International Journal of GEOMATE, Jan., 2021, Vol.20, Issue 77, pp. 197-204
ISSN: 2186-2982 (P), 2186-2990 (O), Japan, DOI: https://doi.org/10.21660/2020.77.j2019
Geotechnique, Construction Materials and Environment

MACHINE LEARNING-BASED MODEL FOR PREDICTING CONCRETE COMPRESSIVE STRENGTH

Tu Trung Nguyen[1], *Long Tran Ngoc[2], Hoang Hiep Vu[1], and Tung Pham Thanh[3]

[1] Faculty of Civil Engineering, Hanoi Architectural University, Hanoi, Vietnam.
[2]Department of Civil Engineering, Vinh University, Nghe An, Vietnam.
[3] Faculty of BIC, National University of Civil Engineering, Hanoi, Vietnam.

*Corresponding Author, Received: 21 Oct. 2020, Revised: 29 Nov. 2020, Accepted: 12 Dec. 2020

ABSTRACT: This study aims at applying a machine learning-based model to establish the relationship between different input variables to the 28-day compressive strength of normal and High-Performance Concrete (HPC). An Artificial Neural Network (ANN) model was trained, validated, and tested using a comprehensive database consisted of 361 records gathered from the previously circulated source. Various models with different learning algorithms and neuron numbers in the hidden layer were examined to attain the best performance model. The examination results revealed that the ANN model using the "trainlm" learning algorithm delivered the best prediction outcomes with the overall coefficient of determination (R^2) of 0.9277. The influence of input parameters on the output was also examined by performing the sensitivity analysis. It was observed that the compressive strength of concrete at 28 days was more responsive to the changes in the cement parameter (CM) and the amount of water (WT). In contrast, the 28-day concrete compressive strength was found less sensitive to the variation of the fly ash (FL) parameter.

Keywords: High-Performance Concrete; Compressive Concrete Strength; Artificial Neural Network; Supervised Learning; Sensitivity Analysis

1. INTRODUCTION

Concrete is one of the most frequently used building materials worldwide. Generally, concrete is made of aggregates, cementitious material, and water. When these components are mixed, the mixture hardens over time thanks to the chemical reaction between cementitious material and water [1]. HPC can be made by adding other components such as fly ash, blast furnace slag, superplasticizer to the ordinary concrete mix. Among many HPC hardened properties, the compressive strength is the most common characteristic employed by the engineer in designing concrete structures [2].

The concrete compressive strength is affected by various variables including water/cement ratio, cement types, supplementary cementitious materials, aggregate, curing condition, mix proportions, method of testing [3]. A lower water/cement ratio increases the compressive strength due to the reduction of porosity in hardened concrete. Added cementitious such as silica fume enhance the strength of concrete [4]. The concrete strength is also affected by the aggregate size and strength, and the bond between the aggregate and the cement paste [3]

Typically, the compressive strength of concrete is determined through the destructive testing of specimens [5-7]. The method, however, is time-consuming and cost-intensive. Researchers also tried methods to predict concrete strength [8]. Nevertheless, these conventional prediction models have been proposed based on a fixed equation form and a limited number of data and parameters. Thus, it might not be adaptable for the new dataset [9]. In recent years, an alternative method using ANN to predict the concrete properties are gaining popularity thanks to its accuracy, adaptability, and effectiveness. The ANN models can establish the non-linear relationship between the input ingredients to the outputs [10]].

Machine learning-based techniques including ANN, Adaptive Network-based Fuzzy Inference System (ANFIS) have been successfully applied to predict concrete properties [11-17] as well as to address various engineering problems [18-24]. For example, Pham et al. [13] utilized 190 geopolymer test samples to train, validate, and test an ANN model for predicting the geopolymer concrete compressive strength. The results revealed that the ANN model can be used to predict the compressive strength of geopolymer concrete with an acceptable level of accuracy. In a recent study, ANN and ANFIS models were employed to predict the compressive strength of Fiber-Reinforced High Strength Self-Compacting concrete. The conclusion from the study showed that the ANN model could perform better in the prediction of concrete strength compared to that of the ANFIS model [14].

