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Research Article

Prediction of tensile strength of concrete produced by using pozzolanic materials and partly replacing natural sand by manufactured sand

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ABSTRACT

The overuse level of cement and natural sand for civil industry has several undesirable social and ecological consequences. As an answer for this, industrial wastes or by-products (pozzolanic materials) such as fly ash, GGBFS, silica fume and metakaolin can be used to interchange partially cement and natural sand by manufacturing sand (M-sand). In this study, Artificial Neural Networks (ANNs) models were developed for predicting the tensile strength, at the age of 28 days, of concretes containing partly pozzolanic materials and partly replacing natural sand by manufactured sand. Tensile strength test were performed and test results were used to construct ANN model. A total of 131 values was used for modeling ANN, 80% in the training phase, and 20% in the testing phase. To construct the model, 25 input parameters were used to achieve one output parameter, referred to as the tensile strength of concrete containing partly pozzolanic materials and manufactured sand. The results obtained in both, the training and testing phases strongly show the potential use of ANN to predict 28 days tensile strength of concretes containing partly pozzolanic materials and manufactured sand.

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1. Introduction

As construction projects are growing day by day, they are utilizing the available sources of natural sand. This haphazard excavation of river beds for natural sand has created some environmental problems. Thus use of manufactured sand has become essential taking precaution of environmental and economical balance (Magudeaswaran et al., 2016). Also the production of huge quantities of cement requires large amount of energy, cause emission of CO2 and carry forward the allied problems. Therefore researchers are concentrating on finding out the supplementary cementitious materials such as fly ash, blast furnace slag, silica fume, metakaolin and rice husk ash which have shown promising results to replace cement partially (Mouli, 2008). The pozzolanic materials and manufactured sand are mostly used in the various huge projects. In order to improve these studies, reducing the amount of material, testing, time and cost, models based on experimental data can predict with an acceptable error range (Dantas et al., 2013). ANN model is a powerful tool that gives viable solutions to problems which are difficult to solve by through conventional techniques such as multiple regression models, not invalidating these existing techniques (Safiuddin et al., 2016).

2. Literature Review and Research Objective

Boukhatem et al. (2017) worked on the combined application of two different techniques, Neural Networks (NN) and principal components analysis (PCA) for improved prediction of concrete properties. The results

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showed that the elimination of the correlation between the input parameter using PCA improved the predictive generalization performance model with smaller architectures and dimensionality reduction.

Goyal et al. (2017) have studied compressive strength for three types of mix designs namely, M15, M20 and M25 is predicted using artificial neural network. The data is collected during the construction of main dam of Rajghar medium irrigation project located at Bhiwani Mandi in Jhalawar district of Rajasthan. Concluded that artificial neural network can be used to predict compressive strength of concrete.

Ashrafi et al. (2017) has used neural network technique to predict the strength of concrete based on mix proportions. He concluded that compressive strength trends are predicted by back propagation method in neural network.

Khademi and Behfarnia (2017) have studied the two different data-driven models, artificial neural network (ANN) and multiple linear regression (MLR) models. They have been developed to predict the 28 day compressive strength of concrete. And concluded that the multiple linear regression model is better to be used for preliminary mix design of concrete, and artificial neural network model is recommended in the mix design optimization and in the case of higher accuracy requirements.

Sayed-Ahmed (2012) has developed statistical model to predict the compressive strength of concrete containing different matrix mixtures at fixed age. The study reveals that the results from the predicted model have high correlation to the experimental results for the concrete compressive strength.

Khademi et al. (2016) have studied the three different data driven models Artificial neural network (ANN), Adaptive Neuro-Fuzzy inference system (ANFIS) and Multiple liner regression (MLR) were used to predict the 28 days compressive strength of recycled aggregate concrete. And conclude that the MLR models is better to be utilized for preliminary mix design of concrete. And ANN and ANFIS models are suggested to be used in mix design optimization and in the case of high accuracy necessities. Agrawal and Sharma (2010) has studied possible applicability of neural networks (NN) to predict the slump in high strength concrete (HSC). Concluded that the neural network model is most versatile to predict the slump in concrete.

Vignesh et al. (2016) have studied the back propagation method for the prediction of compressive strength of concrete .Concluded that ANN model have strong capacity for prediction of strength of concrete. Sonebi et al. (2016) have developed the neural network model for prediction of fresh properties of concrete and concluded that ANN performed well and provided very good correlation coefficients. The results show that the ANN model can predict accurately the fresh properties of SCC.

