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Prediction of compressive strength of concrete at high heating conditions by using artificial neural network-based Bayesian regularization

Marijana Hadzima-Nyarko[1], Son Hoang Trinh[2*]
[1]Josip Juraj Strossmayer University of Osijek, Faculty of Civil Engineering and Architecture Osijek, Vladimira Preloga 3, 31000 Osijek, Croatia
[2]University of Transport Technology, Hanoi 100000, Vietnam

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***Corresponding author:**
E-mail address:
sonth@utt.edu.vn

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Abstract: Cement concrete is the most commonly used material today for constructing residential or commercial buildings, industrial parks, or particular components such as tunnel slabs where there is a high risk of fire. This structure requires concrete to be subjected to high temperatures generated by fires. However, concrete under the influence of high temperature has very complex behavior states with deformations, physical and chemical changes as the temperature rises dramatically. In this study, an artificial neural network-based Bayesian regularization (ANN) model is proposed to predict the compressive strength of concrete. The database in this study includes 208 experimental results synthesized from laboratory experiments with 9 input variables related to temperature change and design material composition. The performance of the ANN model was evaluated using K-fold cross-validation and statistical criteria, including mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2). The results show that the proposed ANN model is a reasonable, highly accurate, and useful prediction tool for saving time and minimizing costly experiments.

Keywords: Machine learning, ANN, compressive strength, Bayesian regularization, K-fold cross-validation.

1. Introduction

Due to its non - flammable properties and low thermal gradient, concrete is known to perform well at high temperatures, ensuring that thermal transients propagate slowly inside structural elements. Nonetheless, high-temperature microstructural transformations in concrete involve complicated physicochemical processes in the component. On concrete, high temperatures cause two primary concerns. One is the damage of concrete's mechanical properties, which includes physicochemical variations in the binder and aggregate, thermal differences between the aggregate and the cement matrix as a temperature level and rate, applied force, and outer coating, which reduces evaporation from the concrete's surface. At higher temperatures, an exact number of physicochemical changes appear in the material: physically-compounded H_2O is delivered over 100°C; dioxolane hydrate dissociates over 300°C; calcium hydroxide hydrolyzed over 500°C; and several aggregates begin transferring or disintegrate at various temperatures (delivery of adsorbed H_2O, quartz SiO_2-conversion, limestone decomposing). Simultaneously, the second issue is concrete spalling. Ordinary concrete spalls due to fast temperature rises (about 20ºC/min) [1]. In the transition zone between these two stages, the contrasting strains of the aggregate (expansion) and the cement matrix (drying shrinkage) initiate a distributed series of micro-cracks [2]. In addition, Spalling is caused by thermal strain and vapor pressure build-up in some situations, exposing deeper layers of concrete to burning and speeding up the heat transfer rate [3].

According to prior published studies [4, 5], the factors associated with the type of concrete have a significant correlation, and the type of material components impact the concrete compressive strength at high thermal conditions. Husem [6] researched how flexural and compressive resistance varied as high-performance concrete (HPC) and conventional Portland concrete (PC) were subjected to the heat of 200, 400, 600, 800, and 1000°C and subsequently cooled in water or air. The results show that (a) the compressive resistance of PC and HPC subjected to high thermal reading reduce as the temperature rises. The quick expansions that occur in the process of the deformation of mineral additive used in the HPC at high temperatures may cause the concrete to drop its strength. The results of the experiments showed that regular and high-performance concretes made with limestone aggregate lost a substantial amount of strength deprivation when chilled in freshwater since being subjected to extreme heat. Chan et al. [7] investigated the compressive and thermal behaviors of HPC at heating from 800 to 1100ºC, and through the cooling process. It is discovered that followed by a gradual (26-34%) and quick (22-28%) cooling procedure, the strength attributes dropped dramatically. Tanyildizi et al [8] evaluated the influence of high temperatures on featherweight concrete's tensile and compressive resistance using fly-ash. Temperatures of 200, 400, and 800ºC were carried out in his study. Concrete's compressive and splitting tensile strength were reduced by 63.8% and 76.45%, respectively, at 800ºC. Chan et al. [9] studied traditional and high-strength concrete put in high thermal conditions. The concrete compressive resistance at 28-day ages was measured after various temperature treatment durations (400,600, 800, 1000, and 1200ºC). According to Tang et al., the concrete compressive strength using rubber-modified-recycled based aggregate was evaluated as rising heat [10].

It is evident that the compressive strength of concrete is affected by temperature variations, input material type, and mix proportions [1, 2, 11]. Typically, the statistical regression method estimates the concrete compressive strength at high thermal conditions based on laboratory test data. Although regression analysis appears to be easy and straightforward, the difficulty in the analysis increases as the number of independent variables grows [12]. More advanced techniques, such as Machine learning (ML), are used in complicated scenarios to improve model prediction accuracy. When considering the temperature changes, ML algorithms perform better and have a lower variance [11]. Some studies on predicting compressive strength of concrete based on ML models [13–22]. It can be seen that ANN is a commonly used model in research on strength prediction of concrete because its effectiveness in nonlinear modeling has been well demonstrated, and its mathematical background is clear [23]. Hocine et al [24] predicted the compressive strength of concrete using limestone powder by applying the ANN model based on 7 input variables related to the proportions and age. The results show that the correlation coefficient (R^2) of all training, testing, and validation phases is very high (over 97%). In addition, Behfernia et al [25]. used ANN and adaptive neural-based fuzzy inference (ANFIS) to predict the compressive strength of conventional concrete (without using admixtures or additives such as fly ash, silica fume, blast furnace slag, etc.) based on 160 samples and 7 input parameters related to proportions. The results show that although both ANFIS and ANN show strong predictive power, ANN has better performance. Several studies [13–16] show that ANN is a very effective model for predicting the compressive strength of self-compacting concrete. Like other ML methods, ANN can suffer from an overfitting problem (especially with too small data but too high model complexity) [26]. The regularization in the ANN allows reducing error for obtaining the highest coefficient of correlation and lowest total square errors [27]. A tuning regularization technique in ANN that has been used very effectively is Bayesian regularization which has been used to successfully study various problems such as stock price prediction, data mining, etc [28–32]. Pre-distribution of model parameters and management of large weights are some of the Bayesian regularization strategies used for ANNs to obtain smoother mapping [33].

