JSTT JOURNAL OF SCIENCE AND TRANSPORT TECHNOLOGY

Journal of Science and Transport Technology
Journal homepage: https://jstt.vn/index.php/en

UNIVERSITY OF TRANSPORT TECHNOLOGY

Estimation of FWD Parameters for Evaluation of the Quality of Portland Cement Concrete Pavement

Hoang Ha[1], Tran Trung Hieu[2,*], Tran Thi Hong Nhung[3], Fazal E. Jalal[4], Mudassir Iqbal[5]

[1]University of Transport and Communications, Lang Thuong, Dong Da, Hanoi, Vietnam; hoangha@mt.gov.vn

[2]Geotechnical and Artificial Intelligence research group, 54 Trieu Khuc, Thanh Liet, Hanoi, Vietnam; hieutrantrung@utt.edu.vn

[3]Hanoi University, Hanoi 100000, Vietnam; nhungtth@hanu.edu.vn

[4]Department of Civil Engineering, State Key Laboratory of Ocean Engineering, Shanghai Jiao Tong University, Shanghai, P.R. China; jalal2412@sjtu.edu.cn

[5]Department of Civil Engineering, University of Engineering and Technology, Peshawar, Pakistan; mudassiriqbal29@sjtu.edu.cn

Article info
Type of article:
Original research paper

DOI:
https://doi.org/10.58845/jstt.utt.2025.en.5.4.107-125

***Corresponding author:**
Email address:
hieutrantrung@utt.edu.vn

Received: 07/09/2025
Received in Revised Form: 08/11/2025
Accepted: 10/12/2025

Abstract: This study aims to accurately predict two important parameters for evaluating the quality of Portland Cement Concrete (PCC) pavement: the modulus of subgrade reaction (Z1) and the elastic modulus of concrete slab (Z2). To achieve this, advanced Machine Learning (ML) models were used, including ANN-TLBO, ANN-BBO, and ANN-GA. These hybrid models combine Artificial Neural Network (ANN) with optimization techniques such as Teaching Learning-Based Optimization (TLBO), Biogeography-Based Optimization (BBO), and Genetic Algorithm (GA). The dataset used for modeling consists of 510 Falling Weight Deflectometer (FWD) tests from National Highway 18 in Quang Ninh Province, Vietnam. Standard statistical measures were used to validate and compare the performance of the models. Results showed that all three models performed well, with ANN-TLBO achieving the best results for predicting Z1 and Z2. Thus, the ANN-TLBO model can be used for accurate prediction of these important parameters for evaluating PCC pavement quality.

Keywords: Falling weight Deflectometer; Elastic modulus; ANN-TLBO; ANN-GA; ANN-BBO.

1. Introduction

Falling Weight Deflectometer, generally known as the FWD test, is a routinely used standard nondestructive test method for structural condition of Portland Cement Concrete (PCC) pavements to estimate the modulus of pavement layers by performing Back-calculation [1] and to simulate the displacement response of traffic loads [2]. FWD evaluates the structural adequacy along with giving considerable information about pavement layers as well as its subsurface conditions, including subgrade [3]. Results of the FWD test are widely utilized as the main strategy of many countries for the maintenance of pavements to estimate the in-situ stiffness of pavement layers [2, 4].Two important parameters are obtained from FWD test namely modulus of subgrade reaction (Z1) and elastic modulus of slab (Z2), which are often used for evaluating the quality of PCC pavement. It is costly and time consuming to determine these important parameters by conducting FWD test. Therefore, there is a need to develop and apply new approaches for the prediction of these parameters based on simple and easily determined factors with high accuracy.

In recent years, Machine learning (ML) or Artificial Intelligence (AI) techniques have been developed and effectively applied in solving various engineering problems including material sciences [5]. Han, Ma, Chen and Fan [6] attempted to evaluate the dynamic modulus of pavement by using Artificial Neural Network (ANN) approach. According to them, one of the major limitations of the conventional FWD algorithm is yielding of unreliable results in the form of non-uniqueness of the solution, which is attained from the back calculation process, thus amplifying the total residual error. However, with the initiation of the AI technology, a new FWD back calculation model was proposed that incorporated ANN, which received immense attention. In another study, Vyas, Singh and Srivastava [3] trained various ANN-based models with different number of hidden layers and neurons and it revealed that these models exhibited superior performance over non-intelligent approaches particularly in the case of non-linear problems of pavement engineering. It also showed that the predicted deflections after deploying the ANN were in good agreement with computed deflections from the hypothetical model. In addition, the back calculated layer moduli determined from a novel ML model namely Genetic Algorithm (GA)-ANN model also compared well with the hypothetical model based on FWD test. However, only few studies have been conducted to explore the ANN deployment for determination of deflection of the road pavement system, by incorporating layer moduli and its thicknesses in the form of input parameters [7]. In addition, in order to improve the performance of ML models, various optimization techniques such as Artificial Bee Colony [8, 9], Ant Colony Algorithm (ACA) [10], Bat Algorithm (BA), Biogeography-Based Optimization (BBO) [11-13], Cuckoo Search (CS) [14], Differential Evolution (DE) [15], Evolutionary Strategies [16, 17], Genetic Algorithms (GAs) [8, 13, 18], Grenade Explosion Method (GEM) [19], Harmony Search (HS) [20], Intelligent Water Drops (IWDs) [21], Particle Swarm Optimization (PSO) [22], Monkey Search [23], and the Teaching Learning-Based Optimization (TLBO) [24, 25] can be used for better prediction.

The main objective of this study is to predict two parameters of the Falling Weight Deflectometer (FWD) test, namely Z1 and Z2, by developing three novel hybrid models: ANN-TLBO, ANN-BBO, and ANN-GA. These ML models combine ANN with various optimization techniques such as Teaching-Learning-Based Optimization (TLBO), Biogeography-Based Optimization (BBO), and GA. The novelty of this paper compared with previous published works is that it is the first time these novel hybrid models (ANN-TLBO, ANN-BBO, and ANN-GA) have been developed and applied to improve the prediction of the properties (Z1 and Z2) of PCC materials using the FWD test data. To achieve the objective, a number of FWD tests conducted at National Highway 18, Quang Ninh province, Vietnam were collected and prepared the database for the modeling. Various validation indices, including Coefficient of Correlation (R), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Error Mean (Em), and Error Standard Deviation (Estd), were used to validate and compare the performance of the models. Matlab software was used for data processing and modeling.

2. Materials and Methods

2.1. Data used

In this study, in order to construct the database for modeling, FWD tests was carried out in Portland cement concrete pavement (PCC pavement) of the National Highway 18, Quang Ninh province, Vietnam [26] (Fig. 1). The testing route has a length of nearly 18.3 km, the road scale includes 2 lanes for cars, the road surface is 11-12m wide, and the roadbed is 12-14m wide. PCC pavement is designed according to AASHTO standard [27]. The structural characteristics of concrete slabs are as follows: the average slab length is 5.0 m, the average slab width is 5.75 m, and the thickness of the PCC slab varies from 24 to 30 cm. Rigid pavement structure consists of 01 surface layer by PCC slab, 01 base layer by 8% Cement treated aggregate base course. Fig. 2 shows the FWD device used in this project. Periodic calibration of the FWD devices is done as per AASHTO standard [28]. The technical specifications of FWD device were suitable for Long-Term Pavement Performance (LTPP) program [29]. FWD test procedure meets ASTM standards [30, 31].

Fig. 1. Location of the study area

Fig. 2. FWD device used in this project

Data collected from 510 FWD tests used for modeling include two output parameters: Z1 and Z2, and 10 input parameters: surface deflections (D_0, D_{12}, D_{24}, D_{36} - deflections at radial distances 0 inch, 12 inch, 24 inch, 36 inch from the load center, respectively), surface temperature (X5), surface load (X6), the thickness of the concrete slab (X7), 8% cement treated aggregate base course thickness (X8), the thickness of the pavement structure (X9), compressive strength of concrete slab (X10) [26]. These input parameters are considered as affecting factors for estimating Z1 and Z2 [32-36]. Calculation of Z1 and Z2 was presented in Nguyen, Vu, Nguyen, Jalal, Iqbal, Dang, Le, Prakash and Pham [26]. Table1 shows the initial statistical analysis of the data used for this study. Fig. 3 shows the correlation analysis of input variables used for the modeling. It can be seen from Fig. 3 that among the input variables, surface deflections (X1 – X4) were highly correlated. In addition, X7 and X9 were also highly correlated. In general, highly correlated variables should be considered to be removed for reducing the dimension of the data used in the modeling. However, considering the importance of the variables of surface deflections (X1 – X4) and the thickness of the concrete slab (X7), and the thickness of the pavement structure (X9) in prediction of the FWD parameters, all the variables were used for generation of the datasets for modeling.

In essence, decision to retain highly correlated parameters was based on the significance of these variables in predicting the FWD parameters (Z1 and Z2), even though it's generally advisable to reduce dimensionality by removing correlated variables. This approach acknowledges the specific context and importance of these variables in this research.

In the model study, normalization of numeric data was done to a common scale for reducing the data redundancy and to improve data integrity. Following equation was used to normalize the data of different ranges of values:

$$X^{scaled} = \left(x^{raw} - \beta\right) / \left(\alpha - \beta\right) \tag{1}$$

where α and β are the maximum (highest) and minimum (lowest) values of the parameter x.

