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Ann-Based HPC Compressive Strength Prediction for Waste Products

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ABSTRACT :

The performance of properly prepared concrete is influenced by the characteristics of the construction components. Cement is one of the essential elements of concrete. A lot of researchers concluded from their experimental studies that the kind of material had a significant influence on the strength and workability of concrete. An ANN-based model is presented in this paper to predict the compressive strength of waste-containing concrete at 28 days of age. A total of 36 samples were cast using twelve different proportions for the concrete mix. The training data for the artificial neural network model is derived from the experimental outcomes. The information utilised to create the multilayer feed forward neural network models is set up in a manner with six input parameters, including the specimen's age, cement, Fly ash, Silica fume, Coir fibre ash, Iron slag, Fine aggregate and Coarse aggregate. Two different models are made by using dissimilar architecture. This study leads to the conclusion that the artificial neural network (ANN) performed well to predict the compressive strength of high performance concrete for 28 days curing period.

1. INTRODUCTION:

Portland cement is widely known as the key material used in concrete construction. Cement is utilized mutually in mortar and concrete, so it is the most vital element of the infrastructure and has been identified as a resilient construction material. Though, the environmental characteristics of cement are now growing anxiety of researchers, as cement manufacturing is to be blame for approximately 2.5% of whole universal waste releases from commercial resources [1]. Using dissimilar types of waste materials in construction trade is recently a rising trend. Reuse of waste materials is a twofold function (a) to lessen the amount of waste to be deposited and (b) to conserve natural resources [3]. Use of recycled or waste materials for the construction of civil structures is a matter of great significance in this century. Use of waste materials in construction industry reduces the utilization of Portland cement per unit volume of concrete. OPC has large energy emanation related with its production, which may be declined by substituting cement partly with waste products. Mixing of mineral admixtures in concrete and mortar enhances compressive strength, pore structure and permeability. Some materials known as Pozzolana, which have no cementitious properties, but when added with OPC reacts to form cementitious materials. Fractional substitution of Pozzolana in concrete decreases the amount of Portland cement. This reduction in cement quantity further decreases the construction cost, energy loss and waste emissions such as carbon dioxide (CO2) emission. This also, decreases the energy consumption and thus, reduces the rate of global warming.

However, the current development of green high performance concrete brings the rich utilization of these mineral mixtures. When these dissimilar reactive mineral admixtures are mixed into concrete at the same time, they establish their own features with the establishment. Silica fume can boost the strength of the concrete considerably; however, it influences the workability of the fresh concrete seriously, while mixing large amount of fly ash to the concrete improves the workability of the concrete but not to the strength. Additionally, those mineral admixtures show dissimilar outcomes on the strength of the concrete with different age group due to their diverse pozzolan reactions. The main objective of this study is to build models which have two different architectures in Artificial Neural Network system to assess the outcome of fly ash, coir fibre ash, silica fume and iron slag on compressive strength of concrete.

CONCRETE COMPOSED OF WASTE MATERIALS:

Cement manufacture is an energy exhaustive procedure which has adverse effects on the environment. Manufacturing one ton of OPC discharges about one ton of carbon-dioxide gas into the environment and as a consequence of this creation 1.6 billion tons of carbon-dioxide is released every year.

Motive behind the increased use of supplementary materials in cement concrete are

1. To decrease the utilization of cement though partially replacing the cement with materials having cementitious features.
2. To get better the properties of fresh and hardened concrete. In recent times, several researchers produced high performance concrete by decreasing water/cement ratio by the application of super-plasticizers and fine mineral admixtures.

Concrete composed by partly replacing cement with industrial wastes are termed as green cement. This improved green cement is put side by side with OPC by many researchers. This “green” material makes less use of natural source, energy and releases a smaller amount CO2 [6].

In developing countries cost-effective construction material plays very vital role in making its structures economical. Waste materials in construction can be utilized to make structures economical and also durable because of their definite properties. Fly ash is a waste material available in the industries which can be substituted by cement well as it can develop the properties of concrete.