Currently, there is no evaluation of the ANN-based Bayesian regularization model's effectiveness in predicting the strength of concrete as subjected to high temperatures. So, the development of this ML model to predict compressive strength and performance comparison was evaluated as part of this study's novelty. Temperature and material composition, including water, cement, coarse aggregate, fine aggregate, nano-silica, fly ash, super-plasticizer, and silica fume, were the 9 input parameters considered and used to evaluate the efficacy of the developed ANN technique in predicting concrete compressive strength.

2. Database construction

This paper develops an ANN model based on Bayesian regularization based on 208 experimental data to forecast concrete's compressive strength. The factors affecting the compressive strength of concrete such as the content of ingredient material in the designed concrete mixture, including water, cement, aggregate (coarse sand/fine), mineral additives (silica-fume, nano-silica, fly ash), chemical additives (super-plasticizers), and subjected temperature have all been demonstrated in previous studies [34–39]. The statistical information of the input and output parameters is shown in Table 1. The input variables are denoted by I1 to I9, and the output parameter is denoted by O.

Table 1. Statistical analysis of the input parameters in this study

Calculate for 1m³ concrete

Parameters	Abbreviation	Unit*	Min	Max	Mean	StD
Inputs						
Cement	I_1	kg	250	786	437.69	95.49
Water	I_2	kg	123	385	182.75	59.95
Fine Aggregate	I_3	kg	0	1345	610.13	317.39
Coarse Aggregate	I_4	kg	0	1681	1052.13	309.41
Fly Ash	I_5	kg	0	150	12.65	33.07
Super Plasticizer	I_6	kg	0	25.9	8.58	7.60
Silica Fume	I_7	kg	0	150	29.32	37.09
Nano Silica	I_8	kg	0	22.5	1.74	5.25
Temperature	I_9	(°C)	20	1000	354.52	287.65
Output						
Compressive strength	O	(MPa)	3	133.6	49.31	25.17

Fig 1 shows correlation matrix analysis, which visualizes the relationship between variables and analyzes each variable's effect on the problem's output variable. Different colors describe the correlation values. The blue square represents the negative correlation, and the red color represents the positive correlation. The pairs of attributes with a high degree of correlation can be removed to reduce the influence of unnecessary variables on the predictive model. The correlations between the inputs and output are not strictly linear, with a maximum correlation value of about

0.5. So, all inputs are considered as independent variables, while output as a dependent variable is predicted based on these independent ones.

The dataset is divided into two groups for training and testing phases with a ratio of 70:30 to build the model. Finally, statistical parameters and K-fold cross-validation validate the generated model.

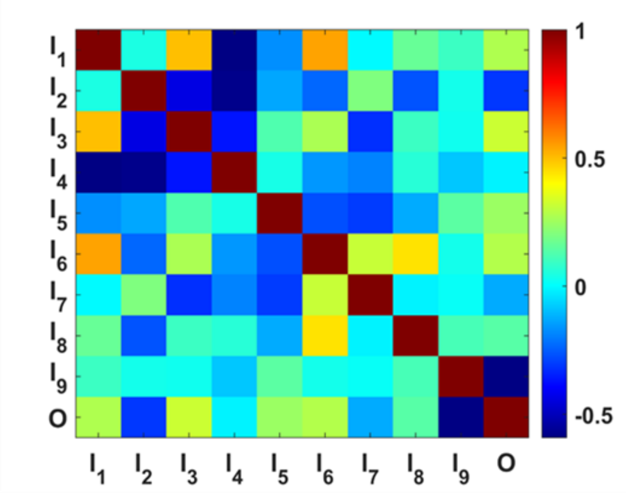


Fig 1. The distribution chart and correlation between inputs and output in this work

3. Model Details

3.1. ANN

Artificial Neural Networks (ANN) have been introduced since the 1940s [23]. ANN is a strong machine learning-based data analysis technique that is based on actual biological neural networks and is used to analyze large amounts of data. This ML technique aims to imitate the knowledge acquisition and inference processes in the human brain to improve performance [40]. The use of artificial neural networks (ANNs) to handle nonlinear regression analysis issues has become more and more popular.

The ANN is set up to work based on biological neurons. A set of neurons is arranged so that all neurons receive an input signal and output signal simultaneously, and such a set is called a network layer [41]. The most straightforward neural network consists of a layer specializing in receiving input signals and input variables (input layer), and the output layer releasing the output signals. Hidden layers are those that exist between the input and output layers. These hidden layers contain hidden neurons, i.e., the intermediate results of the neural network's output value computation process. A neural network can have many hidden layers. If there are too many hidden layers, the model will fit the data well, which also means that the model will be more accurate in estimating the weights but will be less accurate in predicting out-of-sample measurements [42]. In addition, the larger the number of hidden layers, the greater the number of weights in the model thereby making the model estimation time longer [43]. The structure of an ANN model in this study is shown on Fig. 2.

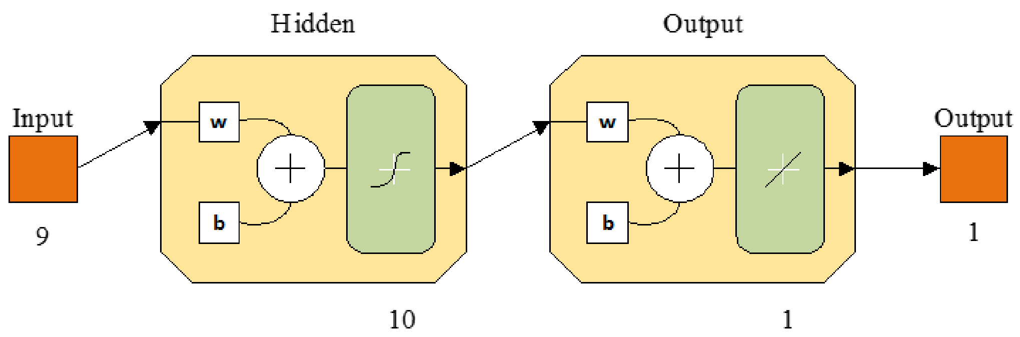


Fig 2. The structure of ANN in this study

The use of Bayesian regularization in artificial neural network training/learning is much more potent than the standard back-propagation algorithm since it decreases or removes the requirement of extensive cross-validation [44]. In the same way, the regression method makes a non - linear model into a "well-posture" statistic issue, Bayesian regularization does the same for a nonlinear regression [33]. As a result, the models are reliable, and the assessment procedure is the advantage of Bayesian regularized-based artificial neural networks.