Regarding the application of the ANN model to deal with engineering issues, Nguyen and Dinh [19] employed ANN to predict the bridge deck condition ratings. A total of 2572 bridge records from the National Bridge Inventory was used. The proposed

ANN model could predict the bridge condition ratings with an accuracy of up to 98.5 percent. Guijo-Rubio et al. [20] applied ANN for predicting solar radiation using satellite-based data. Results from the study revealed that ANN could predict solar radiation from the satellite image data with extreme accuracy. The study also concluded that the ANN outperformed other machine learning approaches such as Support Vector Regressor or Extreme Learning Machine. Besides, the ANN model was utilized to predict the fire-resistance rating of timber structures [21], to detect structural damage [22], and to identify polymers [23].

The applications of other machine learning-based approaches for various issues are also popular among researchers [25-27]. For instance, Truong et al, [25] used various algorithms including Gradient Tree Boosting, Radom Forest, Support Vector Machine to evaluate the safety of steel trusses. The conclusion from the study revealed that the Gradient Tree Boosting provided the best performance for the considered case study. In another study, Behnood et al. [26] successfully applied the N5P model tree algorithm to predict the compressive strength of the normal concrete and HPC.

The main objective of this study is to propose a supervised ANN model for predicting the 28-day compressive strength of normal concrete and HPC based on the data collected from the previously published source [28]. Different learning algorithms and the number of neurons in the hidden layer were investigated to obtain the optimal ANN model. The performance of the selected ANN model was evaluated using various indicators. Additionally, the influence of input variables on the output was examined through sensitivity analysis. The ANN architecture was developed in MATLAB R2020a Runtime Environment.

2. METHODS

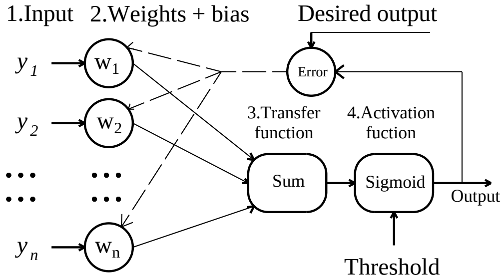
A description of the architecture of a simple ANN model and the operation of a neuron as well as of the back-propagation algorithm were briefly discussed. Furthermore, the evaluation criteria for the performance of the proposed model, and the process of constructing the proposed ANN model (learning algorithms, the number of neurons in the hidden layer) were also presented. Finally, the data collection and preprocessing process was described in detail in the subsequent sections.

2.1 Artificial Neural Network Architecture

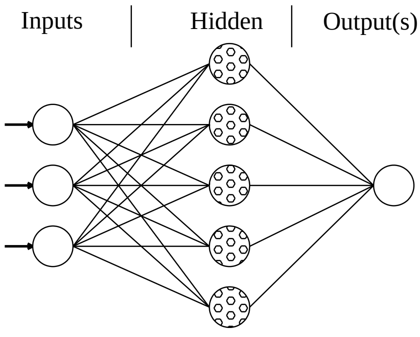
The architecture of the ANN system is inspired by the configurations of the human brain. It includes a series of simple nodes/neurons working independently to process input data and generate outputs. Figure 1a illustrates the architecture of a neuron. The solid line represents the forward direction while the dashed line is the backward way. A neuron consists of four parts namely inputs, weights and bias, transfer function, activation function, and output. The operation of a neuron can be express by Eq. (1)

$$o = f\left(\frac{1}{n}\sum_{i=1}^{n} w_i \times y_i + b\right) \tag{1}$$

where o is the output from neuron; y_i, is the i^{th} input values; w_i, is the i^{th} connection weights; b is the bias value; f is the activation function. In the first part, the inputs are multiplied by the corresponding weights assigned for those inputs. In the second part, the product of each input in the first step is summed and transferred to the activation part where the output is produced. A simple and common ANN structure, called a feed-forward network, has an input layer, one hidden layer, and an output layer, as depicted in Fig. 1b. In this network, the information is processed in one forward direction only.



(a) Neuron weight adjustment loop



(b) A simple structure

Fig. 1 Artificial Neural Network diagram

The weight and bias of connections in the network are randomly selected first. These parameters are then adjusted during the training processed. After the training process is completed, all connection weights and bias in the entire ANN are fixed and ready to predict the outputs for a new dataset. The major goal of the training process is to minimize the difference (Mean Squared Error - MSE) between the predicted outputs and the desired outputs. Among various training algorithms, the back-propagation algorithm is the most used for ANN. The back-propagation algorithm uses the gradient descent method to search the minimum of the function error in the weight space.