Najigivi et al. (2013) have developed two-layer feed-forward neural network was constructed. Study reveals that the novel developed neural network model (NNM) with three outputs will be a useful tool in the study of the permeability properties of ternary blended concrete.

The objective of this study is to evaluate the potential of artificial neural networks to concatenate a large amount of experimental data obtained from experimentation and predict the tensile strength of concrete containing pozzolanic materials and manufactured sand.

3. Artificial Neural Networks (ANN)

Artificial Neural Network (ANN) is a soft computing technique involving an input layer, one or more hidden layer and an output layer. The hidden layer is linked to the other layers by weights, biases and transfer functions. An error function is determined by the difference between network output and the target. The error is propagated back and the weight and biases are adjusted using some optimization technique which minimizes the error. The entire process called training is repeated for number of epochs till the desired accuracy in output is achieved. Once the network is trained it can be used to validate against unseen data using trained weights and biases (Sayed-Ahmed, 2012, Khademi et al., 2016).

4. Data

By referring Indian standard IS 5816-1999 (IS: 5816-1999) the tensile strength test on cylinder 150mm diameter and 300 mm length was conducted. The photograph of tensile strength test shown in Fig. 1, Eq. (1) was used for calculation of tensile strength:

$$\text{Tensile strength} = \frac{2 \times P}{\pi \times L \times D} \tag{1}$$

where: P = failure load applied to the cylinder (N); L = cylinder length (mm), D = cylinder diameter (mm).

Mandatory input parameters as per standard mix design procedures followed all over the world following parameters were treated as mandatory parameters in concrete mix design. The parameters were cement (C), natural sand (N.S), Manufactured sand (MS), Coarse aggregates (C.A), Fly ash (F.A), Silica fume (S.F.), GGBFS, metakaolin (Meta.). These input parameters remained same for all the networks. The maximum and minimum values of input and output parameters are shown in Table 1. A total of 131 values are available in which all values were obtained from fresh experimentation (Vignesh et al., 2016). For ANN model three layered "Feed forward Back propagation" network was developed to predict the 28 day tensile strength of concrete and trained till a very low performance error (mean squared error) was achieved. The numbers of neurons in hidden layer were decided by trial and error. All the networks were trained using Levernberg-Marquardt algorithm with 'log-sigmoid 'transfer functions in between first (input) and second (hidden) layer and 'linear' transfer function between the second and third layer (output).The data was normalized between 0 to 1. From the available data 80% of data was used for training, 20% for validation and testing (Khademi et al., 2016; Vignesh et al., 2016).

Table 1. Input and output parameters.

Sr. no.	Input parameter	Range of values	
		Minimum	Maximum
1	Cement content (C) kg/m^3	337.77	422.22
2	Natural sand content (N.S) kg/m^3	0	612.21
3	Manufactured sand content(M.S.) kg/m^3	0	612.21
4	Course aggregate content (C.A.) kg/m^3	-	1258.21
5	Fly ash content (F.A.) kg/m^3	0	84.85
6	Silica fume content (S.F.) kg/m^3	0	84.85
7	GGBFS content kg/m^3	0	84.85
8	Metakaolin content (Meta.) kg/m^3	0	84.85
	Output parameters		
1	Tensile strength (MPa)	3.73	4.72

Fig. 1. Tensile strength test.

Instead of using single experimentation for each combination of material, we are using different (5 types) of combinations at a time as an input data while training the neural network and hence it shows 25 input layer models as detailed in Fig. 2. The maximum number of hidden layers value is set to 30 out of which neural network consumes as per the requirement and here we can see that maximum 10 hidden layers are used during the experimentation. The target values set which are actual desired results with respect to practical experimentation values are to be achieved in maximum 10,000 iterations with convergence target to be 1e^{-25}.

The learning rate is set to 0.01 with step 0.01 as α and μ values of the network respectively. The entire configuration of the network is set and can be understood from the Table 2.

Table 2. Neural network configuration parameters.