In statistics, the Bayesian approach differs from the probability perspective in hypothesis validating. It is founded on a couple of basic concepts: (1) probability is a metric of confidence of the events occurring, (2) past assumptions affect subsequent assumptions. The Bayes theorem states that [45]:

$$P(H \setminus D) = \frac{P(D \setminus H)P(H)}{P(D)} = \frac{P(D,H)}{\int_H P(D,H')dH'} \tag{1}$$

$$P(D) = \int_H P(D,H')dH' \tag{2}$$

The equation also holds in the probability approach, in which H and D are regarded groups of outcome measures. H is a hypothesis regarding if it has some previous assumption, and D is information that will modify one's assumption about H, according to the Bayesian approach. The probability is defined as P(D|H). It represents the model's unpredictability (aleatoric–uncertainty), i.e., the controversial question or uncertainty by process noise in the model. The prior is P(H) and Eq (2) is subsequent. The posterior is defined as P(H|D).

To put it another way, the Bayesian theory provides a good framework for quantifying uncertainties in ML techniques. Also, it gives an accurate basis for interpreting several of the regularization methods and training tactics utilized in traditional ML [46].

3.2. K-Fold cross-validation

When it comes to estimating the performance of machine learning models, cross-validation is the statistical approach utilized. It is often used to compare and select the most appropriate model for a given situation. Compared to previous approaches, this strategy is simple to grasp and use, providing more reliable estimations [47]. The most critical parameter to consider when using this strategy is K, which specifies the number of groups into which the data will be divided. It is referred to as K-fold cross-validation as a result of this. When a value of K is chosen, that value is used directly in the name of the evaluation method. This technique usually includes the following steps [48]:

- Shuffle the dataset at random
- Divide dataset into K groups. For each group: (i) Use the current group to evaluate model effectiveness; (ii) The remaining groups are used to train the model; (iii) Train the model; (iv) Evaluate and then reject the model
- Synthesize the effectiveness of the model based on the evaluation data

The total results are usually the average of the evaluations. In addition, the addition of variance and standard deviation information to the total results is also used in practice [49]. On the other hand, if K is chosen too large, the training set will be much larger than the testing set, and the evaluation results will not reflect the true nature of the machine learning method, especially with large data sets. That is also the reason why the 10-fold cross-validation is chosen by many researchers [11,48]. Therefore, in this study, K=10 was selected (10-fold cross-validation).

3.3. Performance assessment

The proposed ANN model's performance is evaluated using several indicators, comprising mean absolute error (MAE), root mean square error (RMSE), mean squared error (MSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2).

The following equations reflect these values [43]:

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n} (P_i - E_i)^2}{\sum_{i=1}^{n} (P_i)^2} \right] \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_i - E_i)^2} \tag{4}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |P_i - E_i| \tag{5}$$

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{E_i - P_i}{E_i} \right| \tag{6}$$

Where E is the actual experimental value, P denotes the expected value based on the model's estimate, and n denotes the total sample sizes in the dataset.

R^2 is an important criterion in regression analysis. It is understood as the square of the correlation coefficient between the predicted outcome and the target, varying from 0 to 1. A high R^2 value indicates a good correlation between the predicted and the actual values. RMSE is an error measurement of the mean squared difference between the predicted and actual outputs of an ANN network model, while MAE measures the mean absolute error between them. Moreover, MAPE reflects how much the predicted value differs from the mean value. In contrast to R^2, lower RMSE, MAE, MAPE values indicate better performance of the AI algorithm. All the criteria are necessary to evaluate the network model [50].

4. Results and Discussion

In the case of ANN training, the effectiveness of the model is determined by the topology of the neural network, which includes the number of hidden layers and the number of neurons in each of the hidden layers. Many factors that influence the ANN's performance, including the network's number of input and output parameters, the number of data points in the dataset, the training algorithm, the complexity of the error function, the network architecture, and the noise in the target data. A hidden layer in an ANN architecture, on the other hand, has been proven in several experiments to be sufficient for reaching the model's best performance [12, 40]. To this end, three layers in the proposed ANN structure were used to predict the compressive strength of concrete at high temperatures in this investigation. The input layer consisted of 9 neurons corresponding to 9 input parameters, the output layer consisted of 1 neuron representing the compressive strength value, and there was a single hidden layer between the two layers. It was necessary to experiment with different numbers of neurons in the hidden layer to establish the appropriate number of neurons in the hidden layer. Following multiple trial and error experiments, it was discovered that 10 neurons in the hidden layer produced the best predictionresults in this study. These findings are derived from the training and validation results obtained after 10-fold cross-validation. Figure 3 shows the results of 10-fold cross-validation for a variety of assessment metrics. After 10 iterations, the R2 measures from the training set are higher than those from the testing set, and the values of error (RMSE, MAE, and MAPE) from the training set are lower than those from the testing set, which clearly indicates the model's accuracy in predicting the compressive strength of concrete.