The operation of the back-propagation algorithm is depicted in Fig. 1b. It is an iteration process in which the weight of input in each run is adjusted to obtain the minimum MSE value. The change of the weights during each iteration is expressed as in Eq. (2)

$$\Delta w_n = \alpha \, \Delta \, w_{n-1} - \eta \, \frac{\partial E}{\partial w} \tag{2}$$

where w is the weight between any two nodes; Δw_n and Δw_{n-1} are the changes in this weight at n and $n-1$ iteration; α is the momentum factor; η is the learning rate; E is the error function.

2.2 Performance Criteria

The performance of the ANN model was assessed using three factors: coefficient of determination (R^2) and Mean Squared Error, and Mean Absolute Error (MAE), which were presented in Eq. (3-5), respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{5}$$

where y_i is the i^{th} actual output; $\bar{\boldsymbol{y}}$ is the mean of the actual outputs; $\hat{\boldsymbol{y}}_i$ is the i^{th} predicted outputs; and n is the total number of data records. The higher value of R^2 and the lower values of MSE and MAE indicate a better prediction capacity of the proposed models.

Table 1 Ranges of the input and output variables

Variable	Sym.	Unit	Category	Min.	Mean	Max.	Std.
Cement	CM	kg/m^3	Input	108	274	540	102
Blast Furnace Slag	BF	kg/m^3	Input	0	92	359	87.9
Fly Ash	FL	kg/m^3	Input	0	59	195	62.5
Water	WT	kg/m^3	Input	121	184	247	19.6
Superplasticizer	SP	kg/m^3	Input	0	7	32.2	5.30
Coarse Aggregate	CA	kg/m^3	Input	801	952	1145	81.7
Fine Aggregate	FA	kg/m^3	Input	594	760	992	72.5
28-day compressive strength	f'_c	MPa	Output	20.6	38	69.8	11.6

2.3 Data Collection and Preprocessing

The experimental data from the previously published source contained information about the strength of many concrete types at different ages [28]. This study focused on the application of ANN for predicting the 28-day concrete strength. Thus, only records that contained the compressive strength at 28 days were obtained from the original database. To eliminate the undesirable effects of an outliner, the records with the compressive strength smaller than 20, or larger than 70 MPa were removed from the extracted database. The final data were archived in form of a table with 361 rows and eight columns. The input parameters were stored from column one to column seven, and the output parameter was archived in column eight.

Seven concrete components, namely Cement (CM), Blast Furnace Slag (BF), Fly Ash (FL), Water (WT), Superplasticizer (SP), Coarse Aggregate (CA), and Fine Aggregate (FA) were employed as the inputs of the proposed ANN model. The 28-day compressive strength of concrete (f'_c) was the output. The range of the input and output parameters is shown in Table 1. The classification of the 28-day compressive strength of concrete in each specific interval is presented in Table 2.

Table 2 Number of samples in each specific range of 28 days compressive strength

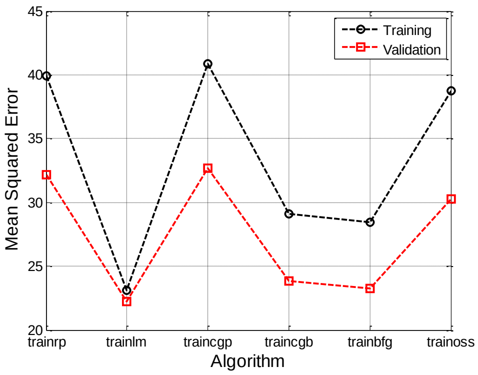
f'_c (MPa)	Records
20 - 30	95
30 - 40	133
40 - 50	68
50 - 60	41
60 - 70	24
Total	361

