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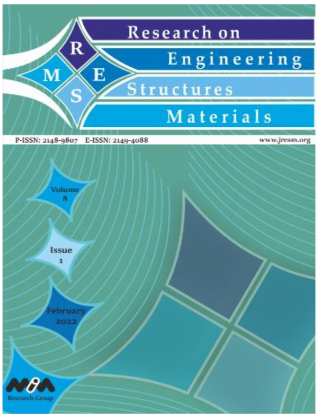

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Technical Note

An artificial neural network for the prediction of the strength of supplementary cementitious concrete

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Abstract

Supplementary materials (SM) for cement replacement became more feasible in the previous decade due to their pozzolanic strength and durability properties. The strength variation according to the age of the binding material is a critical subject for SM concrete. The time of water curing is critical in order to maintain the pozzolanic reaction in SM concrete, which assists in the development of strength in cementitious properties. In this study, the laboratory results of concrete specimens were assessed for various mix designs, and the obtained corresponding strengths were also predicted with ANN techniques. The difference between experimental and ANN predicted values was marginally low. Thus, the ANN model applicability emphasized the productive use in predicting the strength of supplementary materials like fly ash or any similar pozzolanic mineral admixture. This research proposes an ANN-based technique for predicting the strength of fly ash added SM concrete. Typical experimental data is used to build, train, and test the artificial neural network (ANN) model. With ANN and input parameters, a total of 324 distinct data points for SM concrete were utilized to estimate SM concrete strength. Various combinations of layers, number of neurons, and learning rate were examined during the training phase. When the root mean square error (RMSE) reached or remained below 0.001, the training was stopped, and the findings were verified using a test data set. With respect to the relative error provided for trained model data, the results achieved were typically below 10% for compressive strength and below 5% for split tensile strength. The ANN models predict concrete strength with excellent accuracy, and the findings show that utilizing ANNs to predict concrete strength is both practicable and advantageous.

1. Introduction

Cement, water, and coarse and fine particles make up traditional concrete. To improve the quality of fresh or hardened concrete, further components such as chemical or mineral admixtures can be added to the basic constituents. The process of selecting acceptable concrete materials and their relative amounts in order to produce good concrete with the required strength, workability, and durability at the lowest feasible cost has very challenging. Over the last four decades, researchers have been working on developing techniques to determine the optimal strength prediction tool, which can reduce the laboratory effort of specimen testing. The quality of concrete specimens depends on the cementitious combinations. [1] Every project needs a laboratory strength analysis to judge the quality obtained by SM concrete [2]. Concrete strength prediction has long been a prominent issue in the field of concrete technology. Strength is an important parameter in the service life of concrete among repairing and heterogeneous construction works [3]. When the alternative material is used as a supplementary material for traditional Portland cement, then conscious efforts have been required in strength analysis. The needs of the

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world and the demand for sustainability mean the SM plays a crucial role in the environment [4]. The work, like retrofitting, repairs, and massive construction, SM is a strong and promising source. SM offers positive effects on the rheological and mechanical properties of concrete [5]. As the SM is the alternative provision in cementitious materials, the accuracy of strength prediction has become an important agenda to maintain the quality of construction.

The compressive strength of SM concrete is calculated through mix design or evaluated through lots of repetition using a compressive testing machine [6]. In this method, the noteworthy materials are destroyed every time, and specimen casting time is also wasted. An artificial neural network (ANN)–technique, which are powerful approaches for resolving complexity in the testing model [8]. Few researchers agree on the adoptive use of ANN in concrete strength prediction. The feed forward ANN class, also known as multilayer perception (MLP), includes input, hidden, and output layers. These three standard neural nodes are easier to use in the strength predictive model [9,11,12]. The mix design of the SM composite represents the input layer, computational neurons for the hidden layer, and one neuron on behalf of strength prediction. Earlier investigations of concrete mixes are known to have great precision, especially when observations are produced through a single project source [16]. However, also with a strong tool like ANN, test errors are multiplied with the ANN models being trained by data from different sources.