The regression model showing the correlation results between the predicted value from the ANN model and the actual value for the training and testing datasets is shown in Fig. 4. These are the typical prediction results from Fig. 3 (results of the Cross-Validation 2), in which the horizontal axis represents the results of the collected experiment, and the vertical axis represents the results predicted by the developed ANN model. Itis observed that the values obtained from the constructed ANN model for the training data set (Fig. 4a) and the testing dataset (Fig. 4b) are very close to the experimental results. In addition, the performance metrics are RMSE=2.757, MAE=2.004, R^2=0.988, and MAPE=5.387, whereas RMSE=6.159, MAE=4.438, R^2=0.942, and MAPE=14.164 for the test phase. These results show that the ANN model can generalize input and output parameters and provide good predictions. Also seen is that the linear regression lines are quite close to the diagonals, confirming the strong correlation between the anticipated and real compressive strengths. In this study, it is discovered that the produced ANN model can accurately predict the compressive strength of concrete when exposed to high temperatures.

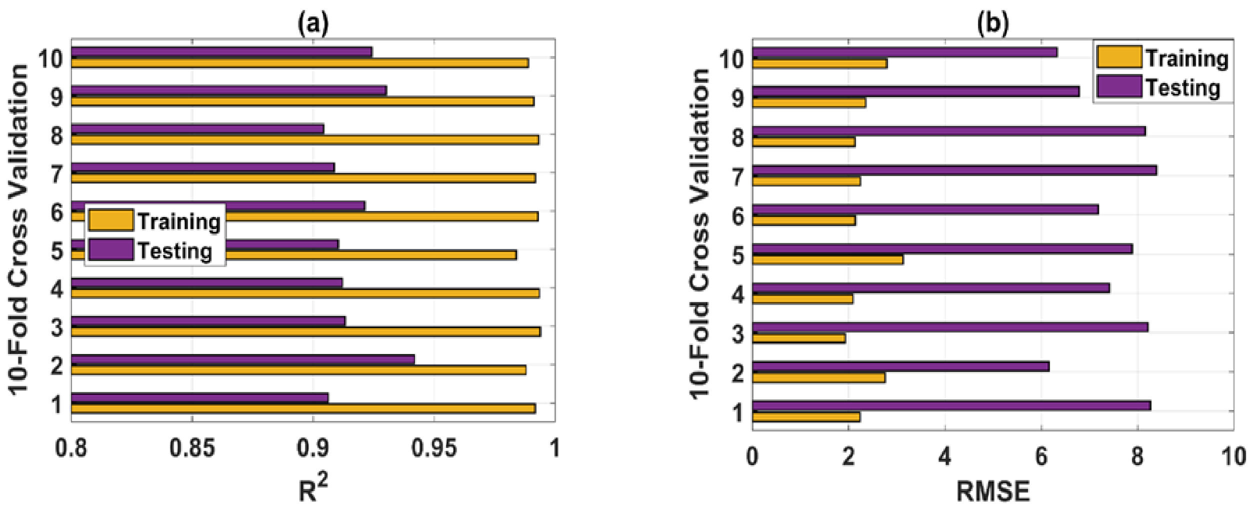
Fig 5a shows the ANN model's distribution plot and cumulative distribution line of error for the training phase, while Fig. 5b shows those for the testing phase. It can be seen that the errors in both phases are concentrated around the 0 MPa position with a high density. In addition, based on the cumulative distribution, about 95% of the errors are concentrated in the very close range of 0 MPa, which confirms the modeling ability simulates the compressive strength of concrete accurately. Only a few cases with high errors (10 MPa, 20 MPa) were detected in the training and testing part, respectively. However, it does notaffect the generalizability of the above machine learning model.

In this next section, the strength prediction result obtained from a multi-variable regression formulation is conducted (Eq. 7).

$$O = 19.047 + 0.095(I_1) - 0.050(I_2) + 0.003(I_3) + 0.007(I_4) + 0.339(I_5) + 0.506(I_6) + 0.015(I_7) + 0.518(I_8) - 0.061(I_9) \quad (7)$$

For the sake of comparison, the same training dataset was used to train the regression model, whereas the same testing data set was used to evaluate the performance of the proposed formulation. Fig. 6a shows the results of statistical indices, the ideal regression line, and the model's fit line for the training set. The values of statistical indices for the training part, including high R^2 value (0.974), and low error (RMSE=4.085, MAE=2.733, and MAPE=8.016) indicated the high accuracy of the proposed formulation. The fit line nearly coincides with the ideal regressionline, which confirms the close correlation between predicted and actual compressive strength. Nevertheless, Fig. 6b shows the formulation results on the testing dataset. It can be seen that there is a very significant difference between the ideal regression line and the fit line in the linear regression, showing the model's insufficient accuracy. In addition, R^2 = 0.718, RMSE=13.334, MAE=10.838, and MAPE=34.315 are much lower than the predicted results from the model on the training data set.

Finally, the results of this study are compared with those of Ahmad's study using Decision Tree (DT), Artificial neural network (ANN), Bagging, and Gradient Boosting (GB) models proposed in [11]. As shown in Table 2, it can be seen that the proposed ANN-based Bayesian regularization model in this paper has better predictiveperformance (the highest R^2, and the lowest errors RMSE and MAE) than the other models. This result is also similar to some previous publications. Artificial neural network-based Bayesian regularization performed better than Partial Least Squares Discriminant Analysis (PLSDA) in chemical and drug metabolism prediction [51]. As compared with some algorithms to improve ANN efficiency, Bayesian regularization shows superiority over Levenberg–Marquardt algorithm [26, 52] and gradient descent with momentum and adaptive learning rate backpropagation – GDX [53], Scaled Conjugate Gradient (SCG) [54]. Besides, Gouravarajua [27] concludes that the artificial neural network-based Bayesian regularization combined with the K-fold cross-section technique which can greatly reduce computation time with high accuracy can be used to successfully study gecko adhesion problems. Thus, it is shown that utilizing the ANN-based Bayesian regularization model to estimate the compressive strength of concrete at high temperatures is achievable, hence saving time and money on trials.