Table 1. Statistical analysis of the inputs and outputs used in this study

No	Variables	Unit	Minimum	Maximum	Mean	Median	StD
1	X1	μm	52.1	641.2	161.522	162.55	59.639
2	X2	μm	36.4	576.1	142.842	146.7	54.787
3	X3	μm	33.8	448.4	126.702	130.3	47.508
4	X4	μm	30.1	317.4	103.154	105.65	37.799
5	X5	°C	23.1	42.4	29.412	28.9	4.091
6	X6	kN	38.7	77.41	61.902	63.25	6.447
7	X7	cm	24	30	27.041	27	1.999
8	X8	cm	17	20	18.486	18	1.126
9	X9	cm	41	50	45.527	46	2.313
10	X10	MPa	18.32	33.33	25.75	25.95	4.377
11	Z1	kPa/mm	25.06	355.78	88.021	69.975	52.978
12	Z2	GPa	3.22	60.12	22.978	21.3	9.36

*St.D. = Standard Deviation.

2.3. Methods used

This study used 510 FWD test records collected from National Highway 18, Vietnam, comprising deflections at radial offsets (D0–D36), pavement layer thicknesses, slab concrete strength, and temperature. Output variables include Z1 and Z2, calculated using standard mechanistic backcalculation formulas. All input variables were normalized using min–max scaling. Two independent ANN models were developed: one predicting Z1 and the other predicting Z2. Each ANN used 10 hidden neurons with sigmoid activation. Optimization of ANN weights and biases was performed using TLBO, BBO, and GA. A baseline ANN with Adam backpropagation was included for comparison. A 70:30 train–test split was used, followed by 5-fold cross-validation to ensure generalization. Hyperparameter sensitivity analyses were performed by varying hidden neurons (5, 10, 15) and evolutionary populations (20–60). The models were then validated using various evaluation indicators such as R, RMSE, and MAE (Fig. 4).

Detail description of the methods used in this study are given as follows:

2.3.1. ANN: Artificial Neural Networks

Proposed by McCulloch and Pitts [37], ANN have been widely used in numerous fields such as renewable energies, civil engineering, traffic accident prediction [38], geotechnical engineering problems [39, 40], heat transfer problems in nuclear engineering [41], stock market [42], medicine [43, 44], voice recognition, text translation [45, 46], among others. It is an efficient tool which tends to simulate the structure and functionalities of biological neural networks. The fundamental building block of each ANN is composed of Artificial neuron (A_n), which is, a simple mathematical model (function) [47]. A main characteristic of the ANNs is their adaptability to changes in the environment by modifying their connection structure or strength [48]. It is composed of 10 input layers, 01 hidden layers with 10 neurons, and 01 output layer with two independent ANN models used (one for Z1, one for Z2).

Out of these, input layers represent the independent variables (X1 to X10), hidden layers represent weighted connections between various nodes in adjacent layers, and output layer consisting of one element, which shows the dependent variables (Z1 or Z2).

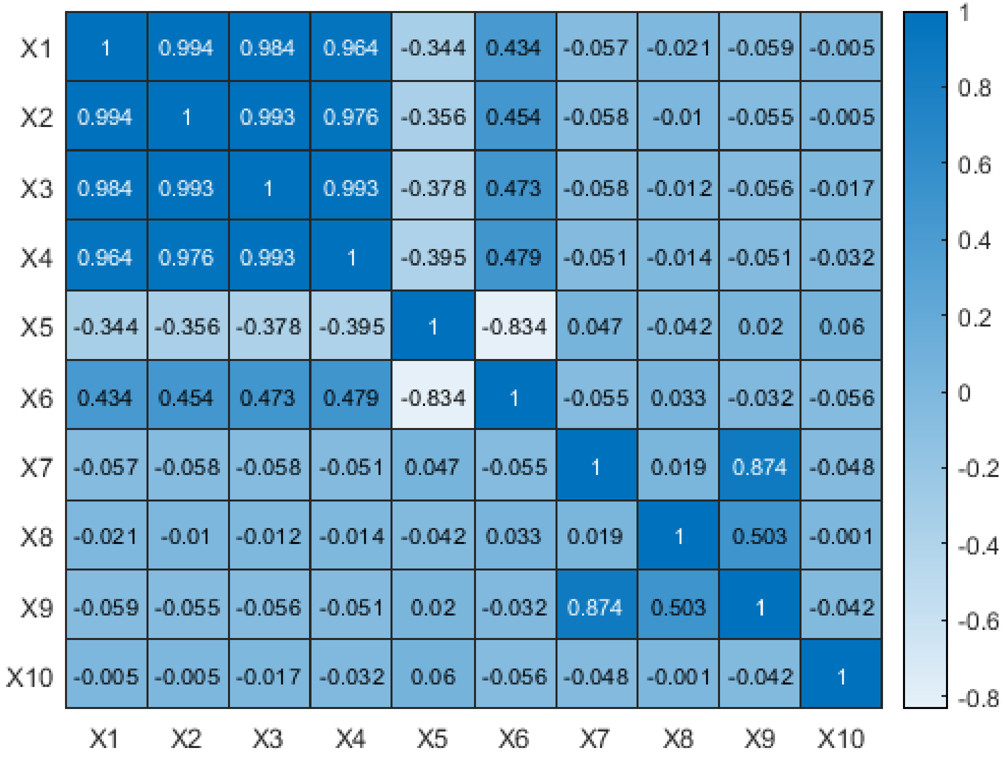

Fig. 3. Correlation matrix analysis input variables in this study

2.3.2. TLBO: Teaching Learning-Based Optimization

TLBO is a newly introduced population-based heuristic stochastic optimization algorithm, resembling the Evolutionary Algorithms (EAs), and it is inspired by passing on knowledge within a classroom environment [24, 25, 49]. The basic concept of TLBO is that the learning process of a classical school is simulated. Unlike EAs and swarm intelligence algorithms (SIs), the learners first of all gain knowledge from a teacher (i.e., teacher phase) and afterwards from classmates (i.e., learner phase). In the first stage, i.e., teacher phase, the better the teacher, the more knowledge the students would acquire and it is generally distributed following the Gaussian law. The right end of the Gaussian distribution represents the exceptional students who are capable to grasp all the materials taught, the mid part of the Gaussian distribution shows the group of students who would partially accept new learning materials, whereas, the left end of the Gaussian distribution is representation of the fact that the teacher would pose approximately no direct impact on students' knowledge. In the second stage, i.e., the learner phase, a student may learn from their fellow students. By and large, the amount of knowledge imparted to a student is not only governed by the efforts of their teacher but also on interacting with fellow students via peer learning [49]. The learners are considered to be the search points that are distributed in the decision variable space and are linked with the population of solutions in EAs and SIs. The learner exhibiting the best fitness is regarded as the teacher of the class. Črepinšek, Liu and Mernik [49] revealed that TLBO out perform ABC, DE, PSO, Evolutionary Strategies [16], and Grenade Explosion Method (GEM) on various continuous non-linear numerical optimization problems. In this study, TLBO was used to optimize the weights and bias of the ANN predictor for prediction of the parameters of FWD test.

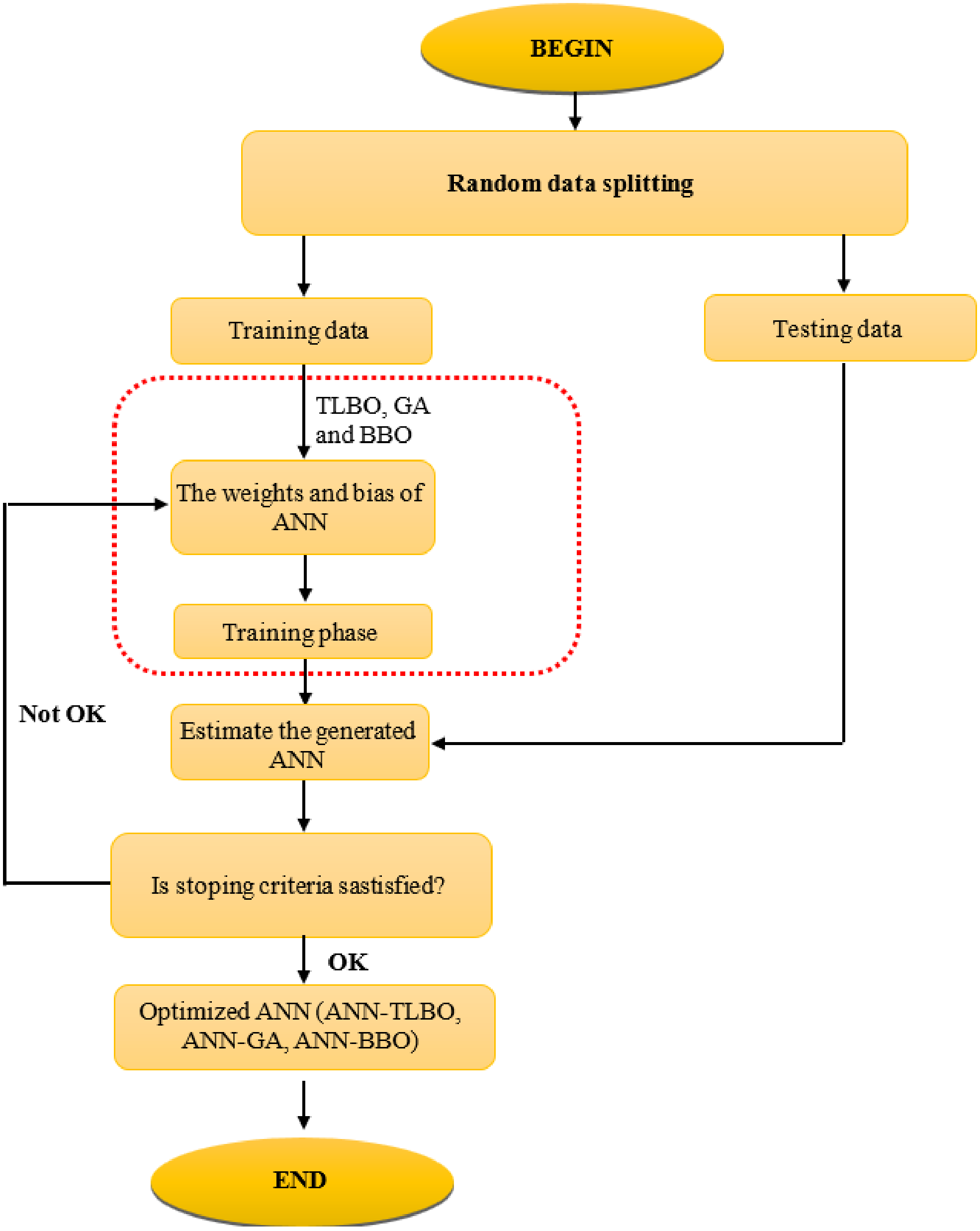

Fig. 4. Methodological flowchart of this study.

