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Prediction of Flexural Strength of Concrete Produced by Using Pozzolanic Materials and Partly Replacing NFA by MS

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ABSTRACT

The use of huge quantity of natural fine aggregate (NFA) and cement in civil construction work which have given rise to various ecological problems. The industrial waste like Blast furnace slag (GGBFS), fly ash, metakaolin, silica fume can be used as partly replacement for cement and manufactured sand obtained from crusher, was partly used as fine aggregate. In this work, MATLAB software model is developed using neural network toolbox to predict the flexural strength of concrete made by using pozzolanic materials and partly replacing natural fine aggregate (NFA) by Manufactured sand (MS). Flexural strength was experimentally calculated by casting beams specimens and results obtained from experiment were used to develop the artificial neural network (ANN) model. Total 131 results values were used to modeling formation and from that 30% data record was used for testing purpose and 70% data record was used for training purpose. 25 input materials properties were used to find the 28 days flexural strength of concrete obtained from partly replacing cement with pozzolans and partly replacing natural fine aggregate (NFA) by manufactured sand (MS). The results obtained from ANN model provides very strong accuracy to predict flexural strength of concrete obtained from partly replacing cement with pozzolans and natural fine aggregate (NFA) by manufactured sand.

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1. Introduction

As construction projects are increasing 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 [1]. Also the production of huge quantities of cement requires large amount of energy, cause release of CO_2 and carry forward the similar problems. Therefore researchers are concentrating on finding out the proper replacing materials to cement like fly ash, metakaoline, silica fume and risk husk has stronger products having large cement properties [2]. The pozzolanic materials and manufactured sand are mostly used in the various huge projects. To minimize the time, cost required to experimental work, ANN model is developed to provide the accurate and fast results [3]. ANN model is strong soft process to give acceptable results as compared to others regular regression process [4]. B. Boukhatem et al. [5] worked on the combined application of Neural Networks (NN) and principal components analysis (PCA) for prediction of concrete properties. The study reveals that PCA performance accurately than the NN. Goyal et al. [6] have predicted the compressive strength of concrete M15, M20 and M 25. The results values were 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. [7] has worked on prediction of concrete strength properties using ANN and study reveals that the ANN is best tool to predict the concrete strength properties. Khademi and Behfarnia [8] have worked on two different models, multiple linear regression (MLR) and artificial neural network (ANN) model developed to predict the compressive strength of concrete . And concluded that, for preliminary mix design of concrete multiple linear regression model is better to be used, and artificial neural network model is recommended in the mix design optimization and in the case of higher accuracy requirements. Mahmoud Sayed-Ahmed [9] has developed model for different matrix mixtures to predict the compressive strength of concrete. The study reveals that the results obtained from model and experimental work was very near to each other. Faezehossadat et al. [10] 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 he MLR models is better to be utilized for preliminary mix design of concrete. And ANN and ANFIS models are suggested to be used in case of high accuracy necessities V. Agrawal and A. Sharma [11] has studied possible applicability of neural networks (NN) to predict the flow property like slump in high strength concrete (HSC).Concluded that the neural network model is most flexible to predict the slump in concrete. Vignesh Shenoy et al. [12] have predict the compressive strength of concrete using back propagation error method. Concluded that ANN model was well-built to prediction of strength of concrete .Mohammed Sonebi et al. [13] 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. Alireza Najigiv et al. [14] have predict the permeability property of ternary blended concrete with ANN tool. And study reveals that the ANN model have strong capacity to predict the ternary blended concrete properties. Mohammad Iqbal Khan have predicted the strength properties of high performance of concrete made by partly replacing cement with pozzolans. Study reveals that it is possible to predict strength and permeability of high performance concrete using artificial neural networks. Ahmet R.B. et al have studied the effect of ground granulated blast furnace slag and calcium based corrosion inhibitor on the mechanical properties of concrete. And ANN and ANFIS model where developed. study concludes that the experimental and predicted data is very closed to each other. Dantas et al. [3] have predicted the compressive strength of concrete made with construction demolished waste. Study reveals that ANN was used to construct an equation for predicting the compressive strength Diaconescu et al. [15] have studied the mechanical properties of concrete made by using powered tire waste. Finely concluded that by direct modeling the maximum compressive strength was obtained for 30% tire powder.

Observing the above research study the unfocused strength of concrete was determined using ANN. The use of this study to predict the flexural strength of concrete using artificial neural network tool for concrete made by using different pozzolans and partly replacing NFA (Natural fine aggregate) by MS (Manufactured sand).