ARTIFICIAL NEURAL NETWORK :

In recent times, there has been a rising interest in applying artificial neural networks (ANNs), in field of civil engineering. Neural network analysis is a logical procedure that can be applied to complex problems described by a huge quantity of data. It does not need a knowledge of physical processes involved (black box modeling), but, rather, it identifies the relationships present in a set of data. Thus it may be applied to problems where more conventional mathematical solutions are not possible. However, knowledge is needed to direct the development of ANN model. Neural networks are generally used to forecast the individual result. Their use in assessing the relationships of the results and influencing variables represents a relatively novel approach.

A neural network is a dominating data modeling tool that is capable to detain and represent complex input/output relationships. The inspiration for the development of neural network technology stemmed from the aspiration to develop an artificial system that can perform intelligent tasks like to those performed by the human mind.

Neural networks resemble to the human brain in the following two ways (Knyziak, 2014):

1. Knowledge is gained by the network through a learning process.
2. Interneuron link strengths known as synaptic weights are used to store the knowledge.

A neural network might be also explained as a system made of several simple processing elements operating corresponding to whose function is determined by network structure, links strengths, and the processing carried out at computing elements or nodes.

2. LITERATURE REVIEW

Seyed et al. (2011) presented the applications of ANN for predicting compressive strength of high strength concrete (HSC). 368 data sets of HSC collected from previous literature. It has been concluded that the relative percentage error) for the training set is 7.02%. Whereas

, for the testing set 12.64% RPE has been observed. The ANNs models shows high prediction accuracy and the research outcomes reveal that using ANNs to forecast concrete strength is practical and valuable.

Hannachi and Nacer (2012) utilized regression analysis models between in-situ concrete compressive strength of existing structure and the NDT values. By statistical analysis equations has been derived to estimate compressive strength of concrete on site and the consistency of the technique for forecasting strength is discussed. It has been noted that by using more than one non-destructive method offers a better correlation and contributes to more consistent strength estimation of concrete.

Vijay et al. (2013) utilized Artificial Neural Network (ANN) for predicting the compressive strength of concrete. Comparison between predicted compressive strength and actual compressive strength of concrete shows a good co-relation and authors proposed equations for different models. Muhit et al. in (2013) examined the properties of concrete due to different types of aggregates. Different shapes have been casted to prepare different groups of concrete with variable water-cement (w/c).

Ryza et al. (2013) observed the significance of the shape of aggregates. In concrete, the shape of aggregate particles has been related to several properties such as reliability, slump or shear flow, resistance against shear, tensile and other behaviors. In recent years, Digital Image techniques have been conducted to find the particle shape characteristics of aggregate.

Ponnada [2014] evaluated combined effect of flaky and elongated aggregates on strength and workability of concrete. M 25 grade concrete has been considered for different ratios of weights of elongated to flaky aggregate and angular to total aggregate had been experienced for different characteristics of prepared concrete. The results reveal that the influence of elongated aggregates is larger than flaky aggregates, on the characteristic compressive strength of concrete.