2.3.3. BBO: Biogeography-based optimization

Introduced by Simon [11], it is also a population-based and an evolutionary algorithm which is inspired from the natural phenomenon of biogeography [13]. It is a random search algorithm which assists to search the optimal solutions in the case of large and perplex nonlinear space [50]. This particular optimization is widely used in variety of domains and fields, for instance, feature extraction, image processing, image classification, and scheduling etc. [51]. It is related to the distributed species in nature that explains speciation and migration of species among the isolated habitats, as well as the extinction of species. The fitness function of the BBO is evaluated by Habitat suitability index - HIS [49]. The BBO contains numerous dependent and independent variables. The independent variables comprise Suitability Index Variables (SIVs) which shows the habitability, for instance, vegetative diversity, topographic diversity, rainfall, land area, among others. Both the SIV and HIS can be regarded as the search space and objective function, respectively [52].

The development and modification in the habitats is with the passage of time and is based on the four main concepts [13]: (i) Habitats residing in high HSI tend to migrate to relatively low HSI's habitats, (ii) Habitats residing in low HSI tend to attract newer immigrants' habitats in contrast with the ones having a reliable health information system, (iii) Habitats may witness unexpected modifications in their habitats irrespective of the corresponding HSI values, and (iv) The elitism solutions are stored in the coming generation. In this study, BBO was used to optimize the weights and bias of the ANN predictor for prediction of the parameters of FWD test.

2.3.4. GA: Genetic Algorithm

It is a heuristic-based searching algorithm incorporating the concepts of natural genetics which is inspired from Darwin's theory of survival of fittest [8, 18]. GA is robust solver to evaluate the combinational optimization problems across past few years [53]. In GA process, the initial population comprising chromosomes is created in the very first step. After that, the fitness of the chromosome within the existing population is determined which is followed by the creation of new population. In this new population, crossover, mutation, accepting, replacing and testing processes are performed to reach the optimal solution. If the criterion is not satisfied, the loop is restarted and perform all the steps (new generation) until the criterion is met to obtain the optimal model [54-56].

2.3.5. Validation indicators

In this work, the performance of the developed ML models was evaluated with the help of five analytical standard parameters: R, RMSE, MAE, E_m, and E_{std}. Equations used for the calculation of these indices are given below [40, 57-59]:

$$R = \frac{\sum_{i=1}^{n}(a_i - \bar{a}_i)(p_i - \bar{p}_i)}{\sqrt{\sum_{i=1}^{n}(a_i - \bar{a}_i)^2 \sum_{i=1}^{n}(p_i - \bar{p}_i)^2}} \quad (2)$$

$$RMSE = \frac{1}{|\bar{a}|}\sqrt{\frac{\sum_{i=1}^{n}(a_i - p_i)^2}{n}} \quad (3)$$

$$MAE = \frac{\sum_{i=1}^{n}|a_i - p_i|}{n} \quad (4)$$

$$E_m = a_i - p_i \quad (5)$$

$$E_{std} = \sqrt{\frac{\sum_{i=1}^{n}(a_i - p_i)^2}{n}} \quad (6)$$

Where a_i and p_i are termed as the i^{th} actual and predicted outputs, respectively; $\bar{a}_i$ and $\bar{p}_i$ refer to the mean of the actual and predicted outputs, respectively, while n represents the total number of specimens. When R exceeds 0.8, it shows robustly high correlation among actual and predicted observations. RMSE is prominent performance measure due to the fact that large errors are addressed more efficaciously in contrast to smaller errors and its closer or equal value to 0 represents minimal error during the prediction [55, 60-62]. But sometimes the RMSE is not expected to yield optimal performance thus MAE is measured owing to its merit of performing better in presence of smooth as well as continuous data. Additionally, higher R and lower values of RMSE and MAE, exhibit a better model calibration [40, 63, 64].

3. Results and discussion

Using training dataset, three novel hybrid models namely ANN-TLBO, ANN-BBO and ANN-GA were trained and build for prediction of Z1 and Z2 whereas using testing dataset these models were validated and compared using different validation indices RMSE, MAE, R, Em, and Estd. Results of models' validation and their comparison are shown in Table 2.

The ANN-TLBO model yielded the highest R values of 0.922 and 0.936 for both the training and testing datasets, respectively, in case of Z1 prediction, followed by ANN-BBO which gave R values: 0.893 and 0.906 for training and testing datasets, respectively. The ANN-GA yielded the lowest values of R with 0.883 and 0.902 for training and testing datasets, respectively. Whereas, RMSE indicator has shown that in case of ANN-TLBO model these values are lowest (0.056 for training and 0.067 testing both) in comparison to other two models: ANN-BBO (0.070 for training and 0.077 for testing) and ANN-GA (0.065 for training and 0.089 for testing). Regarding MAE criteria, the ANN-TLBO similarly received the lowest values (0.032 for training and 0.035 for testing) compared with other models such as ANN-BBO (0.044 for training and 0.051 for testing) and ANN-GA (0.038 for training and 0.051 for testing).

Table 2. Validation and comparison of the models used for prediction of Z1 and Z2

No	Models	Output Z1		Output Z2	
		Training	Testing	Training	Testing
		R			
1	ANN - BBO	0.893	0.906	0.835	0.833
2	ANN - GA	0.883	0.902	0.802	0.794
3	ANN - TLBO	0.922	0.936	0.913	0.911
		MAE			
1	ANN - BBO	0.044	0.045	0.068	0.070
2	ANN - GA	0.038	0.051	0.078	0.083
3	ANN - TLBO	0.032	0.035	0.051	0.054
		RMSE			
1	ANN - BBO	0.070	0.077	0.093	0.089
2	ANN - GA	0.065	0.089	0.104	0.105
3	ANN - TLBO	0.056	0.067	0.072	0.071
		Estd			
1	ANN - BBO	0.076	0.013	0.090	-0.006
2	ANN - GA	0.088	0.011	0.106	-0.005
3	ANN - TLBO	0.009	0.067	0.072	-0.005

In the case of Z2 prediction models, the ANN-TLBO received the highest R values of 0.913 and 0.911 for both the training and testing datasets, respectively. Subsequently, the ANN-BBO yielded R values equal to 0.835 and 0.833 for training and testing datasets, respectively. The ANN-GA yielded the lowest values of R with 0.802 and 0.794 for training and testing datasets, respectively. With RMSE indicator, the ANN-TLBO received the lowest values (0.072 for training and 0.071 for testing) compared with other models such as ANN-BBO (0.093 for training and 0.089 for testing) and ANN-GA 0.104 for training and 0.105 for testing). Regarding MAE criteria, the ANN-TLBO similarly received the lowest values (0.051 for training and 0.054 for testing) compared with other models such as ANN-BBO (0.068 for training and 0.007 for testing) and ANN-GA (0.078 for training and 0.083 for testing).

Overall, it can be concluded that the ANN-TLBO model is superior to the other models (ANN-BBO and ANN-GA) in predicting both Z1 and Z2 parameters. Results of ANN-TLBO were plotted in Fig. 5 to Fig. 9. In Figs. 5a,b,c, the optimization of the training data was achieved beyond 100 iterations for each case of correlation and error for evaluating Z1. The convergence towards the highest correlation and the lowest error was initially fast until 100 iterations, beyond which the convergence rate became slower. On the other side, the optimization of training data for Z2 depicts slower convergence compared to those of Z1. The convergence towards highest correlation flattened beyond 300 iterations whereas, for the MAE and RMSE, the convergence curve flattened beyond 400 iterations (Figs. 5d,e,f).