2. Artificial neural networks (ANN)

ANN (Artificial Neural Network) process having three different layers input layer, one or more hidden layers and one output layer. Each hidden layer is connected to other layers with weights, biases and using transfer function. Each neurons include a numerical data which could be known as weights. The error is determine by observing the target output values and input values. By observing error function the weight and biases are tuned using internal technique to minimize the error called training. The model is trained till the desired accuracy is achieved. Error histogram is shown in Fig. 1. And that trained model is used to validate the output values [10].

3. Data

The 100mmx100mmx500mm beams specimens were casted and two point load test was performed on that specimens under UTM (Universal testing machine) with reference of Indian Standard 516-1959 [16]. The photograph of flexural test shown in Fig .1.The flexural strength is determined using following equation 1

$$Flexural\ strength\ = \frac{Pxl}{bxd^2} \tag{1}$$

Where: P = Failure load on beam (N), l = Supported span of beam (mm), b = Beam width(mm), d = Beam depth (mm).

After mix design, weights of materials are consider as the input parameters as Cement (C), Natural fine aggregate (N.F.A), manufactured sand (MS), Coarse aggregate (C.A), Fly ash (F.A), Silica fume (S.F.), GGBFS, metakaolin (meta.). Weights of input parameters were putting same in all networks, rang of these values are shown in Table 1. A total of 131 values obtained from fresh experimentation [17,18].

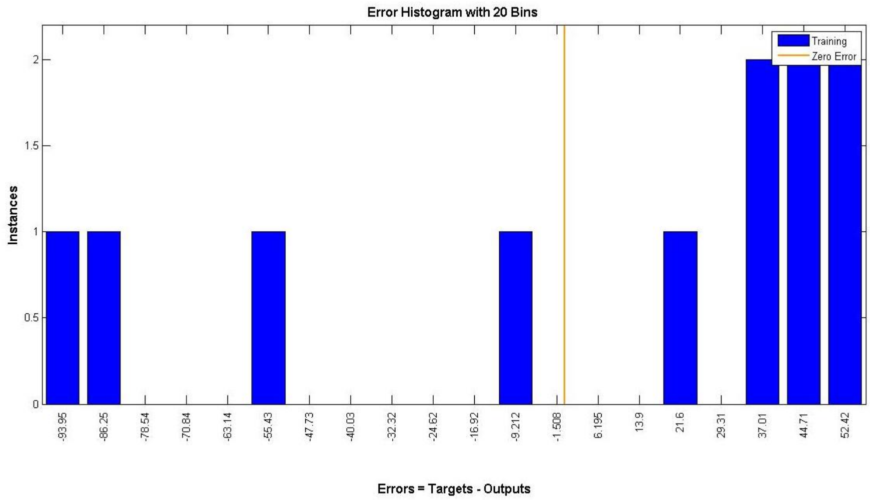

Fig. 1. Error histogram.

Table1
Input and output parameters.

Sr. no.	Input parameter	Range of values		Standard Deviation	Mean
		Minimum	Maximum		
1	Cement content (C) kg/m^3	337.77	422.22	59.71	379.990
2	Natural sand content (N.S) kg/ m^3	0	612.21	203.05	306.100
3	Manufactured sand content(M.S.) kg/ m^3	0	612.21	203.05	306.100
4	Course aggregate content (C.A.) kg/ m^3	-	1258.21	0	1258.210
5	Fly ash content (F.A.) kg/ m^3	0	84.85	59.39	42.425
6	Silica fume content (S.F.) kg/ m^3	0	84.85	59.39	42.425
7	GGBFS content kg/ m^3	0	84.85	59.39	42.425
8	Metakaolin content (Meta.) kg/ m^3	0	84.85	59.39	42.425
	Output parameters				
1	Flexural strength (MPa)	4.50	7.89	1.12	6.19

Input data was conveyed in feed forward process, no cycle formation in three layers to predict the flexural strength and trained till to get very low error. In the feed forward neural network, the artificial neurons are arranged in layers, and all the neurons in each layer connections to all neurons in the next layer. However , there is no connection between neurons of the same layer or the neurons which are not in successive layer. Neuron numbers in hidden layers were fixed by taking trial and error method. For Training Levernberg-Marquaedt method was used. And values minimized between 0 to 1.From all 70% values were trained and remaining 30 % values were validated [9,10].