3. METHODOLOGY ADOPTED:

Following is the methodology to be adopted for performing this study

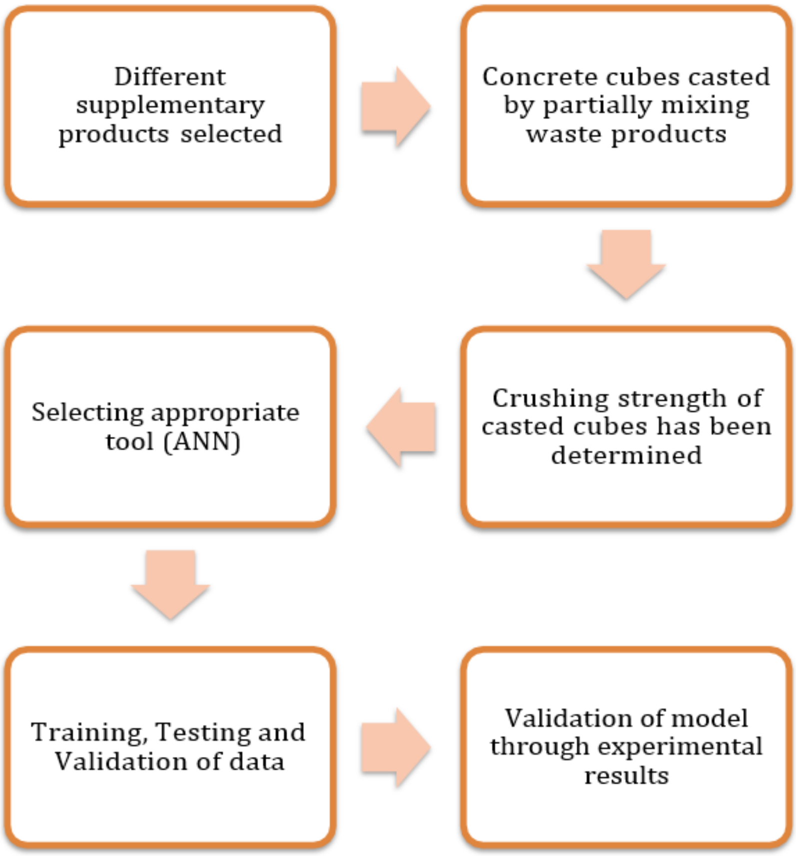

Fig.1 – Methodology adopted

4. EXPERIMENTAL RESULTS

Several laboratory experiments have been conducted to perform investigation. Several concrete mixes of target strength 30 MPa have been casted by partial use of different supplementary products blended with cement and fine aggregates. Ordinary Portland cement of grade 53 has been used for this study. Fine aggregate used was river sand with fineness modulus 2.51, w/c ratio for each concrete mix is taken as 0.45. The mix proportion is given in Table 4.1.

Material	Cement	Sand	Aggregate	Water
Quantity (Kg/m^3)	384	659.6	1220	**172.8 l/m^3**

Table -4.1- Mix Proportion

Total 36 concrete cubes have been casted for 12 different mixes. Combination of these mixes is as follows:

Combinations of Mixes		
S.No	**Mix designation**	**Combinations**
1	M0	(C+S+CA)
2	M1	(C+FA20%)+S+CA)
3	M2	(C+SF10%)+S+CA
4	M3	(C+CFA10%)+S+CA

5	M4	C+(S+IS20%)+CA
6	M5	(C+FA20%)+(S+IS20%)+CA)
7	M6	(C+SF10%)+(S+IS20%)+CA
8	M7	(C+CFA10%)+(S+IS20%)+CA
9	M8	(C+FA20%+SF10%)+(S+IS20%)+CA
10	M9	(C+FA20%+CFA10%)+(S+IS20%)+CA
11	M10	(C+SF10%+CFA10%)+(S+IS20%)+CA
12	M11	(C+FA20%+SF10%+CFA10%)+(S+IS20%)+CA

Table 4.2- Combinations of Mixes

Results of compressive strength:

S.N	**Mix**	**Cement (C)**	**Fly ash (FA)**	**Silica Fume (SF)**	**Coir fibre ash (CFA)**	**Fine Aggregate (FA)**	**Iron Slag (IS)**	**28 days compressive strength**
		(Kg/m^3)	(Kg/m^3)	(Kg/m^3)	(Kg/m^3)	(Kg/m^3)	(Kg/m^3)	(N/mm^2)
1	M0	384	0	0	0	665	0	36.310
		384	0	0	0	665	0	36.890
		384	0	0	0	665	0	36.620
2	M1	307.2	76.8	0	0	623	0	34.540
		307.2	76.8	0	0	623	0	36.4
		307.2	76.8	0	0	623	0	34.450
3	M2	345.6	0	38.4	0	644	0	37.030
		345.6	0	38.4	0	644	0	37.880
		345.6	0	38.4	0	644	0	36.70
4	M3	345.6	0	0	38.4	649	0	41.020
		345.6	0	0	38.4	649	0	41.330
		345.6	0	0	38.4	649	0	41.690
5	M4	384	0	0	0	508	133	35.330
		384	0	0	0	508	133	34.60
		384	0	0	0	508	133	35.40
6	M5	307.2	76.8	0	0	476	133	37.210
		307.2	76.8	0	0	476	133	37.30
		307.2	76.8	0	0	476	133	37.110
7	M6	345.6	0	38.4	0	500	133	39.310