ANN's predictive performance is based on numerous parameters and can be entirely different depending on the type of concrete mixtures. Apart from mix design constraints, there are many more contributing elements to predicting compressive and split tensile strength, such as curing period, curing condition, and handling practices. The training information doesn't contain most of these same characteristics, as they are dependent variables and cannot be used by researchers in a regression scenario. These dependent variable categorical characteristics were regarded one of the causes to decrease predictive accuracy. With cement SM concrete like engineered cementitious Composite in mind, categorization factors such as the source type, mineral admixture type and so on are even more stringent. In order to attain acceptable accuracies in the literature prediction of the SM strength [10,13-15], several ANN models have been constructed for numerous source types or different admixture forms. These models are quite precise, but they are exclusive to particular SM type, and the results of the experiment are acquired from a single lot of SM that have very low noise levels and input data unpredictability [18-20].

In this work, various categorical factors for the compressive strength prediction of SM concrete mixes are incorporated, so that a unified ANN model with highly diverse mixture properties may be constructed. In addition, various SM concrete mixtures as opposed to prior research will apply to the models. The most significant material attribute is the mechanical strength of any cemented composite because it is designed primarily for compression as a construction material. Average compressive strengths were found in the literature ranging from 25 to 115 MPa [2-10, 25-28].

In view of the fact that SM concrete are becoming popular because of their high tensile and flexural strength, it has anticipated the use of data from literature in three strength categories, namely compressive, split tensile, and flexural. Two single SM concrete ANN models having various mineral admixtures, fibre types, age, specimen shape and dimensions have been created to predict the compressive and split strength.

2. Research Significance

Laboratory based experimental activities of CTM machines have been used in the majority of the previous research studies to explore and investigate strength parameter of concrete specimens. There is very little research literature on the use of ANN approaches in determining the strength of concrete specimens in Supplementary Cementitious Concrete. The present research study aims to study an artificial neural network for the prediction of the compressive strength of supplementary cementitious concrete. This technique will effectively reduce laboratory testing time and cost in the future

3. Methodology

Artificial Neural Networks have grown in popularity and are now a hot topic of discussion, with applications in chatbots that are frequently employed in text classification. Artificial Neural Networks should be viewed as weighted categorical data, with nodes formed by artificial neurons and regulating behaviors, and weights expressing the link between neuron outputs and neuron inputs. From the outside environment, the Artificial Neural Network receives input signals in the form of patterns and pictures in the form of vectors. The mathematical notation x(n) is then used to indicate these inputs numerically for each n number of inputs.

The weights provided to the inputs multiply them even further. In general, these weights indicate the strength of connections between neurons inside the ANN. All synaptic weights are pooled inside the processing unit. If the weighted total equals zero, a bias is built to obtain the output non-zero, otherwise the system's reaction is scaled up. The input to bias is almost always equal to one, and it has the weight. The total of weighted inputs might be anywhere from 0 to positive infinity in this case. A particular threshold value is compared to maintain the response within the bounds of the intended value. The activation function then receives the total of the weighted inputs.

The majority of ANN are linked, which implies that each of the hidden layers is independently connected to the neurons in its input layer as well as to its output layer, eliminating no gaps. This allows for a comprehensive learning process, as well as maximal learning, because the weights within the ANN are modified after every iteration. Back Propagation (BP), which was developed in [31,32], was the artificial neural network employed in this investigation. We also employ the single hidden layer network, as described in [32]. We have 10 neurons in the input layer and 2 neurons in the output layer, according to the database of real concrete mix proportioning. Figure 1 depicts the structure of the BP-ANN used in this investigation.

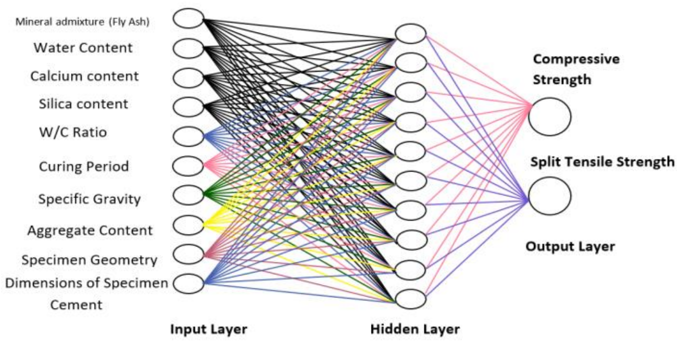

Fig. 1 Input-output relation for predicting the compressive strength and Split strength of concrete and structure of the ANN Model

