talukdar AK, Deka S (2005) Physicochemical characteristics of lime sludge waste of paper mill and its impact on growth and production of rice. J Ind Pollut Contr 21(1):51–58
[15]. Talukdar DK (2015) A study of paper mill lime sludge for stabilization of village road sub-base. Int J Emerg Technol Adv Eng 5(2):389–393
[16]. Singh M, Garg M (2008) Utilization of waste lime sludge as building materials. J Sci Ind Res 67:161–166
[17]. Ghosh A (2010) Compaction characteristics and bearing ratio of pond ash stabilized with lime and phosphogypsum. J Mater Civ Eng 22(4):343–351
[18]. Day WR (2001) Soil testing manual procedures, classification data, and sampling practices. McGraw Hill, New York, p 619
[19]. Sarkhani Benemaran, R. (2017). Experimental and analytical study of pile-stabilized layered slopes. Civil engineering, Tabriz university, Tabriz, Thesis.
[20]. Benemaran, R. S., & Esmaeili-Falak, M. (2020). Optimization of cost and mechanical properties of concrete with admixtures using MARS and PSO. Computers and Concrete, 26(4), 309-316.
[21]. Kin MW (2006) California bearing ratio correlation with soil index properties master of engineering (civil-geotechnics). Thesis, Faculty of Civil Engineering, University Teknology Malaysia
[22]. Yorulmaz, A., Sivrikaya, O., & Uysal, F. (2021). Evaluation of the bearing capacity of poor subgrade soils stabilized with waste marble powder according to curing time and freeze-thaw cycles. Arabian Journal of Geosciences, 14(5), 1-10.
[23]. Caglar N, Arman H (2007) The applicability of neural networks in the determination of soil profiles. Bull Eng Geol Environ 66(3):295–301
[24]. Zhu, W., Huang, L., Mao, L., & Esmaeili-Falak, M. (2021). Predicting the uniaxial compressive strength of oil palm shell lightweight aggregate concrete using artificial intelligence-based algorithms. Structural Concrete.
[25]. Yuan, J., Zhao, M., & Esmaeili-Falak, M. (2022). A comparative study on predicting the rapid chloride permeability of self-compacting concrete using meta-heuristic algorithm and artificial intelligence techniques. Structural Concrete.
[26]. Yang, C., Feng, H., & Esmaeili-Falak, M. (2022). Predicting the compressive strength of modified recycled aggregate concrete. Structural Concrete.
[27]. Sarkhani Benemaran, R., Esmaeili-Falak, M., & Katebi, H. (2020). Physical and numerical modelling of pile-stabilised saturated layered slopes. Proceedings of the Institution of Civil Engineers-Geotechnical Engineering, 1-16.
[28]. Chen, W., Luo, Q., Liu, J., Wang, T., & Wang, L. (2022). Modeling of frozen soil-structure interface shear behavior by supervised deep learning. *Cold Regions Science and Technology*, 103589.
[29]. Das SK, Basudhar PK (2006) Undrained lateral load capacity of piles in clay using artificial neural network. Comput Geotech 33(8):454–459
[30]. Park HI, Cho CH (2010) Neural network model for predicting the resistance of driven piles. Mar Georesour Geotech 28(4):324–344 30. Cho SE (2009) Probabilistic stability analyses of slopes using the ANN-based response surface. Comput Geotech 36:787–797
[31]. Erzin Y, Cetin T (2013) The prediction of the critical factor of safety of homogeneous finite slopes using neural networks and multiple regressions. Comput Geosci 51:305–313
[32]. Erzin Y, Cetin T (2014) The prediction of the critical factor of safety of homogeneous finite slopes subjected to earthquake forces using neural networks and multiple regressions. Int J Geomech Eng 6(1):1–15
[33]. Zhao HB (2008) Slope reliability analysis using a support vector machine. Comput Geotech 35:459–467

[34] Suthar, M., & Aggarwal, P. (2019, June). Modeling CBR value using RF and M5P techniques. In MENDEL (Vol. 25, No. 1, pp. 73-78).
[35]. Raja, M. N. A., Shukla, S. K., & Khan, M. U. A. (2021). An intelligent approach for predicting the strength of geosynthetic-reinforced subgrade soil. International Journal of Pavement Engineering, 1-17.
[36]. Suthar, M., & Aggarwal, P. (2018). Predicting CBR value of stabilized pond ash with lime and lime sludge using ANN and MR models. International Journal of Geosynthetics and Ground Engineering, 4(1), 1-7.
[37] D. Simon, Biogeography-Based Optimization, IEEE Transactions on Evolutionary 505 Computation. 12 (2008) 702–713. doi:10.1109/TEVC.2008.919004.
[38] Basheer, Imad A, and Maha Hajmeer. 2000. Artificial Neural Networks: Fundamentals, Computing, Design, and Application. Journal of microbiological methods 43(1): 3–31.
[39] Gordan, Behrouz et al. 2019. Estimating and Optimizing Safety Factors of Retaining Wall through Neural Network and Bee Colony Techniques. Engineering with Computers 35(3): 945–54.
[40] Hasanipanah, Mahdi et al. 2018. A Risk-Based Technique to Analyze Flyrock Results through Rock Engineering System. Geotechnical and Geological Engineering 36(4): 2247–60.
[41] Koopialipoor, Mohammadreza, Danial Jahed Armaghani, Mojtaba Haghighi, and Ebrahim Noroozi Ghaleini. 2019. A Neuro-Genetic Predictive Model to Approximate Overbreak Induced by Drilling and Blasting Operation in Tunnels. Bulletin of Engineering Geology and the Environment 78(2): 981–90.
[42] Sarkhani benemaran, Reza, Esmaeili-Falak, Mahzad, Javadi, Akbar. 2022. Predicting resilient modulus of flexible pavement foundation using extreme gradient boosting based optimized models. International Journal of Pavement Engineering. DOI: 10.1080/10298436.2022.2095385
[43] Esmaeili-Falak, Mahzad, Sarkhani benemaran, Reza. 2022. Investigating the stress-strain behavior of frozen clay using triaxial test. Journal of Structural and Construction Engineering. https://doi.org/10.1080/10298436.2022.2095385 .