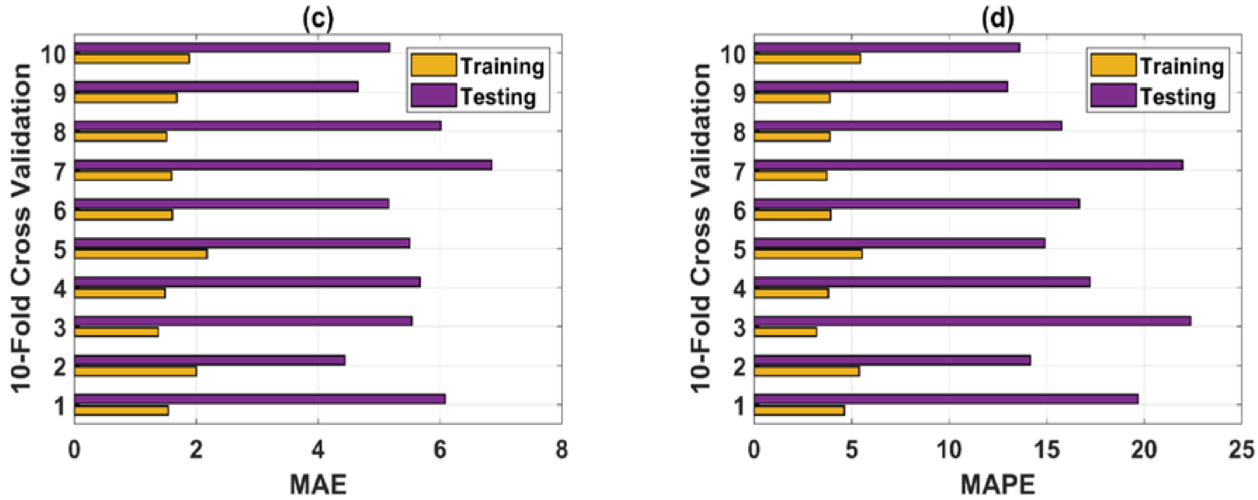


Fig 3. Results of training and validation of ANN model after 10-fold cross-validation based on different performance evaluation criteria: (a) R^2; (b) RMSE; (c) MAE, (d) MAPE

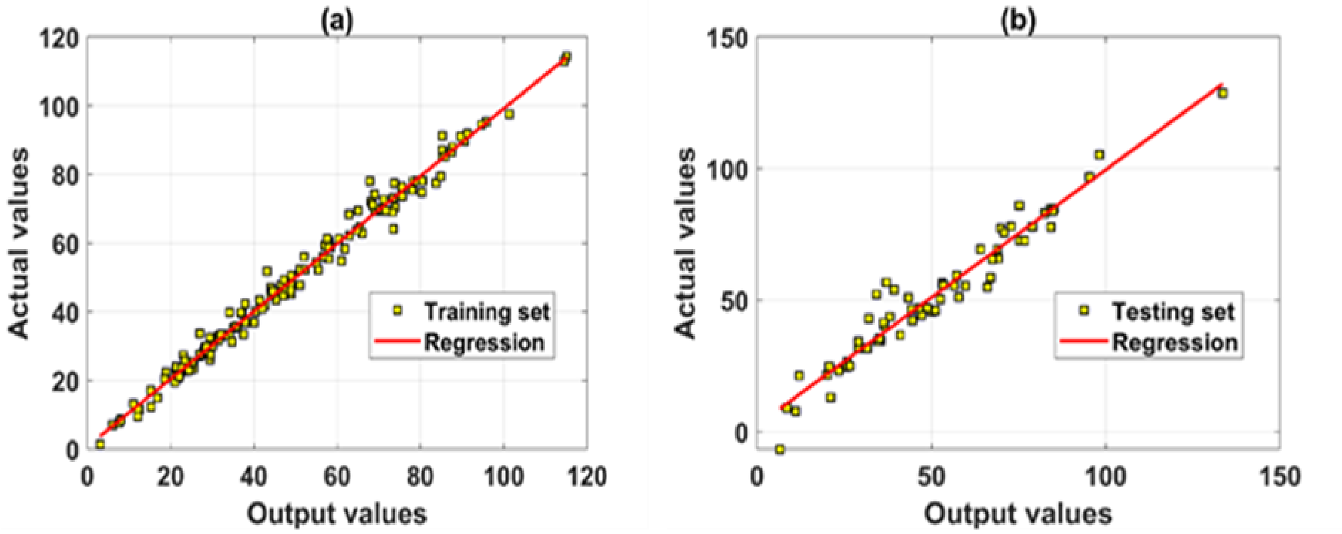


Fig 4. Comparison of the performance of ANN model with the actual values for the (a) training dataset and (b) testing dataset