While training the neural network, instead of using single experimentation for each combination of material, different (5 types) of combinations at a time decided as a input data values and hence it shows 25 input layer models as detailed in figure 2.The maximum number of nodes in hidden layers value is set to 30 out of which neural network consumes as per the requirement ,that maximum 10 nodes in hidden layers were 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 [8].

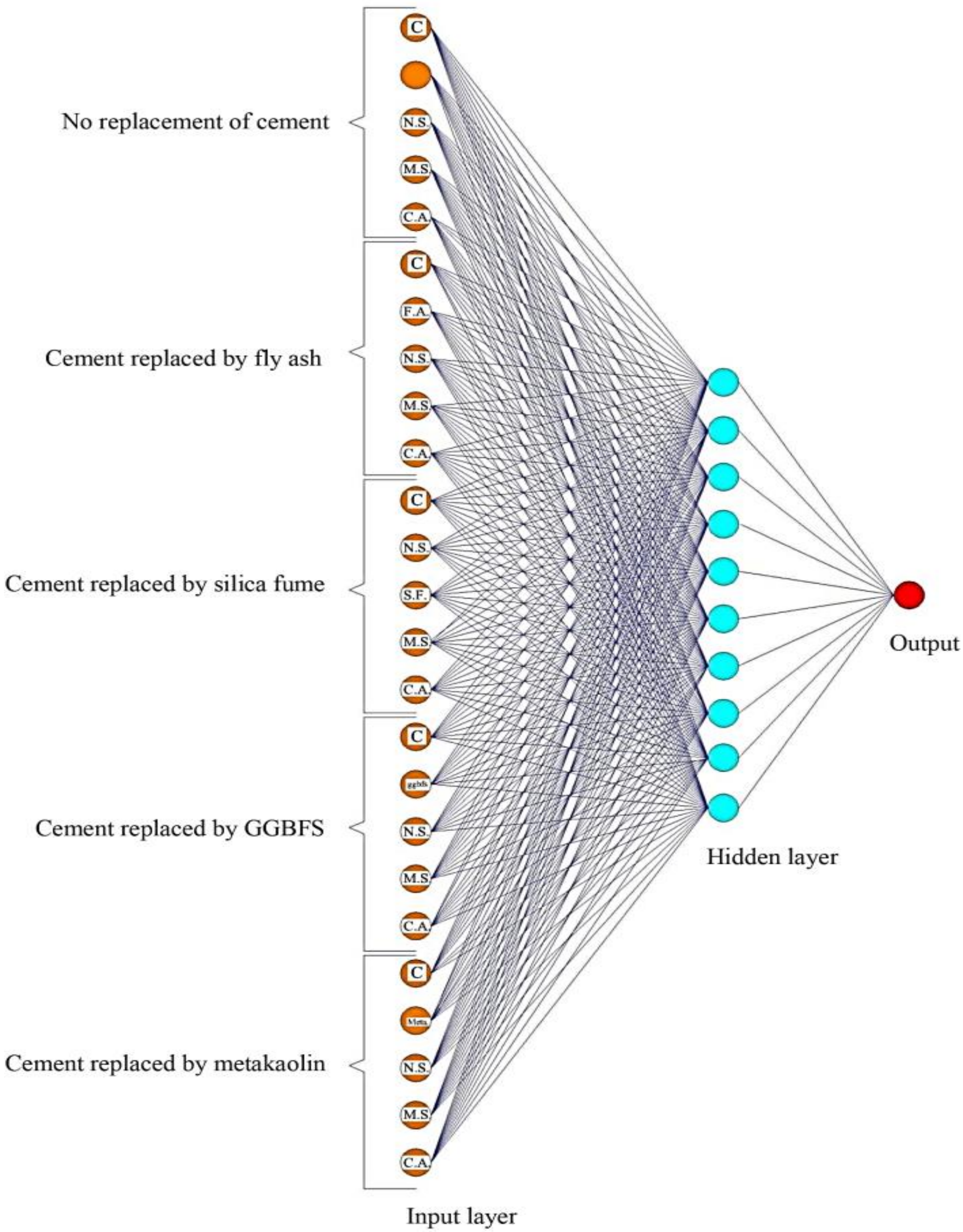

Fig. 2. Neural network layered structure.

Table 2
Neural network configuration parameters.