Parameter	Configuration value
Input layers	25
Hidden layer	10
Output layer	1
Convergence	1e^{-25}
Learning rate (α)	0.01
Step size (μ)	0.01

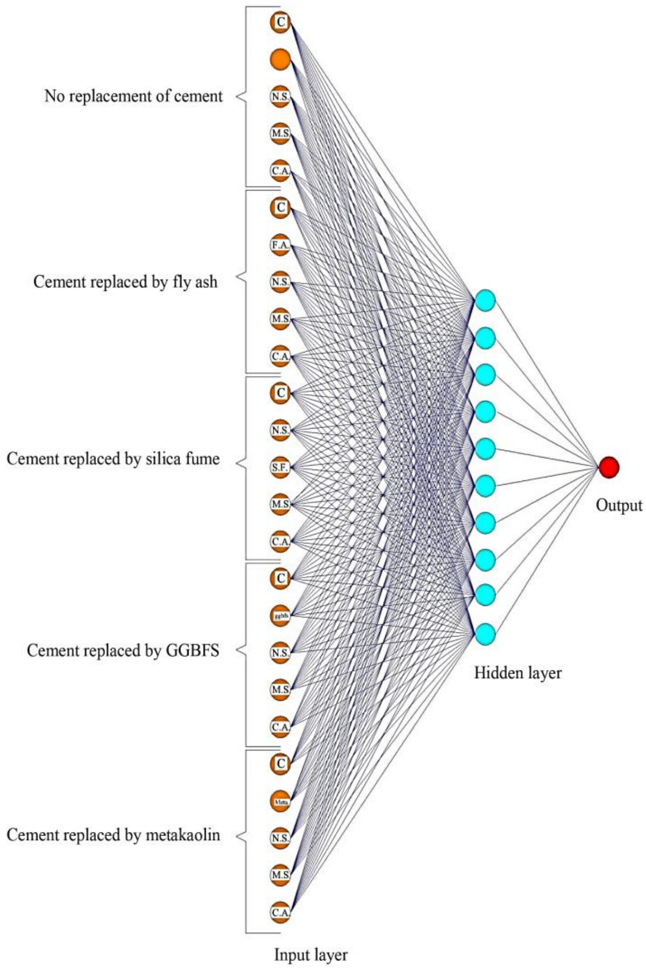

Fig. 2. Neural network layered structure.

5. Results and Discussion

The experimental and predicted tensile strength values for different replacement of natural sand by manufactured sand and 20% cement replaced with fly ash, silica fume, GGBFS and metakaolin in concrete are shown in Table 3. The variation of experimental and predicted tensile strength values are shown in Figs. 3 to 7. It is observed that experimental and predicted tensile strength values are very near to each other. The percentage variation for this model was not increase over 2.93% for no replacement of cement, 0.93% for cement replaced with fly ash. 1.14% for cement replaced with silica fume, 1.94% for cement replaced with GGBFS and 0.88 % for cement replaced with metakaolin which is acceptable variation. It is also observes that correlation coefficients have values between +1 and -1. A correlation coefficient of +1 indicates perfect positive correlation and coefficient of -1 indicates a perfect negative correlation. The correlation coefficient (R) for training, testing, validation and overall data is illustrated in Table 3. The total value of R square for training, validation and test is 0.941 for no replacement, 0.980 for cement replaced with fly ash, 0.979 for cement replaced with silica fume, 0.906 for cement replaced with GGBFS and 0.957 for cement replaced with metakaolin which is satisfactory. R^2 value is a statistical measure of how close the data are to the fitted in regression line (Ni and Wang, 2000; Reddy, 2018; Islam et al., 2012). In all the figures the model presents good results in the case of R values. Results from establishing an artificial neural network illustrates a good degree of coherency between the target and output values. Therefore, using ANN model, the 28 days tensile strength of concrete can be predicted accurately.

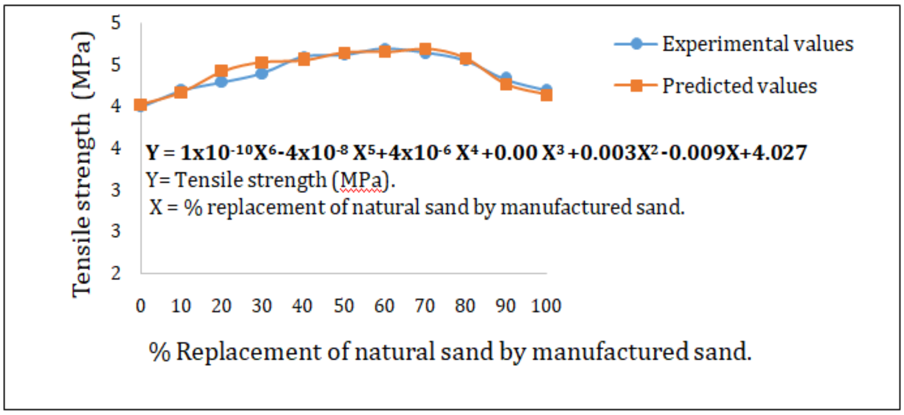

Fig. 3. Variation of predicted and experimental tensile strength for no pozzolans.