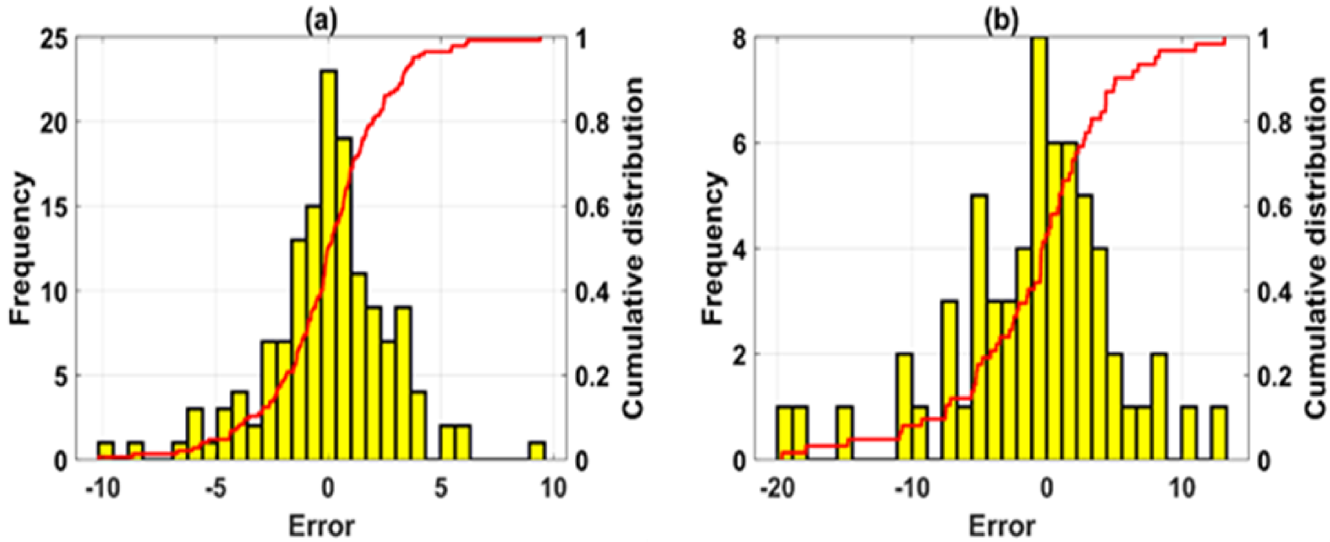


Fig 5. Error and regression charts between experimental values and simulation values calculated by ANN considered in this study for: (a) the training part; and (b) testing part

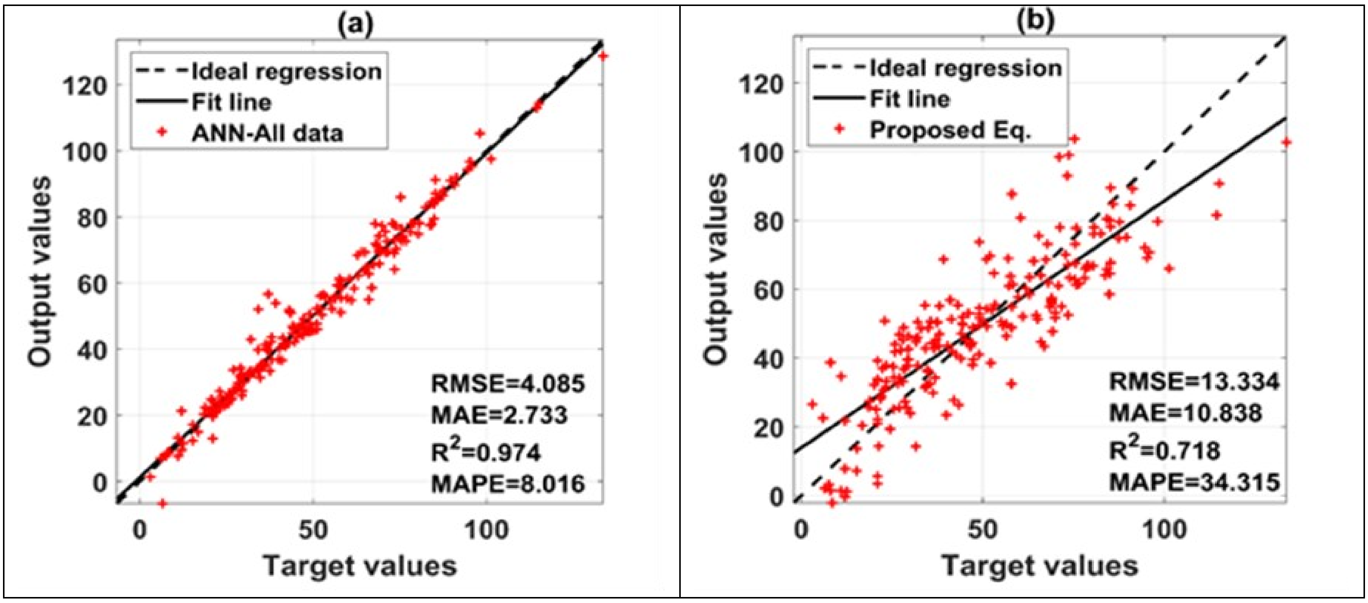


Fig 6. Regression graphs showing a comparison between the experimental values and the predicted results obtained by formulation Eq. (7)

Table 2. Comparison of the prediction results

	ML model	R^2	RMSE	MAE
This study	ANN -Bayesian regularization (Training)	0.988	2.757	2.004
	ANN-Bayesian regularization (Testing)	0.942	6.159	4.438
Ahmad's study [11]	DT	0.8378	10.79	7.54
	Bagging	0.9047	7.81	5.65
	GB	0.8854	9.24	6.93
	ANN	0.8202	11.03	9.15

5. Conclusion

Based on Bayesian regularization, an optimum neural network is presented to forecast the compressive strength of 28-day concrete at high temperatures. A total of 208 experimental results were collected from experimental results used to construct the ANN-based Bayesian regularization model. Water, cement, coarse aggregate, fine aggregate, nano-silica, fly ash, super-plasticizer, silica fume, and temperature were all included in the input space of the collected database. Four statistical criteria were used to evaluate the performance of the model. The prediction accuracy is R^2=0.942, RMSE=6.159, MAE=4.438, and MAPE=14.164. The suggested ANN model's performance in this research was compared to that of the previous study and found to be superior. Concrete's compressive strength under various temperature settings may be accurately predicted using the ANN model, saving time and money otherwise spent on costly experiments. ML hybrid models might need to be developed based on this preliminary study to improve the accuracy of estimating concrete's compressive strength at high temperatures.

References

[1]. G.A. Khoury. (2001). Effect of fire on concrete and concrete structures. *Progress in Structural Engineering and Materials*, 2(4), 429–447

[2]. K.D. Hertz. (2005). Concrete strength for fire safety design. *Magazine of Concrete Research*, 57(8), 445-453.

[3]. D. Gawin, F. Pesavento, B.A. Schrefler. (2006). Towards prediction of the thermal spalling risk

through a multi-phase porous media model of concrete. *Computer Methods in Applied Mechanics and Engineering*, 195(41-43), 5707-5729.

[4]. Z. Fang, K. Roy, B. Chen, C.-W. Sham, I. Hajirasouliha, J.B.P. Lim. (2021). Deep learning-based procedure for structural design of cold-formed steel channel sections with edge-stiffened and un-stiffened holes under axial compression. *Thin-Walled Structures*, 166, 108076.