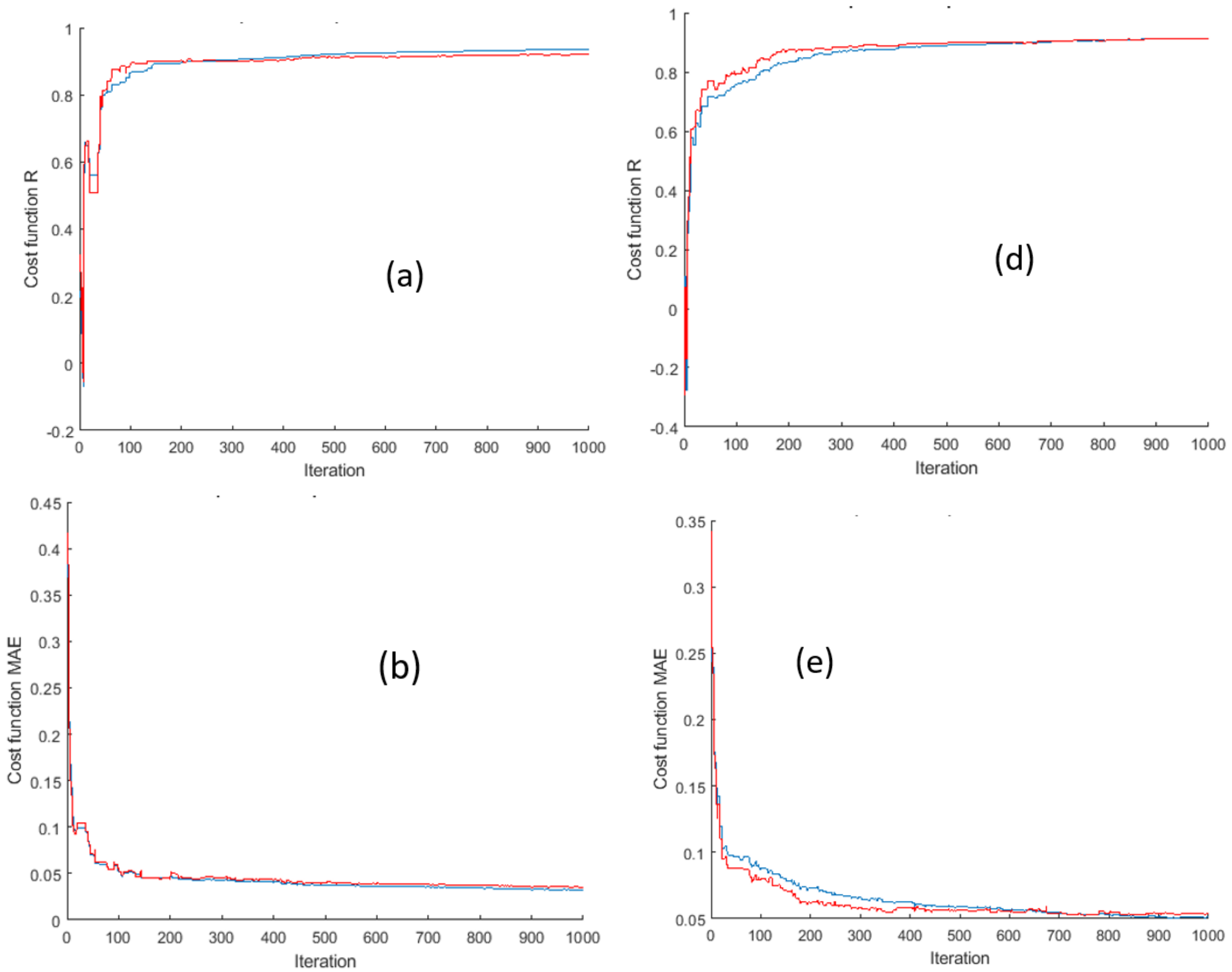

Fig. 5. Optimization procedure of ANN-TLBO for prediction of “Z1” (a) R, (b) MAE, (c) RMSE and “Z2” (d) R, (e) MAE, (f) RMSE

Figs. 6a,b illustrate the comparison of actual and the predicted results for prediction of Z1 using training and testing datasets, respectively. It can be observed that the predicted results closely follow the target values. Moreover, most of the prediction output of Z1 is conservative to the actual values. Figs. 6c,d represent the comparison of predicted and actual values of Z2 for training and testing datasets, respectively. Like the above discussion predicted results in this case also show a close agreement with the actual values. In addition, Fig. 7 and Fig. 8 illustrate error chart and histogram of the ANN-TLBO model whereas Fig. 9 shows the plot of the correlation analysis of the results of ANN-TLBO for prediction of both Z1 and Z2.

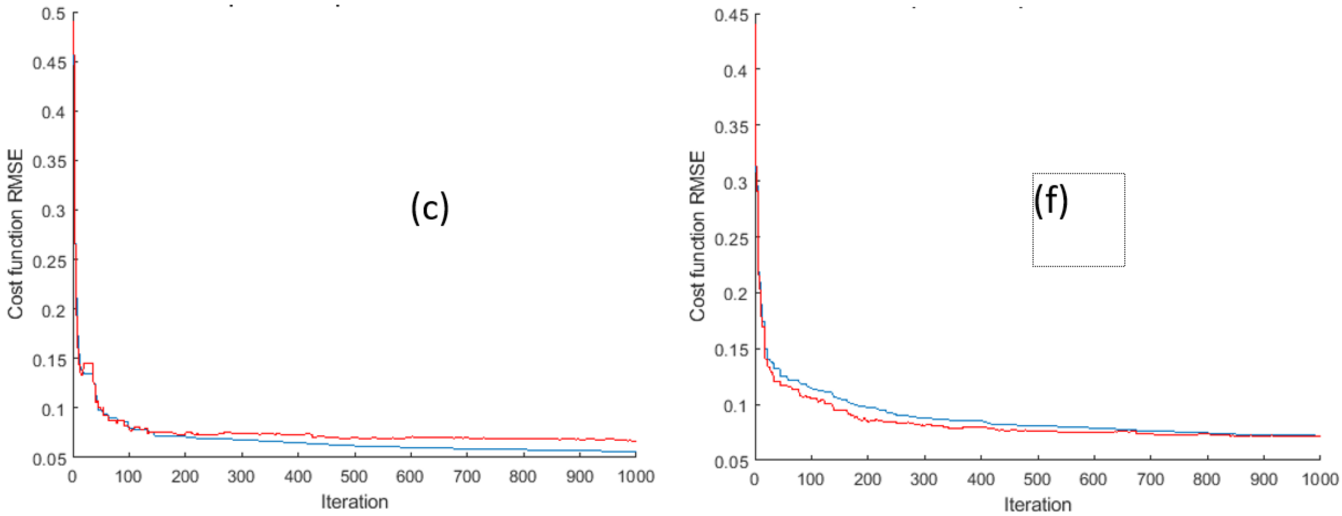

Fig. 5. (continued)

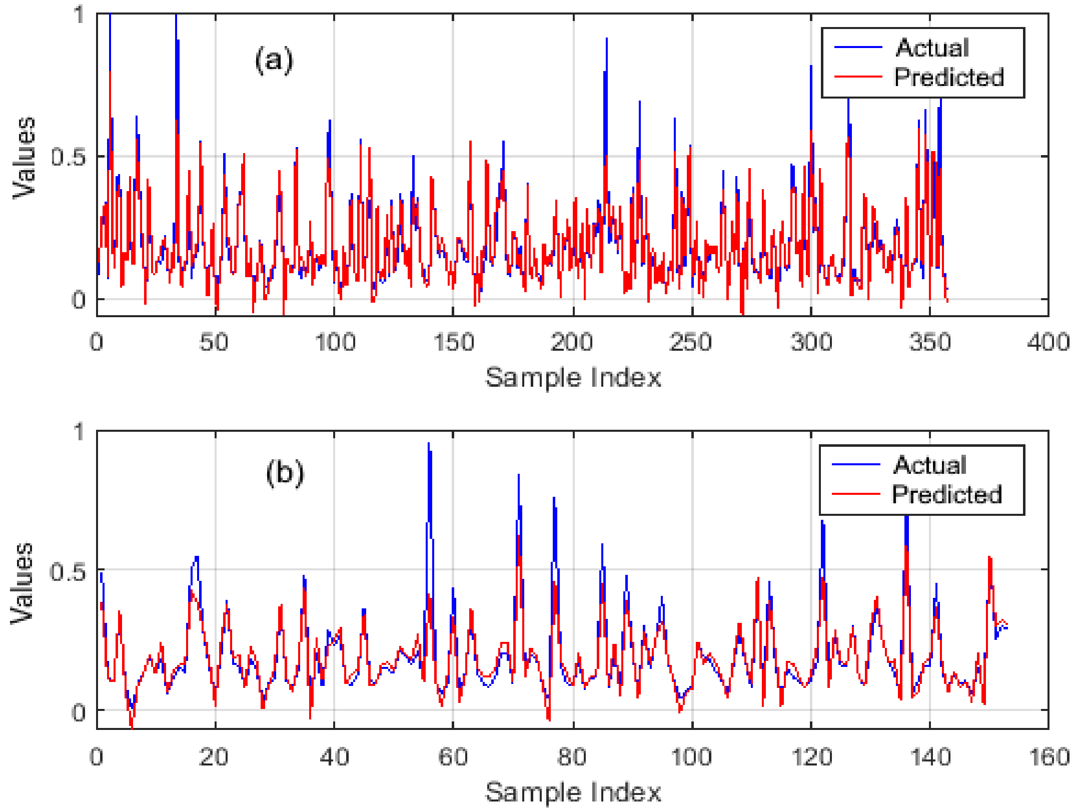

Fig. 6. Comparison of the predicted and actual results of the ANN-TLBO model for prediction of "Z1" with (a) training dataset, (b) testing dataset and "Z2" with (c) training dataset, (d) testing dataset