		345.6	0	38.4	0	500	133	37.20
		345.6	0	38.4	0	500	133	40.80
8	M7	345.6	0	0	38.4	508	133	42.040
		345.6	0	0	38.4	508	133	42.310
		345.6	0	0	38.4	508	133	44.040
9	M8	268.8	76.8	38.4	0	461	133	37.250
		268.8	76.8	38.4	0	461	133	38.30
		268.8	76.8	38.4	0	461	133	36.70
10	M9	268.8	76.8	0	38.4	467	133	41.30
		268.8	76.8	0	38.4	467	133	39.220
		268.8	76.8	0	38.4	467	133	37.120
11	M10	307.2	0	38.4	38.4	492	133	43.960
		307.2	0	38.4	38.4	492	133	44.090
		307.2	0	38.4	38.4	492	133	46.040
12	M11	230.4	76.8	38.4	38.4	463	133	38.980
		230.4	76.8	38.4	38.4	463	133	39.980
		230.4	76.8	38.4	38.4	463	133	41.020

Table 4.3 – Results of compressive strength

5. PREDICTED RESULTS

Two different multilayer artificial neural network architectures namely ANN-I and ANN-II were built. In training and testing of the ANN-I and ANN- II models constituted with two different architectures C, FA, SF, CFA, IS and S were input values, while compressive strength (fc) value were used as output. In the ANN-I & ANN-II, 36 data of experimental results were used for training. In ANN-I model, one hidden layer were selected. In ANN-II model, two hidden layers were selected. In the first hidden layer 10 neurons and in the second hidden layer 10 neurons were determined due to its minimum absolute percentage error values for training sets. In the ANN-I and ANN-II models, the neurons of neighboring layers are fully interconnected by weights. Finally the output layer neuron produces the network prediction as a result. The trained models were only tested with the input values and the results found were close to experimental results.

Table 5.1- Compressive Strength Comparison

Mix Designation	**Experimental result (f_C) in Mpa**	**Predicted results (ANN-I)**	**Predicted results (ANN-I)**	**% Error**
M0	36.5	36.2875426	35.19328728	3.02
	36.9	36.2875426	35.19328728	3.02
	35.2	36.2875426	35.19328728	3.02
M1	34.54	35.51697098	35.19455115	0.91
	36.4	35.51697098	35.19455115	0.91
	34.45	35.51697098	35.19455115	0.91
M2	37.03	37.00891062	37.21322717	-0.55
	37.88	37.00891062	37.21322717	-0.55
	36.7	37.00891062	37.21322717	-0.55
M3	41.34	41.51984418	41.28839277	

				0.56
	42	41.51984418	41.28839277	0.56
	40.5	41.51984418	41.28839277	0.56
M4	35.33	35.02238134	35.42084291	-1.14
	34.6	35.02238134	35.42084291	-1.14
	35.4	35.02238134	35.42084291	-1.14
M5	37.21	37.28853973	37.78788569	-1.34
	37.3	37.28853973	37.78788569	-1.34
	37.11	37.28853973	37.78788569	-1.34
M6	39.31	40.08568458	38.23104492	4.63
	37.2	40.08568458	38.23104492	4.63
	40.8	40.08568458	38.23104492	4.63
M7	42.79	42.82399053	42.78468626	0.09
	42.44	42.82399053	42.78468626	0.09
	43.1	42.82399053	42.78468626	0.09
M8	37.25	37.807926	37.79949395	0.02
	38.3	37.807926	37.79949395	0.02
	36.7	37.807926	37.79949395	0.02
M9	41.3	39.25703637	37.80791284	3.69
	39.22	39.25703637	37.80791284	3.69
	37.12	39.25703637	37.80791284	3.69
M10	44.69	44.18019952	44.8827337	-1.59
	45.12	44.18019952	44.8827337	-1.59
	44.34	44.18019952	44.8827337	-1.59
M11	40	39.98024491	39.89750751	0.21
	42	39.98024491	39.89750751	0.21
	38	39.98024491	39.89750751	0.21