3. MODEL DEVELOPMENT

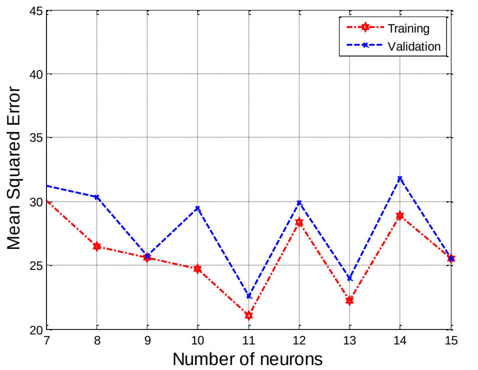
The ANN used in this study had seven neurons, namely CM, BF, FL, WT, SP, CA, and FA in the input layer. Note that these input variables were selected based on the original input parameters from the experimental tests presented in the database. The output layer has one neuron which was presented for the 28-day compressive strength of concrete (f'_c).

Sigmoid was selected as an activate function for the proposed ANN model. The sigmoid function has been widely used for ANN models in [13, 14]. The sigmoid function transforms the values within the range [0 1] using equation $y(x) = 1/(1 + exp(-x))$. The original input data were normalized and randomly separated into three subsets at the ratio of 0.7, 0.15, and 0.15 for training, validation, and testing dataset, respectively. That means 253 records were utilized for training the proposed ANN model, 54 records were used for validation, and 54 records were employed for testing the accuracy of the model.

To determine the learning algorithm to be utilized for the experimental dataset, the proposed ANN model was tested using six popular learning algorithms including trainrp, trainlm, traincgp, traincgb, trainbfg, trainoss. The performance of the model corresponding to each training algorithm was evaluated based on training and validation performance in ten runs. Figure 2a shows the best performance records for each model. It can be seen clearly that the model with "trainlm" algorithm produced the best results for all performance categories. For this reason, the "trainlm" algorithm was chosen for the proposed ANN model. The selection was in line with the previous study [14].



(a) Change of learning algorithms



(b) Change of neuron numbers in the hidden layer

Fig. 2 Evaluation of prospective ANN models

The proposed ANN model in this study had one hidden layer. The number of neurons in the hidden layer was selected based on the performance of the proposed ANN model. According to the previous study [30], the minimum numbers of hidden nodes should be larger than the number of input variables n, and the maximum number should not exceed $2n + 1$. With seven input variables in this study, the number of neurons in the hidden layer should be chosen between seven and 15.

Different ANN models were developed with the number of neurons in the hidden layer varied from seven to 15 neurons. Ten runs were implemented for each ANN model to obtain the average performance results. The performance of ANN models was then evaluated and plotted based on the MSE values, as shown in Fig. 2b. It can be seen the ANN model with 11 neurons generated the best results. Thus, the ANN model with 11 neurons in the hidden layer was picked to utilize in this study. Table 3 provides the architecture properties of the chosen ANN model.

Table 3 Information of ANN model

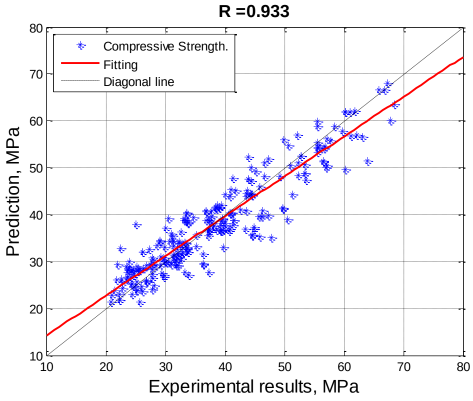
Parameter	Properties
Number of neurons in the input layer	7
Number of neurons in the hidden layer	11
Number of neurons in the output layer	1
Training method	Back-propagation
Learning algorithm	'trainlm'
Activation function	Sigmoid

4. RESULTS AND DISCUSSION

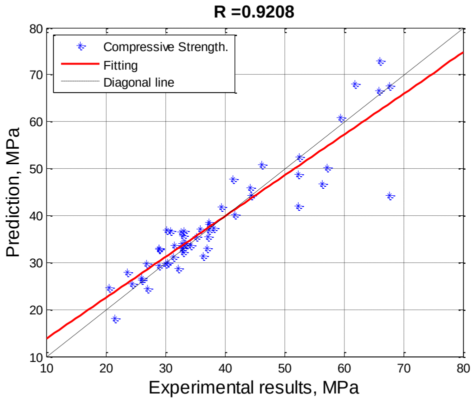
As mentioned earlier, the proposed ANN model with seven inputs, and one output parameter was employed to predict the 28-day concrete compressive strength. The prediction ability of the ANN model for training, validation, and the testing dataset was thoroughly assessed using the coefficient of determination and mean squared error. Besides, the error evaluation and sensitivity analysis were also conducted, and the results were presented in detail in the following sections.