Overall, the three novel hybrid models (ANN-TLBO, ANN-BBO, and ANN-GA) were effective in predicting two key parameters (Z1 and Z2) of PCC pavements. Among these, the ANN-TLBO model outperformed the other two hybrid models (ANN-BBO and ANN-GA). It is reasonable as these models were built from the ML techniques which are well-known as advanced and effective nondestructive testing techniques used in prediction and calculation. In addition, these hybrid techniques take the advantages of both ANN and optimization techniques (TLBO, BBO, and GA) for improving the performance of the prediction. More specifically, while TLBO exhibits fast convergence due to the teaching and learning mechanisms and it requires fewer control parameters and has a simple implementation. In addition, TLBO maintains a population of candidate solutions, allowing it to explore multiple potential solutions simultaneously, and this approach enhances the likelihood of finding better solutions compared to single-solution algorithms. It is a derivative-free optimization algorithm, which means it does not require derivatives of the objective function to perform optimization. This makes it applicable to problems with non-differentiable, noisy, or discontinuous objective functions. TLBO has shown good performance in handling complex and multimodal optimization problems as it is less prone to premature convergence, and TLBO's population-based nature allows it to scale well with increasing problem dimensions, making it useful for high-dimensional optimization tasks [65-67]. BBO is effective for solving optimization problems with multiple objectives and it incorporates migration and exchange of information, allowing it to explore diverse regions [68], and GA can handle a wide range of optimization problems as it allows for parallel processing, and it is suitable for problems with both discrete and continuous variables [69]. In this study, TLBO is more effective than other two optimization techniques (BBO and GA) in improving the performance of the ANN algorithm in prediction of the Z1 and Z2 of the PCC pavements. This finding is also in line with other published works [70, 71].

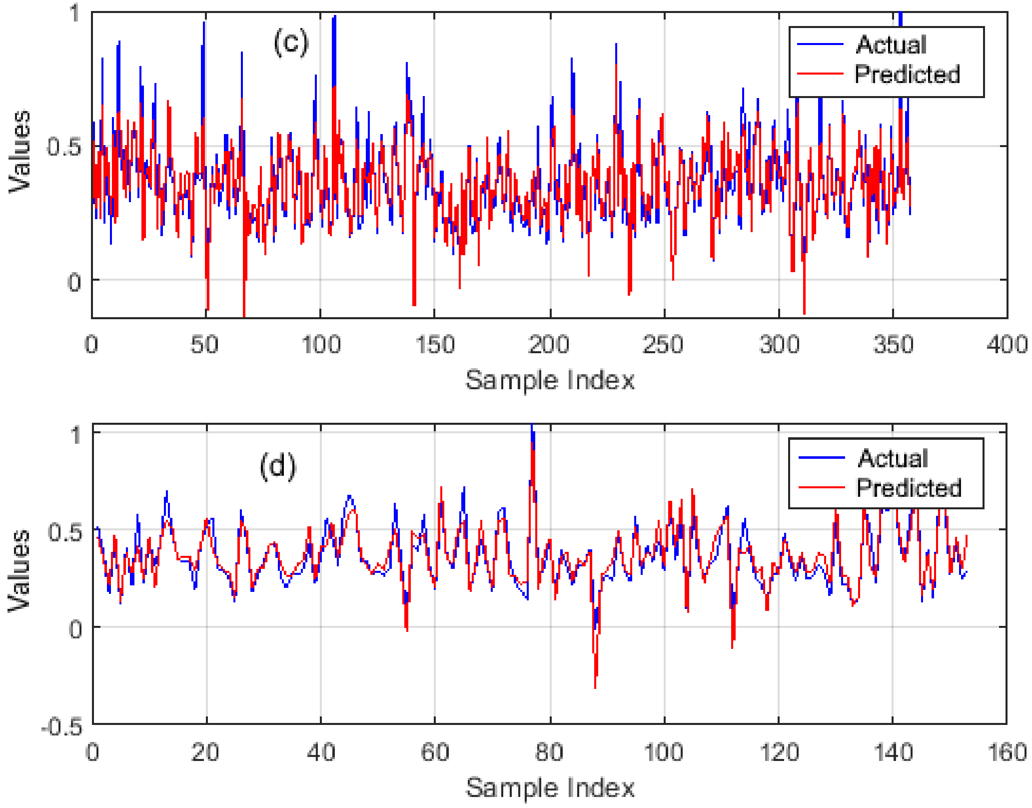

Fig. 6. (continued)

6. Conclusions

The study demonstrates that a hybrid ANN optimized using TLBO can reliably and rapidly estimate subgrade modulus (Z1) and slab modulus (Z2) from FWD deflection data. ANN-TLBO outperformed GA, BBO, and standard ANN models in terms of accuracy, convergence, and residual stability. The model effectively addresses the limitations of mechanistic backcalculation by providing smooth, physically plausible predictions even for noisy FWD datasets.

ANN-TLBO thus represents a practical surrogate tool for large-scale pavement evaluation and can significantly enhance network-level pavement management workflows. Future work will explore physically constrained neural architectures, hybrid mechanistic–ML models, and mechanistically consistent data augmentation for expanding training datasets.

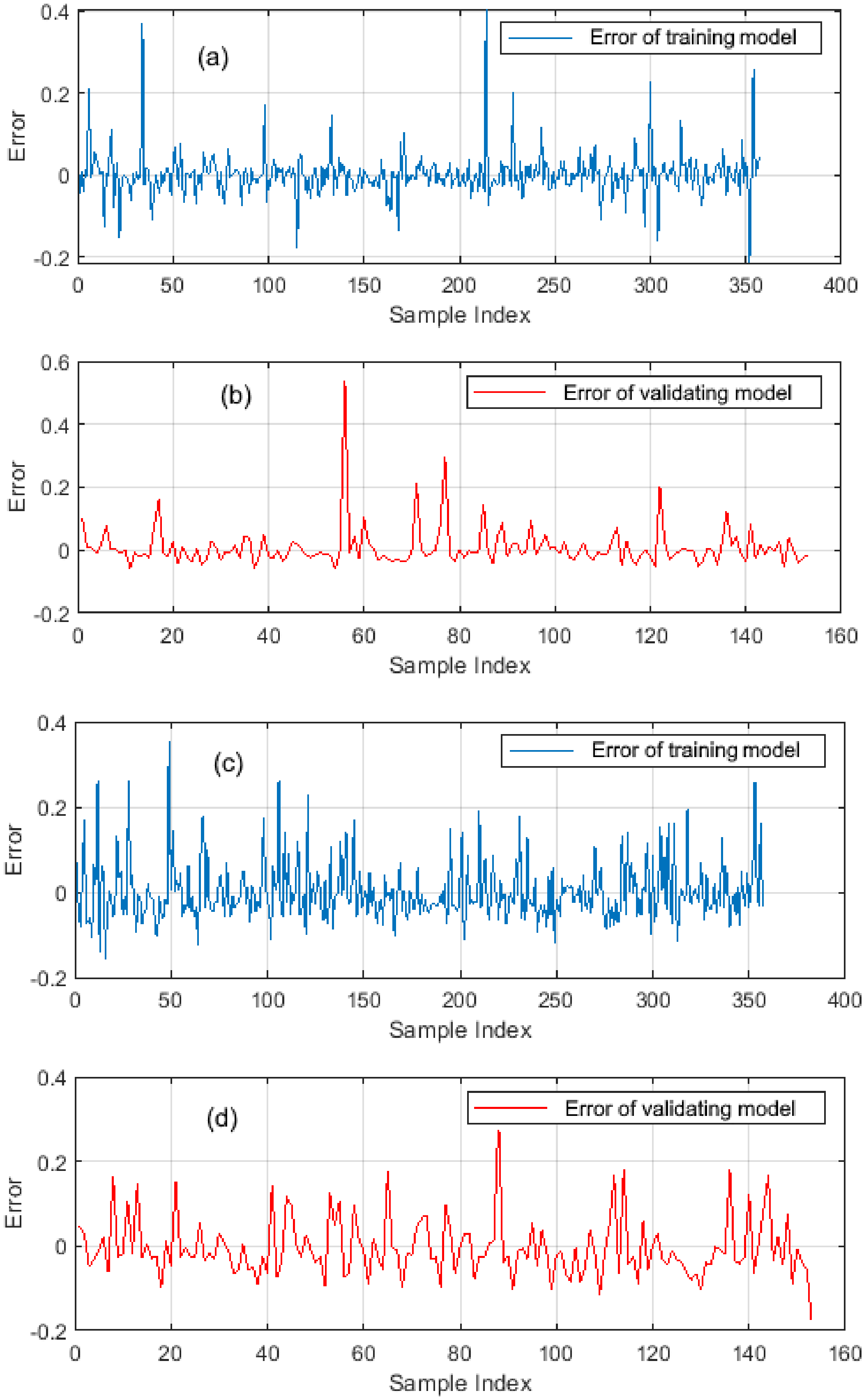

Fig. 7. RMSE values; “Z1” with (a) training, (b) testing and “Z2” with (c) training, (d) testing