The normalized input-output relationship can be formally represented in Equation 1, and 2 as below:

$$z = w_0^{(2)} + \sum_{j=1}^{n}(\frac{w_j^{(2)}}{1+exp(-\alpha v_j})$$ (1)

where;

$$v_j = w_{0,j}^{(1)} + \sum_{i=1}^{10}(w_{i,j}^{(1)}\ \varphi_i)$$ (2)

$w_{0,j}^{(1)}$ & $w_0^{(2)}$ - are known as thresholds

$w_{i,j}^{(1)}$ & $w_j^{(2)}$ – are known as synaptic weights

α – the activation function's shape parameter

i -index of a neuron in the input layer

j -represents the index of a neuron in the hidden layer, and

The total number of neurons in the hidden layer is represented by n. It's up to you to figure out how many neurons should be in the concealed layer (hidden layer). The goal of the training procedure is to discover a set of acceptable thresholds and synaptic weights. All of the thresholds and synaptic weights are first set to modest random integers. For training, the usual back propagation technique is used.

4. Experimental Program

In this study, Artificial neural networks (ANNs) use the back-propagation (BP) technique to modify the weights (w) and bias values (b) during training. The output layer specifies the forward propagation. Equations 3, and 4 was used to consider ANN model.

$$Z_{j"}^{i"} = \sum_{k"}^{n"}.\, w_{j"k"}^{i"} X_{K"}^{i"-1}$$ (3)

$$a"_{j"}^{i"} = f"(z")_{j"}^{i"}$$ (4)

where; Layer of neuron represented by i", neuron in previous layer represented by n, weight related to j" neuron to k" neuron from previous layer represented by wj"k". Output of neuron k" is xk", for layer i" the output of neuron j is z"j". Activation function (aj) applied on z"j" for layer i".

For this study, the optimization concept worked, adjusting weights and the preferred cost function. In the ANN operation, two hidden layers were applied. Tensor flow open source was used in the deployment of the Python interface. The decision-making function of neural features, mainly the activation function, was helpful in setting up, which includes differentiable real functions. The sigmoid function was used to improve the non-linearity model. The usual values of 0 and 1 are targeted for transforming neuron output. The sampling of data is close to the natural clustering, so the perceptron method is adopted to receive activated output. The number 1 was used for extensive, big output and the number 0 was used whenever outcomes were too small [16]. The stochastic gradient descent of backpropagation algorithms is generally used in the ANN model. To get better results, the Adam optimization algorithms of the ANN model were chosen. Adam optimization is an advanced algorithm form for classical stochastic gradient descent. In the literature, Adam optimization reported effective and to be efficient for wide range of optimization scenario. Adam optimization has been found to be successful and efficient for a wide range of optimization scenarios in the literature [16,19].

The general practice of bifurcating datasets is 80–20%, i.e., 80% of the dataset was used for training and 20% was used for testing. 20% data has been found good for validation and for train the model maximum 80% data is understood sufficient. We have observed minute change in the performance of model by changing in train test split ratio by using sk learn library. By using train_test_split of the data science library scikit-learn, the dataset was split into training and testing subsets in a random way. The shuffling of data sets before splitting was possible due to the use of this. The ideal model for architectural searching was cross-validated by term hyper-parameter tuning. This cross-validation approach is useful for small training data sets. Four subsets out of five subsets are used to train the model with available training data, and the remaining subset is used for test data. In the Pandas library, data cleaning and analysis features are applied. A total of 324 and 147 SM concrete mix specimens (Laboratory cast) were checked with various researchers' data for considering compressive strength and split tensile strength, respectively [5-9, 12-30]. The available categorical parameters used for the prediction model are noted in Table 1 and non-categorical mention in Table 2. The values are compared in terms of 1m3 of SM concrete. As per literature, the casting procedure of specimens were included four stages, i.e. mixing raw materials in dry phase, addition of water, insertion in specific molds, and curing. According to the literature [25], the casting technique for specimens consists of four stages: dry mixing of raw materials, water addition, insertion into specialized molds, and curing.