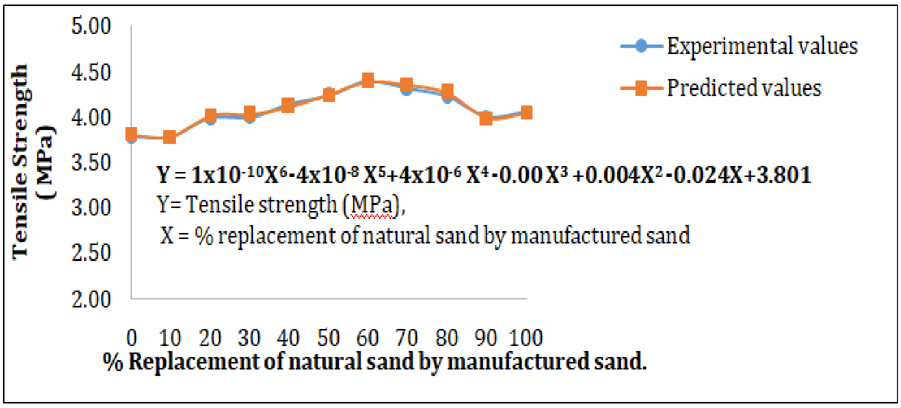

Fig. 4. Variation of predicted and experimental tensile strength for partly replacing cement by FA (fly ash).

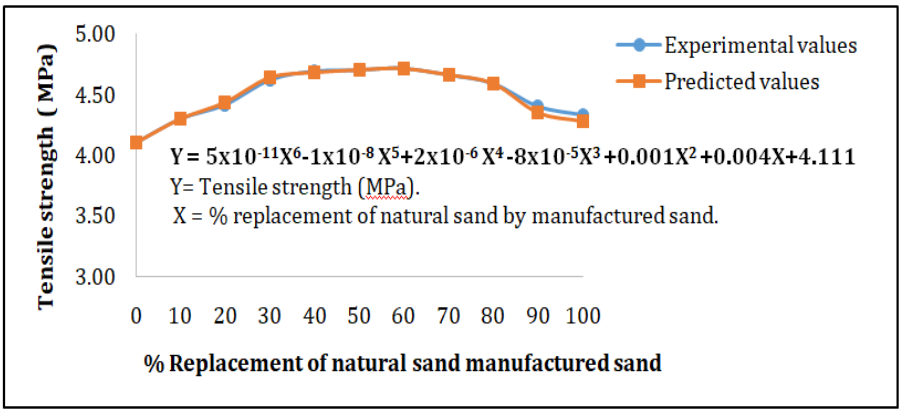

Fig. 5. Variation of predicted and experimental tensile strength for partly replacing cement by SF (silica fume).

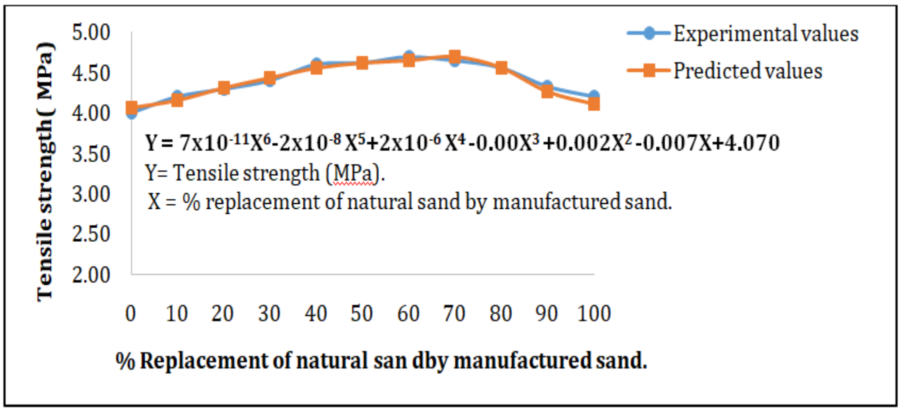

Fig. 6. Variation of predicted and experimental tensile strength for partly replacing cement by GGBFS.