4.1 Prediction Performance of ANN Models

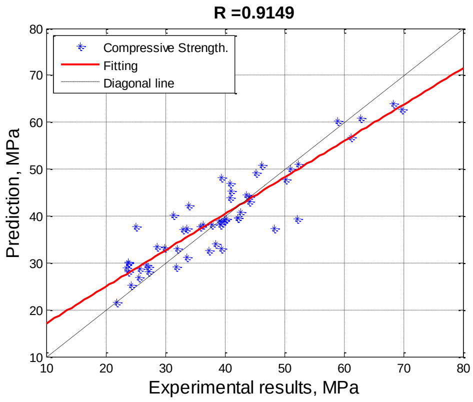
Table 4 presents the performance results from the selected ANN model. As seen, the higher value of R^2 in training and validation datasets indicated that the ANN model could generate reliable outputs with a high degree of fitness compared to the actual values. Also, for the new dataset, the performance of the selected ANN model produced a high level of accuracy in predicting the output. That means the proposed ANN model has a high potential for the prediction of the concrete compressive strength.



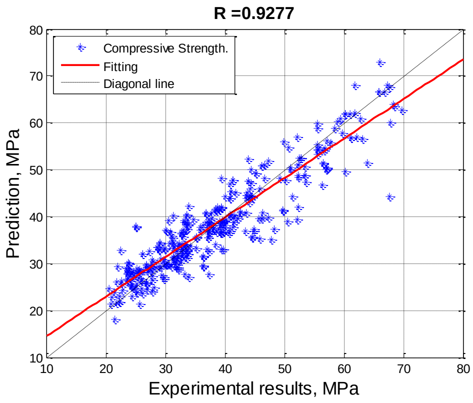
(a) Training



(b) Validation



(c) Testing



(d) Overall

Fig. 3 Scatter of predicted and actual values

Table 4 Measured performance of the selected ANN model

Dataset	R^2	*MSE*	*MAE*	Records
Training	0.9330	17.1	3.18	253
Validation	0.9208	23.1	3.01	54
Testing	0.9149	22.5	3.62	54
Overall	0.9277	18.8	3.22	351

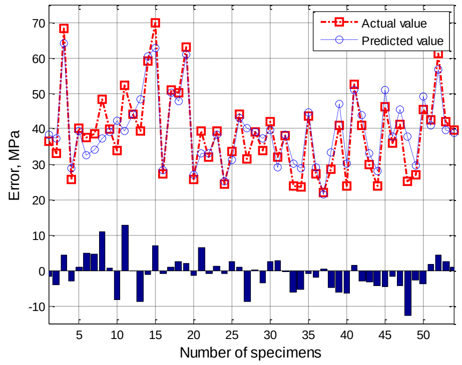
The relationship between the concrete compressive strength values generated from the ANN model and the actual values from the database are shown in Fig. 3. These scatter plots are presented the performance results of the selected ANN for different phases namely, training, validation, testing, and overall. In these figures, the horizontal axis represents the actual values (values from the database), while the predicted values produced from the model are presented on the vertical axis. It is worth noting that the instance that lies on the diagonal line would present a result from an ideal prediction. The fitting line in each figure presents the linear regression of the corresponding dataset

As can be seen from Fig. 3, most concrete test samples were located around the diagonal line. That means the proposed ANN model showed a great ability to predict the output from the inputs. Besides, the ANN model showed a better prediction ability for the concrete samples with a compressive strength of less than 45 MPa, as shown in Fig. 3d. The performance efficiency of the proposed ANN model showed slightly lower for the HPC instances with compressive strength higher than 60 MPa. The potential explanation may be due to the insufficient records with a compressive strength larger than 60MPa in the database, as shown in Table 2.