Parameter	Configuration value
Number of nodes in input layers	25
Number of nodes in hidden layer	10
Number of nodes in output layer	1
Architecture	25:10:1
Convergence	$1e^{-25}$
Learning rate (α)	0.01
Step size (μ)	0.01

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

% replacement of NFA by MS	Flexural strength (MPa) values									
	Cement Without pozzolans		Cement partly replaced by fly ash		Cement partly replaced by silica flume		Cement partly replaced by GGBFS		Cement partly replaced by metakolain	
	Experimental	**Predicted**	**Experimental**	**Predicted**	**Experimental**	**Predicted**	**Experimental**	**Predicted**	**Experimental**	**Predicted**
0	4.50	4.57	4.58	4.62	4.80	4.81	4.59	4.62	4.66	4.67
10	4.75	4.70	4.76	4.76	5.20	5.19	4.78	4.74	4.92	4.92
20	5.08	5.03	5.12	5.12	6.30	6.29	5.4	5.56	5.98	5.97
30	5.82	5.85	5.98	5.99	6.38	6.38	6.2	6.38	6.26	6.29
40	7.14	7.13	7.20	7.19	7.42	7.42	7.33	7.25	7.39	7.38
50	7.60	7.67	7.62	7.69	7.78	7.85	7.64	7.67	7.66	8.37
60	7.62	7.67	7.65	7.72	7.89	7.97	7.67	7.60	7.86	7.91
70	5.50	5.41	6.24	6.20	7.70	7.65	6.6	6.66	6.82	6.70
80	4.98	5.01	6.21	6.22	7.62	7.63	6.3	6.33	6.60	6.64
90	4.82	4.86	5.20	5.21	6.53	6.59	6.1	6.01	6.20	6.25
100	4.48	4.48	5.01	4.96	6.52	6.52	5.76	5.68	5.77	5.76
Details of results of model development										
R^2	0.9650		0.9440		0.9310		0.9300		0.9270	
Max. variation	1.66%		0.91%		1.00%		2.91%		1.79%	
MSE	0.0007		0.0010		0.0023		0.0015		0.0497	
RMSE	0.0270		0.0330		0.0480		0.039		0.2230	
ME	0.1050		0.1280		0.1940		0.2840		0.0850	
MAE	0.0081		0.0100		0.0145		0.0118		0.0672	

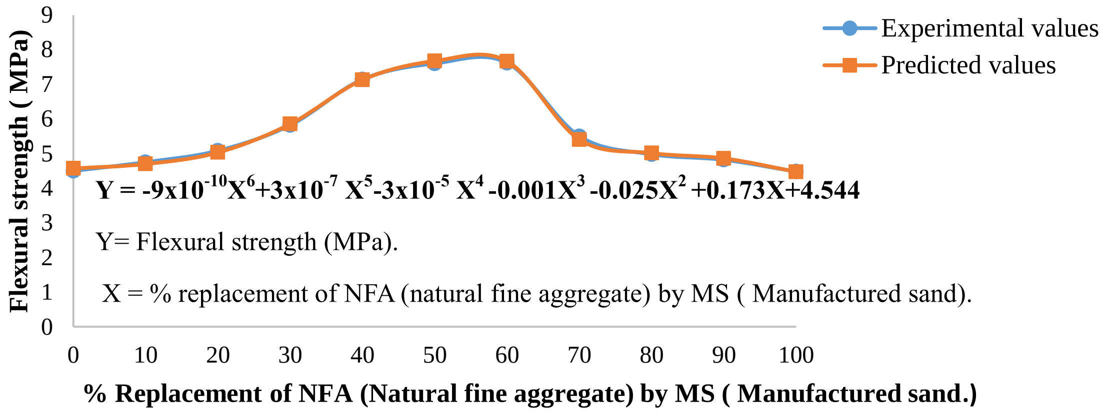

Fig. 3. Variation of Predicted and experimental flexural strength for no pozzolanas.