Table 1. Definite parameters

Parameter	Categories
Cement Type	Ordinary Portland Cement 53 grade
Mineral admixture	Fly ash, Pozzolana, GGBS
Geometry	Cylinder

Table 2. Dataset properties for compressive strength of SM concrete

Parameter	Min value	Max value
Cement (kg/m3)	300	450
Water content (kg/m3)	150	225
Mineral admixture (kg/m3)	0	225
Calcium content (% by mass)	0	70
Silica content (% by mass)	0	70
w/c ratio	0.4	0.6
Curing period (days)	7	180
Specific gravity	1.80	3.15
Compressive strength (MPa)	7	60
Split Strength (MPa)	0.5	5

5. Results and Discussion

Because the SK-Learn model was employed in this work, a directly viable approach known as grid search was used. Every parameter in the grid search algorithm was passed on a range of values that were optimized, and then training and finding validation loss were employed. As per the cross-validation method, every layer used different nodes (12 to 8). As per literature, a learning rate of 0.001 to 0.009 was kept [21-23]. ANN is also recognized to be weight-initializing sensitive. The initial weight might lead to the local minimum algorithm that eliminates the opportunity to discover a comprehensive solution. As a result, the weight initialization impact was eliminated from each architecture 10 times per study rate and the values obtained were recorded. The architecture used for the strength evaluation is shown in Figure 1. The default values of beta 1 and beta 2 were selected as 0.9 and 0.999 for perform Adam optimizer. Output segment were well-defined for two prediction targets. These targets were focused on compressive strength and splitting tensile strength. The average compressive and splitting tensile strengths of training data of SM specimens were found to be 28.1 and 3.0, respectively. The pattern of predicted and experimental values of testing data is represented in Fig. 3 and 4. Figures 3 and 4 show the pattern of expected and experimental testing data values. The best fitted line for predicted strength is plotted by dotted line and actual to prediction range error reported. After all parameters in the learning rate range have been applied, learning rates are presented for the model with the least RMSE. As shown in the figure 2, increasing the number of nodes did sometimes not result in lower RMSE values. With such a learning rate of 0.005, the final design was decided to include 6 and 7 nodes with the first and 2nd hidden layers, respectively. For the split tensile model, a similar grid analysis was done, and the best design was determined to be 8 and 7 nodes during the first and secondary hidden layers, respectively.

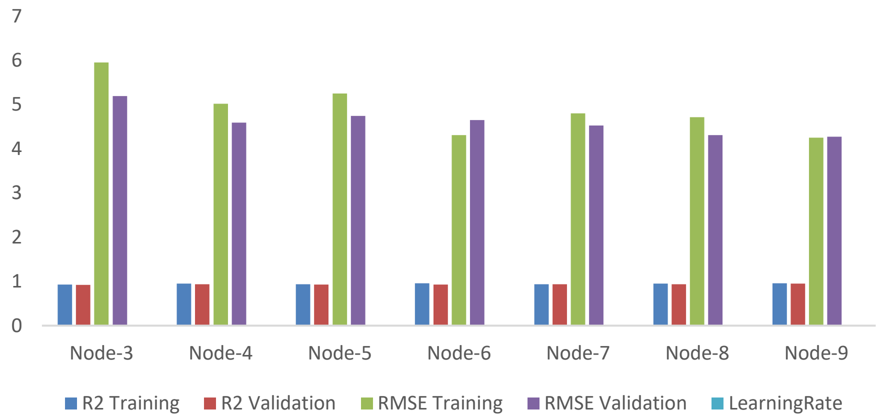

Fig. 2 RMSE yield model with validation and node numbers

The close proximity was seen in the prediction and actual values, with the deviation found below 1 MPa. Root Mean Square Error also found lesser and same pattern reported in literature papers [12-14]. The deviation in the prediction and actual values for predicting split tensile strength was seen very close, it is much lower than compressive strength. The literature [32] also reported that the standard deviation of the residual range were lies between 0.5 and 3 as per test data sets.

The superior prediction of SM concrete is seen in both compressive and tensile strength as compared to literature [5, 12]. The limited literature available for SM concrete prediction for high accuracy model. As variability of SM concrete parameters in the input, ANN model train to predict for considering various ingredients amounts. According to obtained predictive results, the graphical presentation of hyperparameter of ANN provided in the Figure 5. With regards to various statistical variables, the ANN predictive model was found able to run with high accuracy.