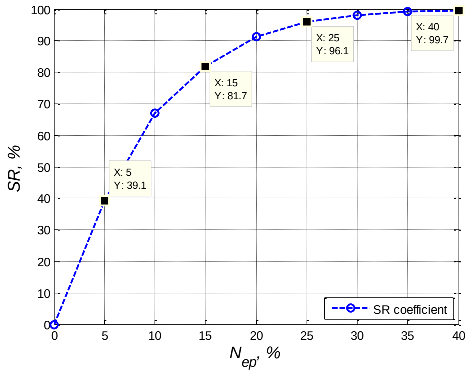
4.2 Errors Evaluation

Figure 4a shows the performance error of the ANN model for the testing dataset. As shown, the proposed ANN model can accurately predict the 28-day concrete compressive strength from the inputs with the average error at around ±5 MPa. Some samples experienced a prediction error as large at around 10 MPa. The lack of test samples in the database could be a possible reason. Due to a limitation in the records, the data might not fully represent the properties of the variables. The potential solution for the issue is to employ the dataset with a larger number of test samples.

To evaluate more detail about the computational efficiency of the selected ANN model, the *SR* coefficient was used [31]. The *SR* is the percentage of data in which the relative error is smaller or equal to the specified error criterion.



(a) For the data test set



(b) SR vs. N_{ep} for the entire database

Fig. 4 Error evaluation of the proposed ANN model

The SR can be calculated using Eq. (6)

$$err_i = \left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\%; SR = \frac{N_{ep}}{N} \times 100\% \quad (6)$$

where err_i is the relative error; y_i is the i^{th} actual output; $\hat{y}_i$ is the i^{th} predicted outputs; N_{ep} is the number of data records with the relative error is smaller than the restrained error bound N_{ep} (i.e., the number of items within the area $err_i < N_{ep}$), and N is the total number of data in the considered set. Figure 4b shows the calculation of SR for the performance of the selected ANN model. As can be seen, about 40 percent of the data was well predicted by the proposed ANN model with a relative error of less than five percent.

4.3 Sensitivity Analysis

Sensitivity analysis is a technique to evaluate the impact of the uncertainty of one or more input parameters on the uncertainty of the output parameters. In this research, the one-at-a-time approach was applied to determine the influence of concrete input variables on the 28-day compressive strength of concrete. The values from each input variable were arranged from low to high regarding five groups, namely Low, ML, Mid, MH, and High, as presented in detail in Table 5. For each variable, the Low and the High are the smallest and the biggest value of the corresponding variable, respectively. The Mid value is half of the Low and the High. While ML is presented for the average value of the Low and the Mid, MH is the value between the Mid and the High.

To perform the sensitivity analysis, for each input, the value of that corresponding input was moved from the Low to the High, while the value of other inputs remain at the Mid position. After completing one input, the identical process was repeated for each of the other inputs. Figure 5 presents the sensitivity analysis results for all seven inputs in this study. This figure consists of five vertical axes positioned from the left to the right. Each axis is related to the value of all inputs at different value levels.

Table 5 Data for sensitivity analysis of seven input variables

Parameters	Low	ML	Mid	MH	High
CM	108	216	324	432	540
BF	0	89.8	179	269	359
FL	0	48.7	97.5	146	195
WT	121	153	184	215	247
SP	0	8.05	16.1	24.1	32.2
CA	801	887	973	1059	1145
FA	594	693	793	89	992

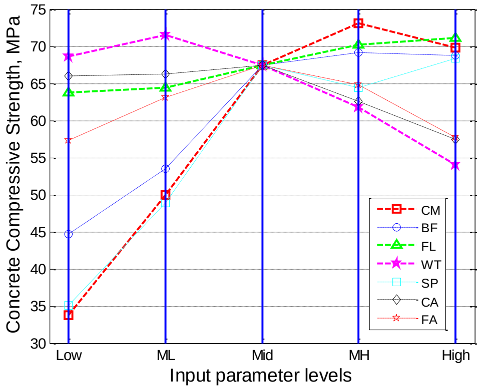


Fig. 5 Results from sensitivity analysis

As can be seen clearly from Fig. 5, the change of cement (CM) and water (WT) variables would significantly affect the 28 days compressive strength of concrete. To be specific, the 28-days concrete compressive strength would increase along with the rise in the amount of cement and vice versa. The opposite trend was applied to the water variable. Additionally, within the context of this study, it is interesting to note that the change of the fly ash parameter (FL) would produce a minimal effect on the 28-day compressive strength of concrete.