[5]. M.A. Khan, A. Zafar, F. Farooq, M.F. Javed, R. Alyousef, H. Alabduljabbar, M.I. Khan. (2021). Geopolymer Concrete Compressive Strength via Artificial Neural Network, Adaptive Neuro Fuzzy Interface System, and Gene Expression Programming With K-Fold Cross Validation. *Frontiers in Materials*, 8, 621163.

[6]. M. Husem. (2006). The effects of high temperature on compressive and flexural strengths of ordinary and high-performance concrete. *Fire Safety Journal*, 41(2), 155-163.

[7]. S.Y.N. Chan, X. Luo, W. Sun. (2000). Effect of high temperature and cooling regimes on the compressive strength and pore properties of high performance concrete. *Construction and Building Materials*, 14(5), 261-266.

[8]. H. Tanyildizi, A. Coskun. (2008). The effect of high temperature on compressive strength and splitting tensile strength of structural lightweight concrete containing fly ash. *Construction and Building Materials*, 22(11), 2269-2275.

[9]. S.Y.N. Chan, G. Peng, J.K.W. Chan. (1996). Comparison between high strength concrete and normal strength concrete subjected to high temperature. *Materials and Structures*, 29, 616-619.

[10]. Y. Tang, W. Feng, W. Feng, J. Chen, D. Bao, L. Li. (2021). Compressive properties of rubber-modified recycled aggregate concrete subjected to elevated temperatures. *Construction and Building Materials*, 268, 121181.

[11]. A. Ahmad, K.A. Ostrowski, M. Maślak, F. Farooq, I. Mehmood, A. Nafees. (2021). Comparative Study of Supervised Machine Learning Algorithms for Predicting the Compressive Strength of Concrete at High Temperature. *Materials*, 14(15), 4222.

[12]. H.-B. Ly, T.-A. Nguyen, H.-V.T. Mai, V.Q. Tran. (2021). Development of deep neural network model to predict the compressive strength of rubber concrete. *Construction and Building Materials*, 301, 124081.

[13]. M.A. Yaman, M.A. Elaty, M. Taman. (2017). Predicting the ingredients of self compacting concrete using artificial neural network. *Alexandria Engineering Journal*, 56(4), 523-532.

[14]. P.G. Asteris, K.G. Kolovos. (2019). Self-compacting concrete strength prediction using surrogate models. *Neural Computing and Applications*, 31, 409-424.

[15]. O.B. Douma, B. Boukhatem, M. Ghrici, A. Tagnit-Hamou. (2017). Prediction of properties of self-compacting concrete containing fly ash using artificial neural network. *Neural Computing and Applications*, 28, 707-718.

[16]. J. Zhang, G. Ma, Y. Huang, J. Sun, F. Aslani, B. Nener. (2019). Modelling uniaxial compressive strength of lightweight self-compacting concrete using random forest regression. *Construction and Building Materials*, 210, 713-719.

[17]. J. Huang, Y. Sun, J. Zhang. (2022). Reduction of computational error by optimizing SVR kernel coefficients to simulate concrete compressive strength through the use of a human learning optimization algorithm. *Engineering with Computers*, 38, 3151-3168.

[18]. F. Aslam, F. Farooq, M.N. Amin, K. Khan, A. Waheed, A. Akbar, M.F. Javed, R. Alyousef, H. Alabdulijabbar. (2020). Applications of Gene Expression Programming for Estimating Compressive Strength of High-Strength Concrete. *Advances in Civil Engineering*, 2020, e8850535.

[19]. M.F. Javed, F. Farooq, S.A. Memon, A. Akbar, M.A. Khan, F. Aslam, R. Alyousef, H. Alabduljabbar, S.K.U. Rehman. (2020). New Prediction Model for the Ultimate Axial Capacity of Concrete-Filled Steel Tubes: An Evolutionary

Approach. *Crystals*, 10(9), 741.

[20]. A.A. Shahmansouri, H.A. Bengar, E. Jahani. (2019). Predicting compressive strength and electrical resistivity of eco-friendly concrete containing natural zeolite via GEP algorithm. *Construction and Building Materials*, 229, 116883.

[21]. B. Vakhshouri, S. Nejadi. (2018). Prediction of compressive strength of self-compacting concrete by ANFIS models. *Neurocomputing*, 280, 13-22.

[22]. M. Nematzadeh, A.A. Shahmansouri, M. Fakoor. (2020). Post-fire compressive strength of recycled PET aggregate concrete reinforced with steel fibers: Optimization and prediction via RSM and GEP. *Construction and Building Materials*, 252, 119057.

[23]. J. Zupan. (1994). Introduction to Artificial Neural Network (ANN) Methods: What They Are and How to Use Them*. *Acta Chimica Slovenica*, 41(3), 327-352.

[24]. H. Ayat, Y. Kellouche, M. Ghrici, B. Boukhatem. (2018). Compressive strength prediction of limestone filler concrete using artificial neural networks. *Advances in Computational Design*, 3(3), 289-302.

[25]. K. Behfarnia, F. Khademi. (2017). A comprehensive study on the concrete compressive strength estimation using artificial neural network and adaptive neuro-fuzzy inference system. *International Journal of Optimaization in Civil Engineering*, 7(1), 71-80.

[26]. M. Kayri. (2016). Predictive Abilities of Bayesian Regularization and Levenberg–Marquardt Algorithms in Artificial Neural Networks: A Comparative Empirical Study on Social Data. *Mathematical and Computational Applications*, 21(2), 20.

[27]. S. Gouravaraju, J. Narayan, R.A. Sauer, S.S. Gautam. (2021). A Bayesian regularization-backpropagation neural network model for peeling computations. *The Journal of Adhesion*, 99(1), 92-115.

[28]. M. Lefik, B.A. Schrefler. (2003). Artificial neural network as an incremental non-linear constitutive model for a finite element code. *Computer Methods in Applied Mechanics and Engineering*, 192(28-30), 3265-3283.

[29]. H.-F. Li, S.-Y. Lee. (2009). Mining frequent itemsets over data streams using efficient window sliding techniques. *Expert Systems with Applications*, 36(2), 1466-1477.