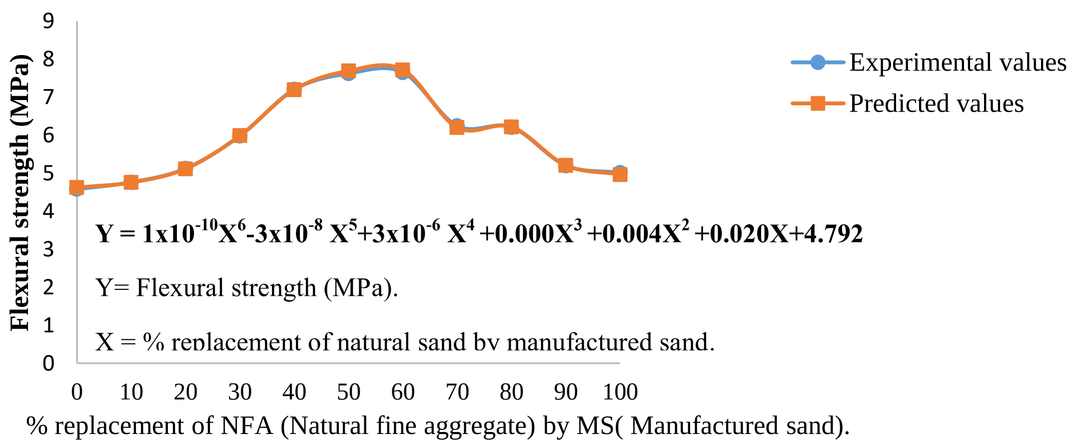

Fig. 4. Variation of predicted and experimental flexural strength for partly replacing cement by fly ash.

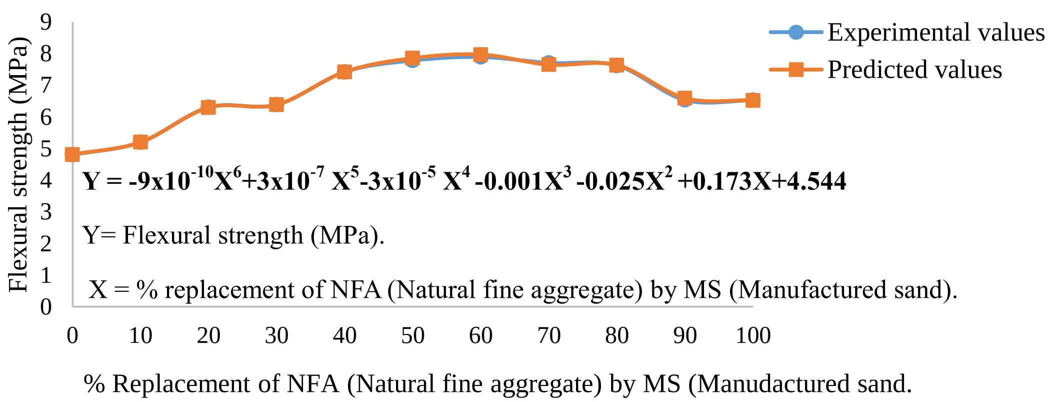

Fig. 5. Variation of predicted and experimental flexural strength for partly replacing cement by silica fume.

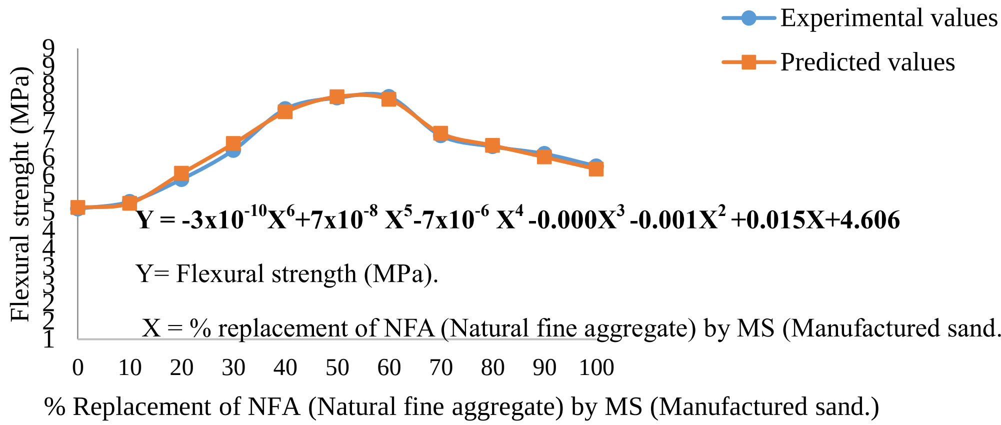

Fig. 6. Variation of predicted and experimental flexural strength for partly replacing cement by GGBFS.