5. CONCLUSIONS

In this paper, a feasible method of predicting the 28-day compressive strength of concrete using data from previously published data was presented. Seven input variables including cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, and fine aggregate were employed to predict the concrete compressive strength at 28 days. A total of 351 experimental records were utilized to train, validate, and test the proposed ANN model. Various learning algorithms and the number of hidden nodes were explored. The ANN model using 'trainlm' learning algorithm with 11 neurons in the hidden layer produced the best outcome.

Regarding the performance of the ANN model, it was shown the ANN model was able to predict the concrete compressive strength with a high level of accuracy. The value of R^2 for the training, validation, and testing dataset was 0.9330, 0.9208, and 0.9149, respectively. With respect to the sensitivity analysis, the results revealed that the concrete compressive strength was more sensitive with the change of cement and water variables and less responsive with the adjustment of the fly ash parameter.

It is worth noting that the proposed ANN model showed great performance for the dataset. However, the lack of employing other unsupervised machine learning-based models such as Gradient Tree Boosting, Radom Forest for the current dataset was a limitation of this study. The comparison should be conducted in future research to obtain the best performance model.

REFERENCES

[1] America's Cement Manufacturers, online at https://www.cement.org/cement-concrete-applications/how-concrete-is-made, Retrieved on 10 October 2020.

[2] Bastos G., Patiño-Barbeito F., Patiño-Cambeiro F., Armesto J., Admixtures in Cement-Matrix Composites for Mechanical Reinforcement, Sustainability, and Smart Features, Materials (Basel). 9(12):972, 2016.

[3] Jams K. Wight, and James G. MacGregor, Reinforced Concrete: Mechanics and Design (6th ed.), Pearson Education, Inc., Upper Saddle River, New Jersey 07458, 2012.

[4] ACI Committee 211, Standard Practice for Selecting Proportions for Normal, Heavyweight, and Mass Concrete (ACI 211.1-91, Reapproved 2002), American Concrete Institute, Farmington Hills, MI, 2002.

[5] Zatar W., Nguyen T. T., Mixture Design Study of Fiber-Reinforced Self-Compacting Concrete for Prefabricated Street Light Post Structures, Advances in Civil Engineering, 2020, 8852320, https://doi.org/10.1155/2020/8852320

[6] National Ready Mixed Concrete Association, https://www.nrmca.org/aboutconcrete/cips/35p.pdf, Retrieved on 10 October 2020.

[7] Vu H. H., Do T. G., Nguyen T. T., The application of polypropylene fiber for reinforced concrete beams and slabs, In IOP Conference Series: Materials Science and Engineering. Vol. 869, No. 7, 2020, p. 072042.

[8] Abd elaty, M. abd allah, Compressive strength prediction of Portland cement concrete with age using a new model, HBRC Journal, 10(2), 2014, 145–155.

[9] Lee S. C., Prediction of concrete strength using artificial neural networks, Engineering Structures, 25(7), 2003, 849–857.

[10] Aref M. al-Swaidani, Waed T. Khwies, Applicability of Artificial Neural Networks to Predict Mechanical and Permeability Properties of Volcanic Scoria-Based Concrete, Advances in Civil Engineering, vol. 2018, 5207962.

[11] Nguyen T. T., Dinh K., An artificial intelligence approach for concrete hardened property estimation, Journal of Science and Technology in Civil Engineering (STCE) - NUCE, 14(2), 2020, 40-52.

[12] Khademi F., Akbari M., Jamal S. M., Nikoo, M., Multiple linear regression, artificial neural network, and fuzzy logic prediction of 28 days compressive strength of concrete, Frontiers of Structural and Civil Engineering, 11(1), 2017, 90–99.