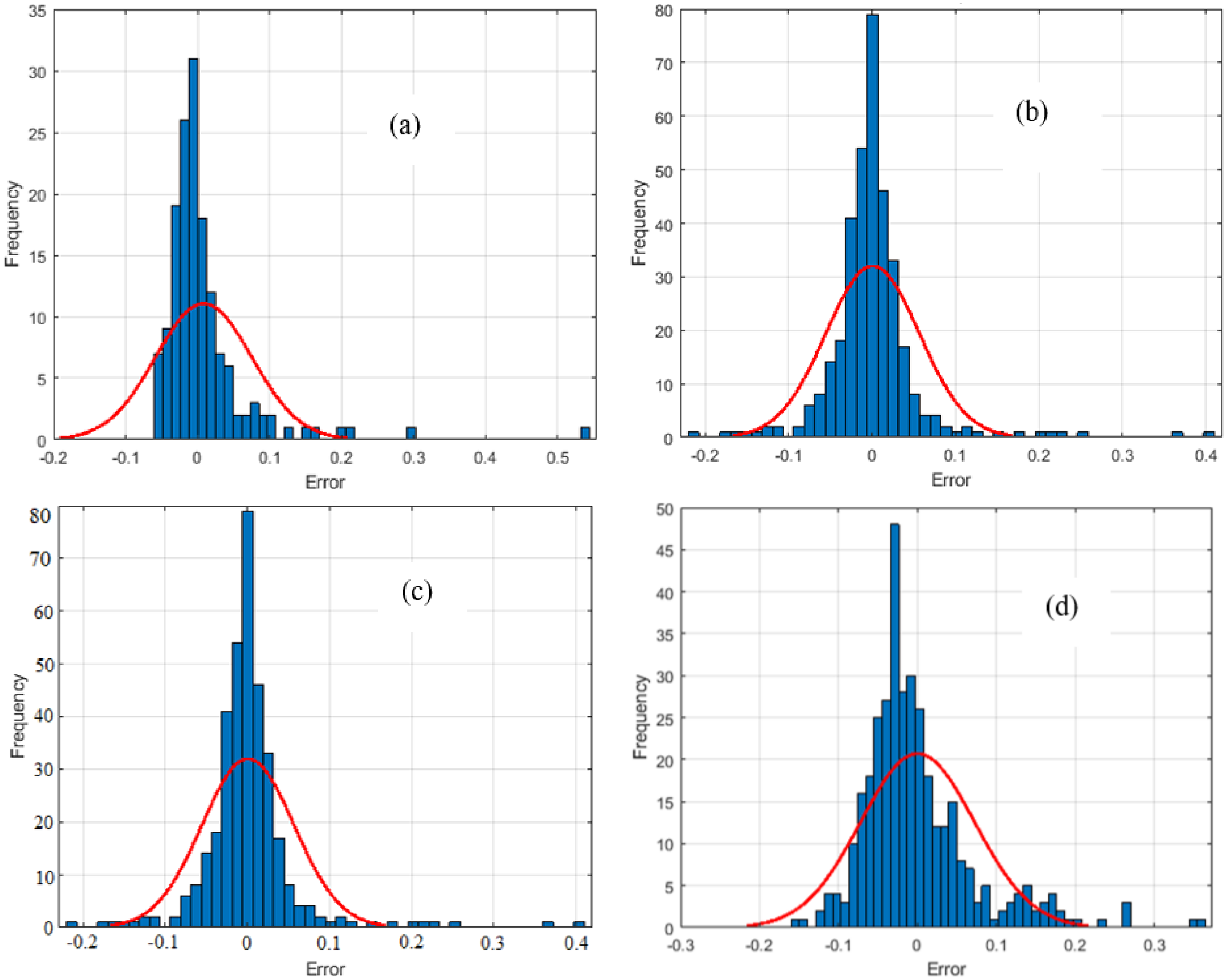

Fig. 8. Em and Estd values of the ANN-TLBO model for prediction of “Z1” with (a) training dataset, (b) testing dataset and “Z2” with (c) training dataset, (d) testing dataset

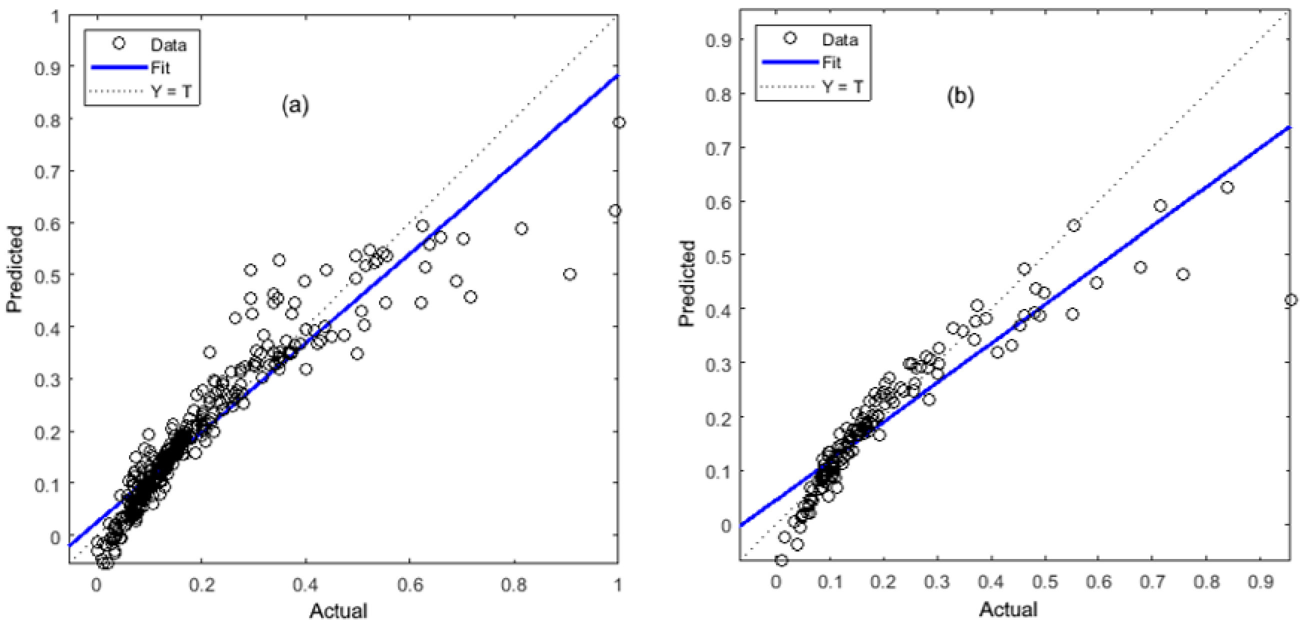

Fig. 9. R values of the ANN-TLBO model for prediction of “Z1” with (a) training dataset, (b) testing dataset and “Z2” with (c) training dataset, (d) testing dataset

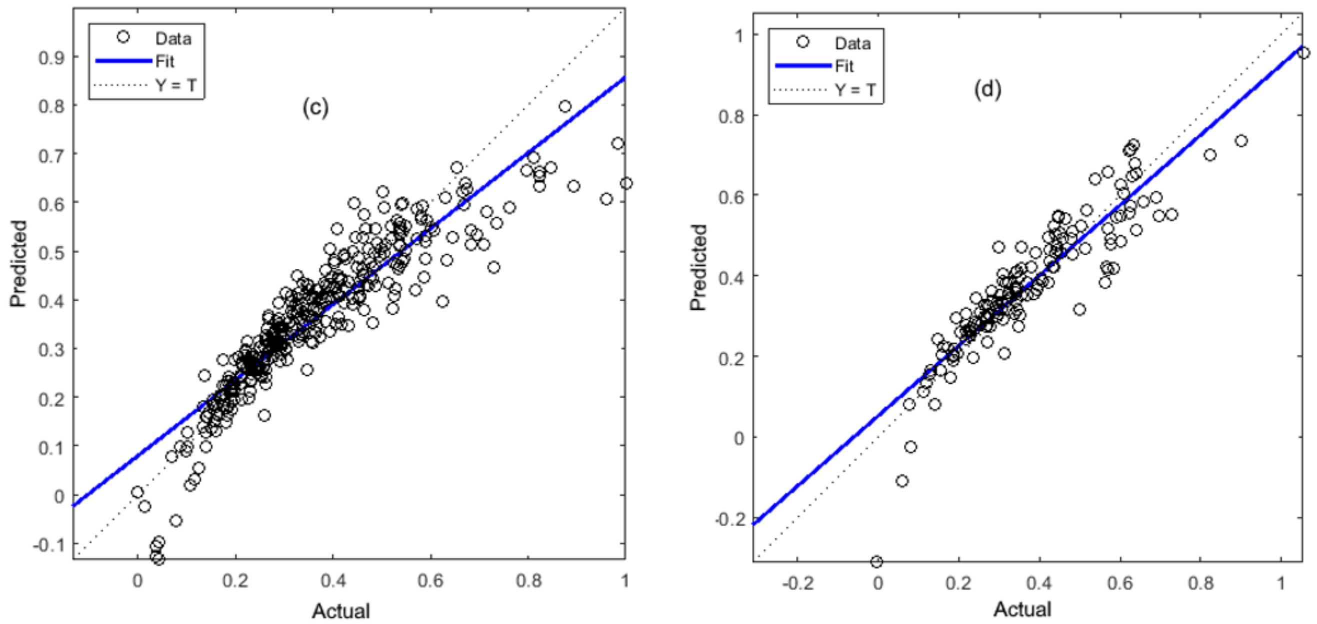

Fig. 9. (continued)

Compliance with Ethical Standards:

Conflict of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding: The author(s) received no financial support for the research, authorship, and/or publication of this article.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