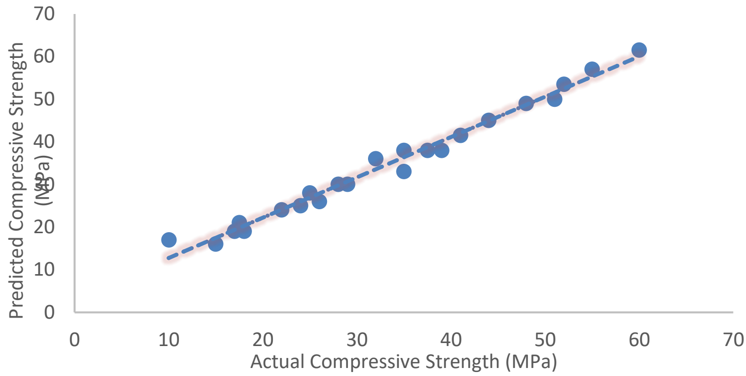

Fig 3 Predicted compressive strength versus actual strength

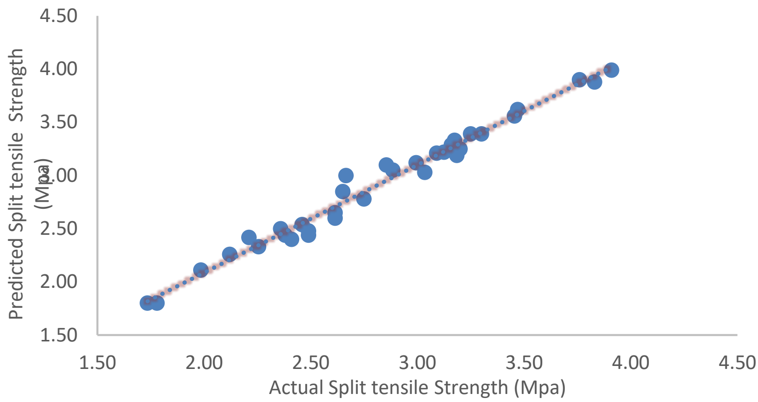

Fig. 4 Predicted split tensile strength versus actual strength

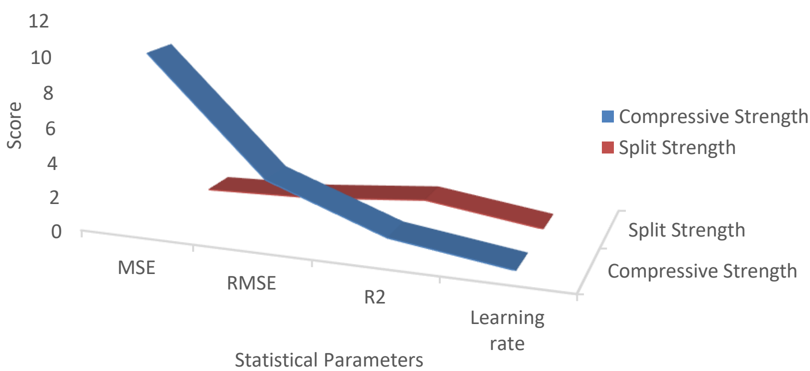

Fig. 5 ANN model results for compressive and splitting tensile strength test data

The ANN methods consider SM strength with diverse components gathered from a diversity of data with the same precision as particular processing studies, which is a significant change from the restricted literature on SM strength prediction. Unlike comparable models trained inside the literature [25], the model's results are validated by using categorical parameters. Figure 5 shows the predictive scores from test data as well as the final hyperparameters of the ANN models for strength prediction.

6. Conclusion

The traditional method of finding SM concrete strength by using a compressive testing machine in laboratory work experimentation can be replaced with ANN model predictive analysis. A wide range was evaluated in this study, and literature data sets of considerable variances were used to predict with high accuracy. There is very little literature available on SM concrete strength prediction. The results obtained with respect to the relative error reported for trained model data were ranges below 10% for compressive strength and below 5% for split tensile strength. For SM concrete prediction, two ANN models are effective for massive concrete data sets. Almost the same learning rate was proved to be optimal for the architecture of hyperparameter models in grid search. Two-layer architecture was found to be optimal, since cementitious materials and concrete decided for 2 layers. Relative errors for the ANN model were 5% and 2.5% for compressive and split tensile strength, respectively. With regards to various variables, the ANN predictive model was able to run with high accuracy.