[13] Pham T. T., Nguyen T. T., Nguyen L. N.,

Nguyen P. V., A neural network approach for predicting hardened property of Geopolymer concrete, International Journal of GEOMATE, Oct. 2020, Vol.19, Issue 74, 2020, pp.193–201.
[14] Nguyen T. T., Pham D. H., Pham T. T., Vu H. H., Compressive strength evaluation of Fiber-Reinforced High Strength Self-Compacting Concrete with artificial intelligence, Advances in Civil Engineering, vol. 2020, 3012139, 2020, https://doi.org/10.1155/2020/3012139.
[15] A. Ferhat Bingöl, Ahmet Tortum, Rüstem Gül, Neural networks analysis of compressive strength of lightweight concrete after high temperatures, Materials & Design (1980-2015), Volume 52, 2013.
[16] Dinh K., Gucunski N., Kim J., Duong T. H., Improved GPR-based condition assessment of reinforced concrete bridge decks using artificial neural network, HDKBR INFO Magazin, 5(2), 2015, 3-13.
[17] Eugene Hong, Anteneh Mesfin Yeneneh, Tushar Kanti Sen, Ha Ming Ang, Ahmet Kayaalp, ANFIS based Modelling of dewatering performance and polymer dose optimization in a wastewater treatment plant, Journal of Environmental Chemical Engineering, Volume 6, Issue 2, 2018.
[18] Hung T. V., Viet V. Q., Thuat D. V., A deep learning-based procedure for estimation of ultimate load carrying of steel trusses using advanced analysis, Journal of Science and Technology in Civil Engineering (STCE) - NUCE, 13(3), 2019, 113-123.
[19] Nguyen T. T., Dinh K., Prediction of bridge deck condition rating based on artificial neural networks, Journal of Science and Technology in Civil Engineering (STCE) - NUCE, 13(3), 2020, 15-25.
[20] Guijo-Rubio D., Durán-Rosal A. M., Gutiérrez P. A., Gómez-Orellana A. M., Casanova-Mateo C., Sanz-Justo J., Salcedo-Sanz S., Hervás-Martínez C., Evolutionary artificial neural networks for accurate solar radiation prediction, Energy, 210., 2020
[21] Tung P. T., Hung P. T., Predicting fire resistance ratings of timber structures using artificial neural networks, Journal of Science and Technology in Civil Engineering (STCE) - NUCE, 14(2), 2020, 28-39.
[22] Hung D. V., Hung H. M., Anh P. H., Thang N. T., Structural damage detection using hybrid deep learning algorithm, Journal of Science and Technology in Civil Engineering - NUCE, 14(2), 2020, 53-64.
[23] Rabiej M., Rabiej S., Application of the artificial neural network for identification of polymers based on their X-ray diffraction curves, Computational Materials Science, 186, 110042, 2021.
[24] Doan Q. H., Thai D.-K., Tran N. L., A hybrid model for predicting missile impact damages based on k-nearest neighbors and Bayesian optimization, Journal of Science and Technology in Civil Engineering (STCE) - NUCE, 14(3), 2020, 1-14.
[25] Truong V. H., Vu Q. V., Thai H. T., Ha M. H., A robust method for safety evaluation of steel trusses using Gradient Tree Boosting algorithm, Advances in Engineering Software, 147, 102825, 2020.
[26] Behnood A., Behnood V., Modiri Gharehveran M., Alyamac K. E., Prediction of the compressive strength of normal and high-performance concretes using M5P model tree algorithm, Construction and Building Materials, 142, 2017, 199–207.
[27] Kim S.-E., Vu Q.-V., Papazafeiropoulos G., Kong, Z., Truong V.-H., Comparison of machine learning algorithms for regression and classification of ultimate load-carrying capacity of steel frames, Steel and Composite Structures, 37(2), 2020, 193–209.
[28] UCI., Machine Learning Repository, online dataset resources https://archive.ics.uci.edu/ml/ datasets.html, Retrieved on Oct 2020.
[29] Nikbin M I., Rahimi R. S., Allahyari H., A new empirical formula for prediction of fracture energy of concrete based on the artificial neural network, Engineering Fracture Mechanics, 186, 2017, 466–482.
[30] Hunter D., Yu H., Pukish III M. S., Kolbusz J., and Wilamowski B. M., Selection of proper neural network sizes and architectures: a comparative study, IEEE Transactions on Industrial Informatics, vol. 8, n. 2, 2012, pp. 228–240.
[31] Han I. J., Yuan T. F., Lee J. Y., Yoon Y. S., Kim J. H., Learned prediction of compressive strength of GGBFS concrete using hybrid artificial neural network models, Materials, 12(22), 2019.