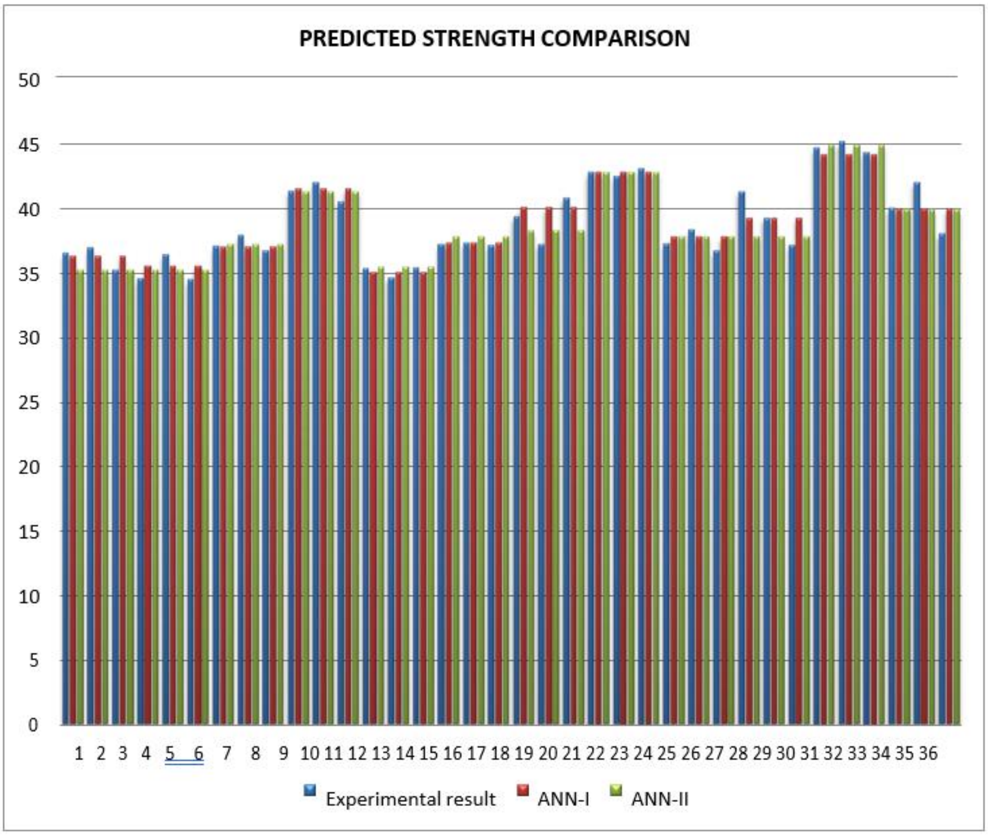

Fig. 5.1-Compressive Strength Comparison among actual values and predicted values through different ANN models