References

[1] Gursel AP, Masanet E, Horvath A, Stadel A. Life-cycle inventory analysis of concrete production: a critical review. Cement and Concrete Composites, 2014; 51: 38-48. https://doi.org/10.1016/j.cemconcomp.2014.03.005

[2] Mehta PK. Greening of the concrete industry for sustainable development. Concrete International, 2002; 24:7 23- 28.

[3] Mahajan LS, Bhagat SR. Strength Assessment of Concrete using Fly Ash and Metakaolin, In proceeding: International Conference on Advances in Concrete Technology materials and construction practices, Excel India Publishers, New Delhi, 2016; 113-114.

[4] Li VC, Wang S, Wu C, Tensile Strain-Hardening Behavior of Polyvinyl Alcohol Engineered Cementitious Composite (PVA-ECC). Materials Journal, 2001; 98: 483-492 https://doi.org/10.14359/10851

[5] Wang S, Li VC. Engineered Cementitious Composites with High-Volume Fly Ash., ACI Materials Journal, 2007; 104: 233-241. https://doi.org/10.14359/18668

[6] Yang EH, Yang Y, Li VC. Use of high volumes of fly ash to improve ECC mechanical properties and material greens. ACI Materials Journal, 2017; 104: 620-628.

[7] Oztas A, Pala M, Ozbay E, Kanca E, Caglar N, Bhatti MA. Predicting the Compressive Strength and Slump of High Strength Concrete using Neural Network. Construction and Building Materials, 2006; 20: 769-75. https://doi.org/10.1016/j.conbuildmat.2005.01.054

[8] Gunasekara C, Setunge S, Law DW, Willis N, Burt T. Engineering Properties of Geopolymer Aggregate Concrete. Journal of Materials in Civil Engineering, 2018; 30:11 04018299 https://doi.org/10.1061/(ASCE)MT.1943-5533.0002501

[9] Hong-Guang N, Ji-Zong W. Prediction of Compressive Strength of Concrete by Neural Networks. Cement and Concrete Research, 2000; 30: 1245-50. https://doi.org/10.1016/S0008-8846(00)00345-8

[10] Priyadharshini P, Mohan Ganesh G; Santhi AS. (2011) Experimental Study on Cold Bonded Fly Ash Aggregates. International Journal of Civil and Structural Engineering 2011; 2:2 493-501

[11] Peng CH, Yeh IC, Lien LC. Building Strength Models for High-Performance Concrete at Different Ages using Genetic Operation Trees, Nonlinear Regression, and Neural