[30]. J.L. Ticknor. (2013). A Bayesian regularized artificial neural network for stock market forecasting. *Expert Systems with Applications*, 40(14), 5501-5506.

[31]. S. Koroglu, P. Sergeant, N. Umurkan. (2010). Comparison of analytical, finite element and neural network methods to study magnetic shielding. *Simulation Modelling Practice and Theory*, 18(2), 206-216.

[32]. K. Yang, M. Xiong. (2019). Prediction of CH4 adsorption on different activated carbons by developing an optimal multilayer perceptron artificial neural network. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 41(17), 2061-2072.

[33]. H. Kaur, D.S. Salaria. (2013). Bayesian Regularization based Neural Network Tool for Software Effort Estimation. *Global Journal of Computer Science and Technology*, 13(2), 45-50.

[34]. S. Ahmad, Y.S. Sallam, M.A. Al-Hawas. (2014). Effects of Key Factors on Compressive and Tensile Strengths of Concrete Exposed to Elevated Temperatures. *Arabian Journal for Science and Engineering*, 39, 4507-4513.

[35]. N. Al-Mutairi, F. Al-Rukaibi, A. Bufarsan. (2010). Effect of microsilica addition on compressive strength of rubberized concrete at elevated temperatures. *Journal of Material Cycles and Waste Management*, 12, 41-49.

[36]. Phan, L.T., Carino, N.J. (2002). Title no. 99-M8 Effects of Test Conditions and Mixture Proportions on Behavior of High-Strength Concrete Exposed to High Temperatures. *ACI Materials Journal*, 99(1), 54-66.

[37]. R. Sarshar, G.A. Khoury. (1993). Material and environmental factors influencing the compressive strength of unsealed cement paste and concrete at high temperatures. *Magazine of Concrete Research*, 45(162), 51-

61.
[38]. J. Xiao, L.Li, L. Shen, C.S. Poon. (2015). Compressive behaviour of recycled aggregate concrete under impact loading. *Cement and Concrete Research*, 71, 46-55
[39]. H.L. Malhotra. (1956). The effect of temperature on the compressive strength of concrete. *Magazine of Concrete Research*, 8(23), 85-94.
[40]., H.-V.T. Mai, T.-A. Nguyen, H.-B. Ly, V.Q. Tran. (2021). Investigation of ANN Model Containing One Hidden Layer for Predicting Compressive Strength of Concrete with Blast-Furnace Slag and Fly Ash. Advances in Materials Science and Engineering, 2021, e5540853.
[41]. B.T. Pham, M.D. Nguyen, H.-B. Ly, T.A. Pham, V. Hoang, H.V. Le, T.-T. Le, H.Q. Nguyen, G.L.Bui. (2020). Development of Artificial Neural Networks for Prediction of Compression Coefficient of Soft Soil. *CIGOS 2019, Innovation for Sustainable Infrastructure*, pp. 1167–1172. Springer, Singapore.
[42]. S. Agatonovic-Kustrin, R. Beresford. (2000). Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. *Journal of Pharmaceutical and Biomedical Analysis*, 22(5), 717-727.
[43]. H.-B. Ly, M.H. Nguyen, B.T. Pham. (2021). Metaheuristic optimization of Levenberg–Marquardt-based artificial neural network using particle swarm optimization for prediction of foamed concrete compressive strength. *Neural Computing and Applications*, 33, 17331-17351.
[44]. F. Burden, D. Winkler. (2009). Bayesian Regularization of Neural Networks. *Livingstone, D.J. (ed.) Artificial Neural Networks: Methods and Applications*, pp 23-42. Humana Press, Totowa, NJ.
[45]. M.S. Khan, P. Coulibaly. (2006). Bayesian neural network for rainfall-runoff modeling. *Water Resources Research*, 42, W07409.
[46]. C. Maschio, D.J. Schiozer. (2014). Bayesian history matching using artificial neural network and Markov Chain Monte Carlo. *Journal of Petroleum Science and Engineering*, 123, 62-71.
[47]. P. Refaeilzadeh, L. Tang, H. Liu. (2016). Cross-Validation. *Encyclopedia of Database Systems*, pp 1-7. Springer, New York, NY.
[48]. D. Anguita, L. Ghelardoni, A. Ghio, L. Oneto, S. Ridella. (2012). The 'K'in K-fold cross validation. *20th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning (ESANN)*, pp 441-446.
[49]. T. Fushiki. (2011). Estimation of prediction error by using K-fold cross-validation. *Statistics and Computing*, 21, 137-146.
[50]. L. Rodríguez-Lado, M. Rial, T. Taboada, A.M. Cortizas. (2015). A Pedotransfer Function to Map Soil Bulk Density from Limited Data. *Procedia Environmental Sciences*, 27, 45-48.
[51]. M.J. Sorich, J.O. Miners, R.A. McKinnon, D.A. Winkler, F.R. Burden, P.A. Smith. (2003). Comparison of Linear and Nonlinear Classification Algorithms for the Prediction of Drug and Chemical Metabolism by Human UDP-Glucuronosyltransferase Isoforms. *Journal of Chemical Information and Computer Sciences*, 43(6), 2019-2024.
[52]. D.T. Bui, B. Pradhan, O. Lofman, I. Revhaug, O.B. Dick. (2012). Landslide susceptibility assessment in the Hoa Binh province of Vietnam: A comparison of the Levenberg–Marquardt and Bayesian regularized neural networks. *Geomorphology*, 171-172, 12-29.
[53]. S. Mohanty, M.K. Jha, A. Kumar, K.P. Sudheer. (2010). Artificial Neural Network Modeling for Groundwater Level Forecasting in a River Island of Eastern India. *Water Resources Management*, 24, 1845-1865.
[54]. N.P. Singh, S.M. Usman, V. Maurya, T. Dutt, N. Bhatt, A. Kumar. (2020). Comparative Analysis of Artificial Neural Network Algorithms for Prediction of FL305DMY in Murrah Buffalo. *International Journal of Livestock Research*, 10(9), 205-209.