References

[1] A. Nega, H. Nikraz, I.L. Al-Qadi. (2016). Dynamic analysis of falling weight deflectometer. *Journal of Traffic and Transportation Engineering (English Edition)*, 3(5), 427-437. https://doi.org/10.1016/j.jtte.2016.09.010

[2] Z. Han, L. Yang, H. Fang, J. Zhang. (2020). Dynamic simulation of falling weight deflectometer tests on flexible transversely isotropic layered pavements. *Soil Dynamics and Earthquake Engineering*, 139, 106353. https://doi.org/10.1016/j.soildyn.2020.106353

[3] V. Vyas, A.P. Singh, A. Srivastava. (2021). Prediction of asphalt pavement condition using FWD deflection basin parameters and artificial neural networks. *Road Materials and Pavement Design*, 22(12), 2748-2766. https://doi.org/10.1080/14680629.2020.1797855

[4] H. Nabizadeh, E.Y. Hajj, R.V. Siddharthan, S. Elfass, M. Nimeri. (2017). Application of falling weight deflectometer for the estimation of in-situ shear strength parameters of subgrade layer. *Bearing Capacity of Roads, Railways and Airfields, 743-749. Taylor & Francis Group, London.*

[5] H.-B. Ly, T.-A. Nguyen, B.T. Pham, M.H. Nguyen. (2022). A hybrid machine learning model to estimate self-compacting concrete compressive strength. *Frontiers of Structural and Civil Engineering*, 16, 990-1002. https://doi.org/10.1007/s11709-022-0864-7

[6] C. Han, T. Ma, S. Chen, J. Fan. (2022). Application of a hybrid neural network structure for FWD backcalculation based on LTPP database. *International Journal of Pavement Engineering*, 23(9), 3099-3112. https://doi.org/10.1080/10298436.2021.1883016

[7] D.-V. Le, C.-T. Phan. (2021). A study on Artificial Neural Networks–Genetic Algorithm model and its application on back-calculation of road pavement moduli. *2020 Applying New Technology in Green Buildings (ATiGB), IEEE,*

2021, pp. 53-59. doi: 10.1109/ATiGB50996.2021.9423109.
[8] K.M. Hamdia, X. Zhuang, T. Rabczuk. (2021). An efficient optimization approach for designing machine learning models based on genetic algorithm. *Neural Computing and Applications,* 33, 1923-1933. https://doi.org/10.1007/s00521-020-05035-x
[9] D. Karaboga, B. Basturk. (2007). A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. *Journal of Global Optimization*, 39, 459-471. DOI:10.1007/S10898-007-9149-X
[10] Y. Eroğlu, S.U. Seçkiner. (2012). Design of wind farm layout using ant colony algorithm. *Renewable Energy*, 44, 53-62. https://doi.org/10.1016/j.renene.2011.12.013
[11] D. Simon. (2008). Biogeography-based optimization. *IEEE Transactions on Evolutionary Computation*, 12(6), 702-713. doi: 10.1109/TEVC.2008.919004
[12] H. Ma, D. Simon, P. Siarry, Z. Yang, M. Fei. (2017). Biogeography-based optimization: a 10-year review. *IEEE Transactions on Emerging Topics in Computational Intelligence*, 1(5), 391-407. doi: 10.1109/TETCI.2017.2739124
[13] D. Albashish, A.I. Hammouri, M. Braik, J. Atwan, S. Sahran. (2021). Binary biogeography-based optimization based SVM-RFE for feature selection. *Applied Soft Computing*, 101, 107026. https://doi.org/10.1016/j.asoc.2020.107026
[14] A.H. Gandomi, X.-S. Yang, A.H. Alavi. (2013). Cuckoo search algorithm: a metaheuristic approach to solve structural optimization problems. *Engineering with Computers*, 29, 17-35. https://doi.org/10.1007/s00366-011-0241-y
[15] K.V. Price. (2013). Differential evolution. *Handbook of Optimization. Springer, pp. 187-214*. https://doi.org/10.1007/978-3-642-30504-7_8
[16] S. Mindess, J.F. Young. (1981). Concrete. *Prentice-Hall, Inc., Englewood Cliffs, NJ*.
[17] G.W. Greenwood. (1997). Training partially recurrent neural networks using evolutionary strategies. *IEEE Transactions on Speech and Audio Processing*, 5(2), 192-194. doi: 10.1109/89.554781
[18] S.N. Sivanandam, S.N. Deepa. (2008). Genetic algorithms. *Introduction to Genetic Algorithms. Springer, pp. 15-37*. https://doi.org/10.1007/978-3-540-73190-0_2
[19] A. Ahrari, A.A. Atai. (2010). Grenade explosion method—a novel tool for optimization of multimodal functions. *Applied Soft Computing*, 10(4), 1132-1140. https://doi.org/10.1016/j.asoc.2009.11.032
[20] Z.W. Geem, J.H. Kim, G.V. Loganathan. (2001). A New Heuristic Optimization Algorithm: Harmony Search. *Simulation*, 76, 60-68. DOI:10.1177/003754970107600201
[21] H.S. Hosseini. (2007). Problem solving by intelligent water drops. *2007 IEEE Congress on Evolutionary Computation, IEEE, pp. 3226-3231*. doi: 10.1109/CEC.2007.4424885
[22] F. Marini, B. Walczak. (2015). Particle swarm optimization (PSO). A tutorial. *Chemometrics and Intelligent Laboratory Systems*, 149, 153-165.https://doi.org/10.1016/j.chemolab.2015.08.020
[23] R.M.S. Cruz, H.M. Peixoto, R.M. Magalhães. (2011). Artificial neural networks and efficient optimization techniques for applications in engineering. *Artificial Neural Networks-Methodological Advances and Biomedical Applications, pp. 45-68. InTech*.
[24] R.V. Rao, V.J. Savsani, D.P. Vakharia. (2011). Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems. *Computer-Aided Design*, 43(3), 303-315. https://doi.org/10.1016/j.cad.2010.12.015
[25] F. Zou, D. Chen, Q. Xu. (2019). A survey of teaching–learning-based optimization. *Neurocomputing*, 335, 366-383. https://doi.org/10.1016/j.neucom.2018.06.076
[26] L.H. Nguyen, D.Q. Vu, D.D. Nguyen, F.E. Jalal,

M. Iqbal, V.T. Dang, H.V. Le, I. Prakash, B.T. Pham. (2023). Prediction of falling weight deflectometer parameters using hybrid model of genetic algorithm and adaptive neuro-fuzzy inference system. *Frontiers of Structural and Civil Engineering*, 17, 812-826. https://doi.org/10.1007/s11709-023-0940-7

[27] AASHTO. (1993). Guide for Design of Pavement Structures. American Association of State Highway and Transportation Officials, Washington, DC.

[28] AASHTO. (2010). AASHTO R32-09 Calibrating the Load Cell and Deflection Sensors for a Falling Weight Deflectometer. Standard Specifications for Transportation Materials and Methods of Sampling and Testing, Part 1B: Specifications, Association of State Highway and Transportation Officials, Washington, DC.

[29] P.N. Schmalzer. (2006). LTPP Manual for Falling Weight Deflectometer Measurements, Version 4.1. Federal Highway Administration, Office of Infrastructure Research and Development.

[30] ASTM. (2015). D4694-09, Standard Test Method for Deflections with a Falling-Weight-Type Impulse Load Device. ASTM International.

[31] ASTM. (2015). D4695-03, Standard Guide for General Pavement Deflection Measurements, ASTM International.

[32] L. Khazanovich, S.D. Tayabji, M.I. Darter. (2001). Backcalculation of Layer Parameters for LTPP Test Sections, Volume I: Slab on Elastic Solid and Slab on Dense-Liquid Foundation Analysis of Rigid Pavements, No. FHWA-RD-00-086. Federal Highway Administration, Washington, DC.

[33] L.M. Pierce, J.E. Bruinsma, K.D. Smith, M.J. Wade, K. Chatti, J.M. Vandenbossche. (2017). Using Falling Weight Deflectometer Data with Mechanistic-Empirical Design and Analysis, Volume III: Guidelines for Deflection Testing, Analysis, and Interpretation, No. FHWA-HRT-16-011. Federal Highway Administration, Washington, DC.

[34] K.D. Smith, J.E. Bruinsma, M.J. Wade, K. Chatti, J.M. Vandenbossche, H.T. Yu. (2017). Using Falling Weight Deflectometer Data with Mechanistic-Empirical Design and Analysis, Volume I: Final Report, No. FHWA-HRT-16-009. Federal Highway Administration, Washington, DC.

[35] J.M. Vandenbossche. (2003). Interpreting Falling Weight Deflectometer Results for Curled and Warped Portland Cement Concrete Pavements. University of Minnesota.

[36] C. Plati, K. Gkyrtis, A. Loizos. (2021). Integrating non-destructive testing data to produce asphalt pavement critical strains. *Nondestructive Testing and Evaluation*, 36(5) 546-570. https://doi.org/10.1080/10589759.2020.1834555

[37] W.S. McCulloch, W. Pitts. (1943). A logical calculus of the ideas immanent in nervous activity. *The Bulletin of Mathematical Biophysics*, 5, 115-133. https://doi.org/10.1007/BF02478259

[38] I. Santos, L. Castro, N. Rodriguez-Fernandez, A. Torrente-Patiño, A. Carballal. (2021). Artificial Neural Networks and Deep Learning in the Visual Arts: A review. *Neural Computing and Applications*, 33, 121-157. https://doi.org/10.1007/s00521-020-05565-4

[39] Z. Waszczyszyn. (2017). Artificial neural networks in civil engineering: another five years of research in Poland. *Computer Assisted Methods in Engineering and Science*, 18(3), 131-146.