Networks. Engineering Composites, 2010; 26: 61-73. https://doi.org/10.1007/s00366-009-0142-5
[12] Shi L, Lin STK, Lu Y, Ye L, Zhang YX. Artificial Neural Network Based Mechanical and Electrical Property Prediction of Engineered Cementitious Composites. Construction and Building Materials, 2018; 174: 667-74. https://doi.org/10.1016/j.conbuildmat.2018.04.127
[13] Karnam Prabhakara BK, Guda PV, Balunaini U. Optimum Mixing Ratio and Shear Strength of Granulated Rubber-Fly Ash Mixtures. Journal of Materials in Civil Engineering 2019; 31:4 04019018 https://doi.org/10.1061/(ASCE)MT.1943-5533.0002639
[14] Dwivedi A, Jain MK. Fly ash - Waste Management and Overview: A Review. Recent Research in Science and Technology 2014; 6:1 30-35.
[15] Surabhi S. (2017) Fly Ash in India: Generation vis-a-vis Utilization and Global Perspective. International Journal of Applied Chemistry, 2017; 13:1 29-52.
[16] Hossain KMA, Anwar MS, Samani SG. Regression and Artificial Neural Network Models for Strength Properties of Engineered Cementitious Composites. Neural Computing Applications, 2018; 29: 631-645. https://doi.org/10.1007/s00521-016-2602-3
[17] Liu TY, Zhang P, Wang J, Ling YF. Compressive Strength Prediction of PVA Fiber-Reinforced Cementitious Composites Containing Nano-SiO2 Using BP Neural Network. Materials, 2020; 13: 1215-1229 https://doi.org/10.3390/ma13030521
[18] Ding Y, Yu K, Mao W. Compressive Performance of All-Grade Engineered Cementitious Composites: Experiment and Theoretical Model, Construction and Building Materials, 2020; 24:1-11. https://doi.org/10.1016/j.conbuildmat.2020.118357
[19] Choucha S, Benyahia A, Ghrici M, Mansour MS. Effect of Natural Pozzolana Content on the Properties of Engineered Cementitious Composites as Repair Material. Frontiers of Structural and Civil Engineering, 2018; 12: 261-269. https://doi.org/10.1007/s11709-017-0394-x
[20] Chung KL, Ghannam M, Zhang C. Effect of Specimen Shapes on Compressive Strength of Engineered Cementitious Composites (ECCs) with Different Values of Water-to-Binder Ratio and PVA Fiber. Arabian Journal for Science and Engineering, 2018; 43: 1825-1837. https://doi.org/10.1007/s13369-017-2776-8
[21] Sahmaran M, Yucel HE, Demirhan S, Arik MT, Li VC. Combined Effect of Aggregate and Mineral Admixtures on Tensile Ductility of Engineered Cementitious Composites. Materials Journal, 2012; 109: 115-124. https://doi.org/10.14359/51684160
[22] Ramanathan P. Baskar I, Muthupriya P, Venkatasubramani R. Performance of Self-Compacting Concrete Containing Different Mineral Admixtures. KSCE Journal of Civil Engineering, 2013; 17: 465-472. https://doi.org/10.1007/s12205-013-1882-8
[23] Ji J, Zhang S, Jiang L, Zhou L, Xu Z, Liu Y, Yu D. Feasibility of Developing Engineered Cementitious Composite with High Volumes of Fly Ash using Cost-Effective PVA fiber. Journal of Testing and Evaluation, 2018; 48: 1188-1205 https://doi.org/10.1520/JTE20170596
[24] Freedonia (2016) World Construction Aggregates - Industry Study with Forecasts for 2019 and 2024. The Freedonia Group Report, Cleveland, OH, USA.
[25] Mahajan LS, Bhagat SR. Investigation of the Relationship between Splitting Tensile Strength and Compressive Strength for Prediction of Splitting Tensile Strength of Fy Ash Concrete, In: Proceedings, 3rd International Conference on Innovative Technologies for Clean and Sustainable Development at NITTTR, Chandigarh, India 2020.
[26] Ankur M, Rafat S, Pratap SB, Salima A, Grzegorz L, Danuta BH. Influence of Various Parameters on Strength and Absorption Properties of Fly Ash Based Geopolymer Concrete Designed by Taguchi Method, Construction and Building Materials, 2017; 150: 817-824. https://doi.org/10.1016/j.conbuildmat.2017.06.066

[27] Hashmi AF, Shariq M, Baqi A. Haq Moinul, Optimization of Fy Ash Concrete Mix - a Solution for Sustainable Development, Materials Today: Proceedings, 2020; 26:2 3250-3256. https://doi.org/10.1016/j.matpr.2020.02.908
[28] Sahoo S, Das BB, Mustakim S. Acid, Alkali, and Chloride Resistance of Concrete Composed of Low-Carbonated Fly Ash. Journal of Materials in Civil Engineering, 2016; 29:3 1-12, 04016242. https://doi.org/10.1061/(ASCE)MT.1943-5533.0001759
[29] Eskandari-Naddaf H, Kazemi R. (2017) ANN Prediction of Cement Mortar Compressive Strength, Influence of Cement Strength Class, Construction and Building Materials138: 1-11. https://doi.org/10.1016/j.conbuildmat.2017.01.132
[30] Bilim C, Atis CD, Tanyildizi H, Karahan O. Predicting the Compressive Strength of Ground Granulated Blast Furnace Slag Concrete using Artificial Neural Network, Adv. Eng. Soft., 2009; 40 (5) :334-340. https://doi.org/10.1016/j.advengsoft.2008.05.005
[31]https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html
[32] Hao CY, Shen CH, Jan JC, Hung SK. A Computer-Aided Approach to Pozzolanic Concrete Mix Design. Adv. Civ. Eng. 2018, 2018, 4398017. https://doi.org/10.1155/2018/4398017