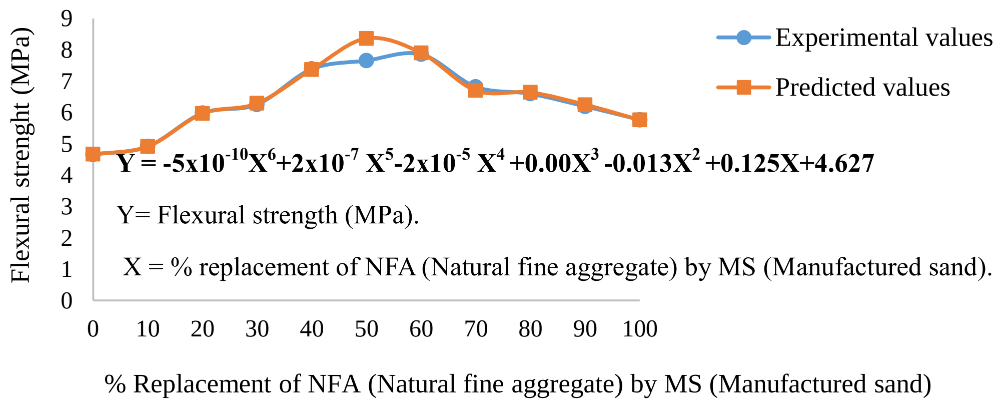

Fig. 7. Variation of predicted and experimental flexural strength for partly replacing cement by metakaolin.

4. Results and discussion

The experimental and predicted flexural strength values for different replacement of NFA (Natural fine aggregate) by MS (Manufactured sand) and partly cement replaced with GGBFS, silica fume, fly ash, and metakaolin in concrete are shown in table 3. And the graphical presentation of experimental and flexural strength values are shown in figures 2,4,5,6 and 7. It is observed that, flexural strength values obtained from model and experimental values are very close to each other. The percentage variation for this model was not increase over 1.66 % for mix with no pozzolans, 0.91% for cement partly replaced with fly ash. 1.00% for cement partly replaced with silica fume, 2.91% for cement partly replaced with GGBFS and 1.79 % for cement partly replaced with metakaolin which is acceptable variation. It is also observes that coefficient of correlation values varying between +1 to -1. A +1 relates that correct positive correlation and -1 relates the negative correlation of fit [19]. The R values are illustrated in table 3. The R square is 0.965 for no replacement, 0.944 for cement partly replaced with fly ash,0.931 for cement partly replaced with silica fume.,0.930 for cement partly replaced with GGBFS and 0.927 for cement partly replaced with metakaolin. , which is agreeable. R^2 value shows that close relation between obtained values from model and experimental values. In all of 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. The mean square error (MSE), root mean square error (RMSE), mean error (ME) and mean absolute error (MAE) are shown in the table 3. Lower values of RMSE and MSE suggest better ability of ANN to predict the flexural strength of concrete [20]. The RMSE value is 0.027 for no replacement, 0.033 for cement partly replaced with fly ash,0.048 for cement partly replaced with silica fume.,0.039 for cement partly replaced with GGBFS and 0.223 for cement partly replaced with metakaolin, which are acceptable values. Therefore, using ANN model, the 28 days flexural strength of concrete can be predicted both accurately and easily [21,22].

The variation of experimental and predicted flexural strength results for concrete made by partially replacing NFA by MS and partially cement replacing with fly ash or Silica fume or GGBFS or metakaolin are shown in figure 3,4,5,6 to7 respectively. By observing all experimental and predicted result values it is noted that the concrete made by using no manufactured sand and no pozzolans shows lesser experimental and predicted flexural strength values. Up to 60% replacement the flexural strength values are go on increasing after that the all values go on reducing. From this observation it is clear that, at 60% replacement experimental and predicted flexural strength values are high .The same observations are noted for concrete made with replacing partly cement by GGBFS, fly ash or metakaolin 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 microstructure. Due to denser concrete experimental and predicted flexural strength shows maximum values [15].

5. Conclusions

- Lower values of RMSE and MSE advise better skill of ANN to predict the flexural strength of concrete.
- The test of the model by input parameters shows acceptable maximum percentage of error.
- The mean absolute error value is 0.0081 for no replacement, 0.0100 for cement partly replaced with fly ash,0.0145 for cement partly replaced with silica fume.,0.0118 for cement partly replaced with GGBFS and 0.0672 for cement partly replaced with metakaolin, which are acceptable values.
- ANN model with R^2 values very close to 1, was found brilliant in predicting the 28 days flexural strength of concrete made with pozzolanic materials and manufactured sand.
- On any construction site fast strength is required but minimum 28 day are required to find strength. The produced ANN model predict fast strength in very short time so there is no need to wait for 28 days.
- All obtained simulations results are agreeable and a strong correlation was observed between experimental and predicted flexural strength values.

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Conflicts of interest

No conflict of interest.

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