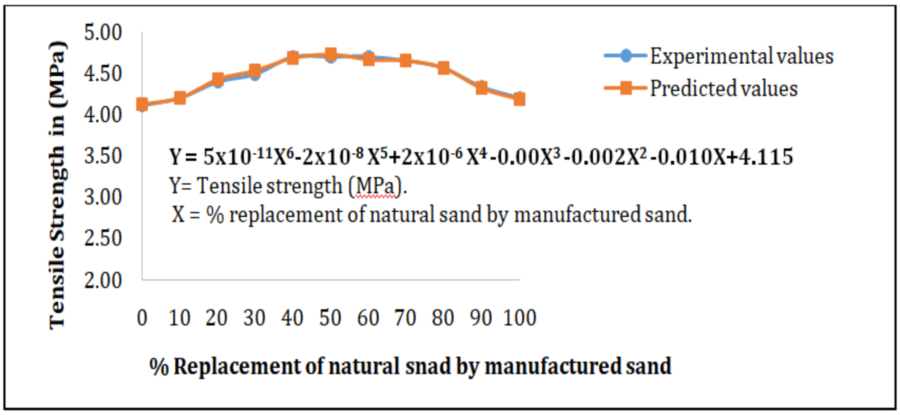

Fig. 7. Variation of predicted and experimental tensile strength for partly replacing cement by metakaolin.

Table 3. Overall experimental and predicted tensile strength (MPa) values.

Percentage replacement of natural sand by manufactured sand	Tensile strength (MPa) values									
	No replacement of cement		Cement replaced by fly ash		Cement replaced by silica flume		Cement replaced by GGBFS		Cement replaced by metakaolin	
	$R^2 = 0.941$		$R^2 = 0.980$		$R^2 = 0.979$		$R^2 = 0.906$		$R^2 = 0.957$	
	Experimental	Predicted	Experimental	Predicted	Experimental	Predicted	Experimental	Predicted	Experimental	Predicted
0	3.73	3.75	3.78	3.81	4.10	4.11	4.00	4.07	4.10	4.12
10	3.74	3.71	3.78	3.78	4.30	4.30	4.20	4.16	4.20	4.20
20	3.95	4.06	3.98	4.01	4.42	4.43	4.30	4.31	4.40	4.43
30	3.98	4.09	3.99	4.03	4.62	4.64	4.40	4.43	4.49	4.53
40	4.1	4.05	4.14	4.11	4.69	4.69	4.60	4.55	4.69	4.69
50	4.21	4.23	4.23	4.24	4.70	4.71	4.62	4.62	4.69	4.73
60	4.35	4.31	4.39	4.39	4.72	4.72	4.70	4.65	4.70	4.66
70	3.65	3.68	4.31	4.35	4.66	4.66	4.65	4.70	4.65	4.65
80	3.53	3.54	4.22	4.26	4.59	4.59	4.56	4.56	4.56	4.57
90	3.37	3.32	4.00	3.98	4.40	4.35	4.33	4.27	4.33	4.31
100	3.35	3.30	4.05	4.04	4.33	4.29	4.20	4.12	4.20	4.19
	Max. variation = 2.91%		Max. variation = 0.93%		Max. variation = 1.14%		Max. variation = 1.94%		Max. variation = 0.88%	

The grading curve of natural sand and manufactured sand are shown in Fig. 8 and fineness modulus for each replacement of natural sand and manufactured sand are given in Table 4. It is clearly observed that the concrete made by using no replacement of natural sand by manufactured sand and no pozzolans with fineness modulus 2.81 shows lesser experimental and predicted tensile strength values. Up to 60% replacement the experimental and predicted tensile strength values and fineness modulus values go on increasing after that the experimental and predicted tensile strength values go on reducing. From this observation it is clear that, at 60 % replacement with fineness modulus 2.87, experimental and predicted tensile strength values are high. The same observation are noted for concrete made by partly replacing cement with fly ash or metakaolin or GGBFS or silica fume. The reason behind this at 60% replacement of natural fine aggregate by manufactured sand shows very compactable concrete with less voids and optimal particle size distribution resulting strong experimental and predicted tensile strength (Yalley and Sam, 2018).

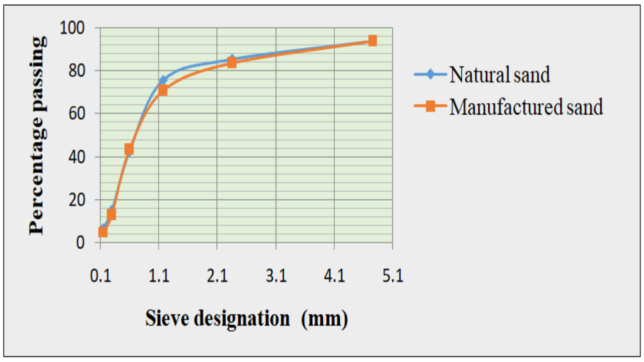

Fig. 8. Grading curve for natural and manufactured sand.