[40] F.E. Jalal, Y. Xu, M. Iqbal, M.F. Javed, B. Jamhiri. (2021). Predictive modeling of swell-strength of expansive soils using artificial intelligence approaches: ANN, ANFIS and GEP. *Journal of Environmental Management*, 289 112420.https://doi.org/10.1016/j.jenvman.2021.112420

[41] T. Cong, G. Su, S. Qiu, W. Tian. (2013).

Applications of ANNs in flow and heat transfer problems in nuclear engineering: a review work. *Progress in Nuclear Energy*, 62, 54-71. https://doi.org/10.1016/j.pnucene.2012.09.003

[42] S. Soni. (2011). Applications of ANNs in stock market prediction: a survey. *International Journal of Computer Science & Engineering Technology*, 2(3), 71-83.

[43] S. Walczak. (2019). Artificial neural networks. Advanced Methodologies and Technologies in Artificial Intelligence, Computer Simulation, and Human-Computer Interaction. IGI Global 2019, pp. 40-53.

[44] K. Suzuki. (2011). Pixel-based artificial neural networks in computer-aided diagnosis. *Artificial Neural Networks - Methodological Advances and Biomedical Applications, pp. 71-92. InTech*. doi: 10.5772/16084

[45] G.K. Venayagamoorthy, V. Moonasar, K. Sandrasegaran. (1998). Voice recognition using neural networks. *Proceedings of the 1998 South African Symposium on Communications and Signal Processing-COMSIG'98 (Cat. No. 98EX214), IEEE, pp. 29-32*. doi: 10.1109/COMSIG.1998.736916

[46] Y. Huang. (2009). Advances in artificial neural networks–methodological development and application. *Algorithms*, 2(3), 973-1007. https://doi.org/10.3390/algor2030973

[47] E. Grossi. (2011). Artificial neural networks and predictive medicine: a revolutionary paradigm shift. *Artificial Neural Networks-Methodological Advances and Biomedical Applications, pp. 139-150. InTech.*

[48] L.G. Kabari, F.S. Bakpo. (2009). Diagnosing skin diseases using an artificial neural network. *2009 2nd International Conference on Adaptive Science & Technology (ICAST), IEEE, pp. 187-191.* doi: 10.1109/ICASTECH.2009.5409725

[49] M. Črepinšek, S.-H. Liu, L. Mernik. (2012). A note on teaching–learning-based optimization algorithm. *Information Sciences*, 212, 79-93. https://doi.org/10.1016/j.ins.2012.05.009

[50] M. Kaveh, M.S. Mesgari. (2019). Improved biogeography-based optimization using migration process adjustment: An approach for location-allocation of ambulances. *Computers & Industrial Engineering*, 135, 800-813. https://doi.org/10.1016/j.cie.2019.06.058

[51] M. Alweshah. (2019). Construction biogeography-based optimization algorithm for solving classification problems. *Neural Computing and Applications*, 31, 5679-5688. https://doi.org/10.1007/s00521-018-3402-8

[52] B.T. Pham, M.D. Nguyen, K.-T.T. Bui, I. Prakash, K. Chapi, D.T. Bui. (2019). A novel artificial intelligence approach based on Multi-layer Perceptron Neural Network and Biogeography-based Optimization for predicting coefficient of consolidation of soil. *Catena*, 173, 302-311. https://doi.org/10.1016/j.catena.2018.10.004

[53] L. Lin, C. Wu, L. Ma. (2021). A genetic algorithm for the fuzzy shortest path problem in a fuzzy network. *Complex & Intelligent Systems*, 7, 225-234. https://doi.org/10.1007/s40747-020-00195-8

[54] A. Ardakani, A. Kordnaeij. (2019). Soil compaction parameters prediction using GMDH-type neural network and genetic algorithm. *European Journal of Environmental and Civil Engineering*, 23(4), 449-462. https://doi.org/10.1080/19648189.2017.1304269

[55] I.O. Alade, M.A. Abd Rahman, T.A. Saleh. (2019). Modeling and prediction of the specific heat capacity of Al2 O3/water nanofluids using hybrid genetic algorithm/support vector regression model. *Nano-Structures & Nano-Objects*, 17, 103-111. https://doi.org/10.1016/j.nanoso.2018.12.001

[56] S. Hanandeh, A. Ardah, M. Abu-Farsakh. (2020). Using artificial neural network and genetics algorithm to estimate the resilient modulus for stabilized subgrade and propose new empirical formula. *Transportation Geotechnics*, 24, 100358. https://doi.org/10.1016/j.trgeo.2020.100358

[57] D.Q. Vu, D.D. Nguyen, Q.-A.T. Bui, D.K. Trong, I. Prakash, B.T. Pham. (2021). Estimation of California Bearing Ratio of Soils Using Random Forest based Machine Learning. *Journal of Science and Transport Technology*, 1(1), 45-58. https://doi.org/10.58845/jstt.utt.2021.en.1.1.45-58

[58] B.T. Pham, M. Amiri, M.D. Nguyen, T.Q. Ngo, K.T. Nguyen, H.T. Tran, H. Vu, B.T.Q. Anh, H.V. Le, I. Prakash. (2021). Estimation of shear strength parameters of soil using Optimized Inference Intelligence System. *Vietnam Journal of Earth Sciences*, 43(2), 189-198. https://doi.org/10.15625/2615-9783/15926

[59] T.-A. Nguyen, H.-B. Ly, A. Jaafari, T.B. Pham. (2020). Estimation of friction capacity of driven piles in clay using artificial neural network. *Vietnam Journal of Earth Sciences*, 42(3), 265-275. https://doi.org/10.15625/0866-7187/42/3/15182

[60] I. Rehamnia, B. Benlaoukli, M. Chouireb, I. Prakash, M. Amiri, B.T. Pham. (2023). Estimation of Seepage Flow Using Optimized Artificial Intelligent Models. *Geotechnical and Geological Engineering*, 41, 2727-2739. https://doi.org/10.1007/s10706-023-02423-7

[61] T.T. Nguyen, D.D. Nguyen, S.D. Nguyen, I. Prakash, P.V. Tran, B.T. Pham. (2022). Forecasting Construction Price Index using Artificial Intelligence Models: Support Vector Machines and Radial Basis Function Neural Network. *Journal of Science and Transport Technology*, 2(4), 9-19. https://doi.org/10.58845/jstt.utt.2022.en.2.4.9-19

[62] M.D. Nguyen, R. Costache, A.H. Sy, H. Ahmadzadeh, H.V. Le, I. Prakash, B.T. Pham. (2022). Novel approach for soil classification using machine learning methods. *Bulletin of Engineering Geology and the Environment*, 81, 468. https://doi.org/10.1007/s10064-022-02967-7

[63] M. Iqbal, D. Zhang, F.E. Jalal, M.F. Javed. (2021). Computational AI prediction models for residual tensile strength of GFRP bars aged in the alkaline concrete environment. *Ocean Engineering*, 232, 109134. https://doi.org/10.1016/j.oceaneng.2021.109134

[64] D.D. Nguyen, M.D. Nguyen, I. Prakash, N.V. Huong, H.V. Le, B.T. Pham. (2025). Prediction of safety factor for slope stability using machine learning models. *Vietnam Journal of Earth Sciences*, 47(2), 182-200. https://doi.org/10.15625/2615-9783/22196

[65] R.K. Sahu, S. Panda, U.K. Rout, D.K. Sahoo. (2016). Teaching learning based optimization algorithm for automatic generation control of power system using 2-DOF PID controller. *International Journal of Electrical Power & Energy Systems*, 77, 287-301. https://doi.org/10.1016/j.ijepes.2015.11.082

[66] L. Kok Foong, B. Nguyen Le, Teaching–learning–based optimization (TLBO) in hybridized with fuzzy inference system estimating heating loads, Energies 15(21) (2022) 8289.

[67] L. Wang, F. Zou, X. Hei, D. Yang, D. Chen, Q. Jiang, Z. Cao. (2014). A hybridization of teaching–learning-based optimization and differential evolution for chaotic time series prediction. *Neural Computing and Applications*, 25, 1407-1422. https://doi.org/10.1007/s00521-014-1627-8

[68] M. Zhang, W. Jiang, X. Zhou, Y. Xue, S. Chen. (2019). A hybrid biogeography-based optimization and fuzzy C-means algorithm for image segmentation. *Soft Computing*, 23, 2033-2046. https://doi.org/10.1007/s00500-017-2916-9

[69] J. Solomon, P. Chung, D. Srivastava, E. Darve. (2014). Method and advantages of genetic algorithms in parameterization of interatomic potentials: Metal oxides. *Computational Materials Science*, 81, 453-465. https://doi.org/10.1016/j.commatsci.2013.08.054

[70] A. Debroy, S. Chakraborty. (2013). Non-

conventional optimization techniques in optimizing non-traditional machining processes: a review. *Management Science Letters*, 3(1), 23-38. DOI:10.5267/J.MSL.2012.10.038

[71] W. Chen, M. Panahi, K. Khosravi, H.R. Pourghasemi, F. Rezaie, D. Parvinnezhad. (2019). Spatial prediction of groundwater potentiality using ANFIS ensembled with teaching-learning-based and biogeography-based optimization. *Journal of Hydrology*, 572, 435-448. https://doi.org/10.1016/j.jhydrol.2019.03.013