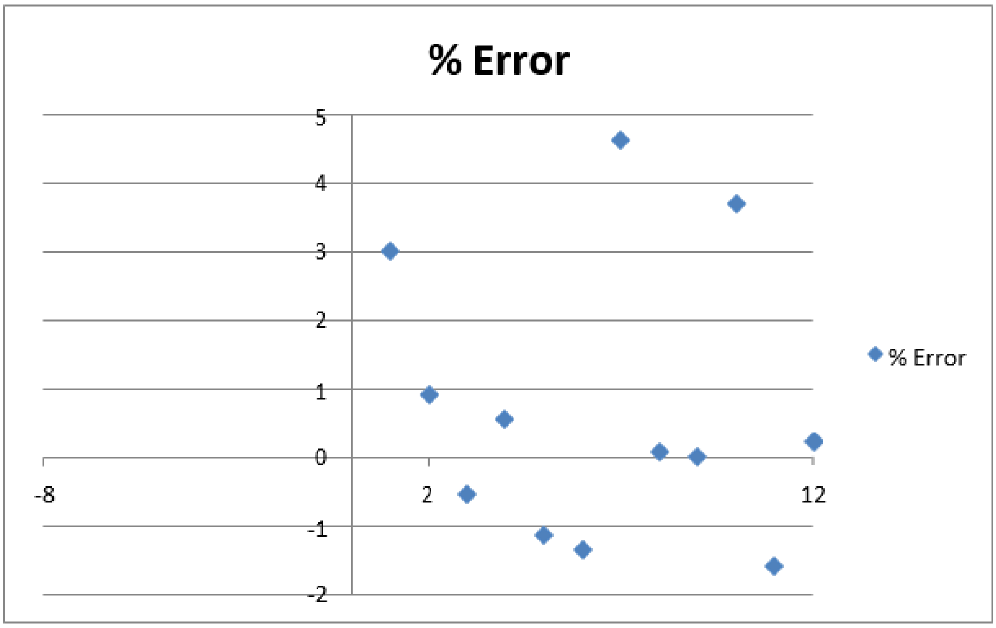

Fig.5. 2 -Range of error

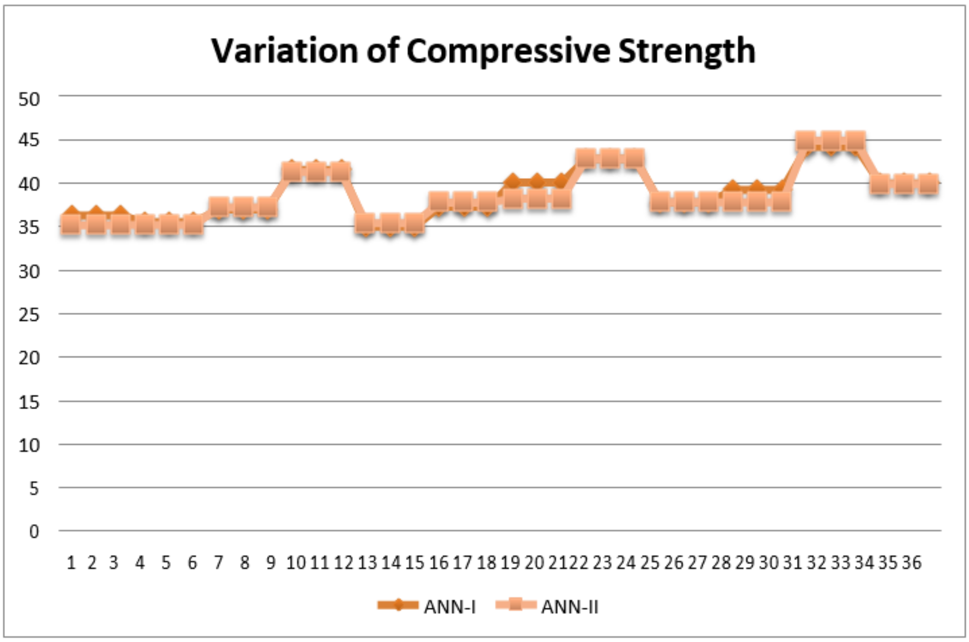

Fig.5.3- Variation of Compressive Strength

Fig. 5.1 shows the comparison between the forecasted results of different ANN models and experimental obtained compressive strength of cubes. The difference between actual and forecasted values of each data set is very less.

Fig. 5.2 shows the error between the predicted results of ANN-I and ANN-II of compressive strength, percentage error is found to be very less.

Fig. 5.3 shows the variation of compressive strength in both predicted cases, it has been observed that both the graphs are following the same path.

5. CONCLUSION

Following are the conclusions of research:

1. In this Study, using these beneficial properties of artificial neural networks in order to predict the 28 days compressive strength values of concrete containing Industrial Byproducts with attempting experiments were developed two different architectures namely ANN-I and ANN-II.
2. In ANN-I model, one hidden layer were selected. In the hidden layers 10 neurons were determined. In ANN-II model, two hidden layers were selected. In the first hidden layers 10 neurons and in the second hidden layer 10 neurons were determined.
3. The compressive strength values predicted from training for ANN-I & ANN-II models were very close to the experimental results. Furthermore, according to the compressive strength results predicted by using ANN-I and ANN-II models, the results of ANN-II model are closer to the experimental results.
4. As a result, compressive strength values of concretes containing Industrial Byproducts can be predicted in the multilayer feed forward artificial neural networks models with attempting experiments in a quite short period of time with tiny error rates. ANN can be suggested to predict the concrete compressive strength with high accuracy.
5. ANN prediction would have been more accurate if the experimental results were more.
6. This study indicates the ability of the neural network tool as a brilliant technique in order to predict values of compressive strength with varying input variables.
7. The model implemented satisfactorily in the prediction of compressive strength of concrete with different variables.

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