Table 4. Fineness modulus of each replacement of natural sand to manufactured sand.

% Replacement of natural sand by manufactured sand	Fineness modules
0%	2.81
10%	2.83
20%	2.84
30%	2.85
40%	2.85
50%	2.86
60%	2.87
70%	2.88
80%	2.89
90%	2.89
100%	2.91

6. Conclusions

- The model is used successfully for predicting the tensile strength of concrete. The test of the model by input parameters shows acceptable maximum percentage of error.
- The ANN model may be used successfully for predicting the tensile strength of concrete. On any construction site fast tensile strength is required but minimum 28 day are required to find tensile strength. The produced ANN model predict fast strength in very short time so there is no need to wait for 28 days. So ANN model is capable to predict 28 days tensile strength.
- ANN model were found to be efficient in predicting the 28 days tensile strength.
- At fineness modulus 2.87, experimental and predicted tensile strength values are high.

References

Agrawal V, Sharma A (2010). Prediction of slump in concrete using artificial neural networks. *International Journal of Civil and Environmental Engineering*, 4(9), 279-286.

Ashrafi HR, Jalal M, Garmsiri K (2017). Prediction of compressive strength of composite fibers reinforced concrete (FRC) using artificial neural network. *Proceedings of 3rd International Conference on Concrete and Development*, 824-830.

Boukhatem B, Kenai S, Hamou AT, Ziou Dj, Ghrici M (2017). Prediction concrete properties using neural network (NN) with principal component analysis (PCA) technique. *Computers and Concrete*, 10(6), 1-17.

Dantas ATA, Leite MB, Nagahama KJ (2013). Prediction of compressive strength of concrete containing construction and demolition waste using artificial neural networks. *Construction and Building Materials*, 38, 717-722.

Goyal PK, Prajapati R (2017). Prediction of compressive strength of concrete using artificial neural network: A case study. *International Journal of Engineering Technology Science and Research*, 4(3), 276-280.

Islam MN, Zain MF, Jamil M (2012). Prediction of strength and slump of rice husk ash incorporated high-performance concrete. *Journal of Civil Engineering and Management*, 18(3), 310-317.

Khademi F, Behfarnia K (2017). Evaluation of concrete compressive strength using artificial network and multiple linear regression models. International *Journal of Optimization in Civil Engineering*, 6(3), 423-432.

Khademi F, Jamal SM, Deshpande N, Londhe S (2016). Predicting strength of recycled aggregate concrete using artificial neural network, adaptive neuro-fuzzy Inference system and multiple linear regression. *International Journal of Sustainable Built Environment*, 5, 355-369.

Magudeaswaran P, Eswaramoorthi P (2016). High performance concrete using M sand. *Asian Journal of Research in Social Sciences and Humanities*, 6(6), 372-386.

Mouli M (2008) Performance characteristics of light weight aggregate concrete containing natural pozzolans. *Building and Environments*, 43(1), 31-36.

Najigivi A, Khaloo A, Iraji zad A, Abdul Rashid (2013). An artificial neural networks model for predicting permeability properties of nano silica–rice husk ash ternary blended concrete. *International Journal of Concrete Structures and Materials*, 7(3), 225-238.

Ni HG, Wang JZ (2000). Prediction of compressive strength of concrete by neural networks. *Cement and Concrete Research*, 30(8), 1245-1250.

Reddy TCS (2018) Prediction the strength of slurry infiltrated fibrous concrete using artificial neural network. *Frontiers of Structural and Civil Engineering*, 12(4), 490-503.

Safiuddin M, Raman SN, Abdus Salam M, Jumaat MZ (2016). Modeling of compressive strength for self-consolidating high-strength concrete incorporating palm oil fuel ash. *Materials (MPDI)*, 9(396), 2-13.

Sayed-Ahmed M (2012). Statistical modelling and prediction of compressive strength of concrete. *Concrete Research Letters*, 3(2), 452-458.

Vignesh SB, Alisha BB, Karthik, Pai S, Prasad S (2016). Prediction of compressive strength of concrete by artificial neural network. *International Journal of Informative & Futuristic Research*, 3(9), 3385-3397.

Yalley PP, Sam A (2018). Effect of sand fines and water/cement ratio on concrete properties. *Civil Engineering Research Journal*, 4(3), 1-7.