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Estimation of Strength of Reactive Powder Concrete using Artificial Neural Network

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Abstract

Objective: Attempt is made to estimate the compressive strength of Reactive Powder Concrete (RPC) by developing Artificial Neural Network model. **Methods/Analysis:** RPC is a complex composite material made using a combination of constituent materials *viz.* fine quartz, silica fume and cement to form a cementitious matrix. Mix design for RPC is more complicated as it excludes the coarse aggregates and a low water/cement ratio is maintained. The mix proportioning methods applicable to normal concrete cannot be applied readily to RPC. The complexity in behavior of concrete with special constituents makes the mix design complicated. Artificial neural network (ANN) techniques can capture complex relations among input/output variables in a given system and this method has been implemented in Reactive Powder Concrete mix proportion design, for predicting its strength. **Findings:** This paper presents the development and application of ANN for predicting the strength of RPC using data related to 112 mix proportions and the results of the model are checked experimentally. Compressive strength of concrete is chosen as a function of the 'Water/Cement' ratio (w/c), 'Silica Fume/Cement' ratio (sf/c), and 'Quartz Sand/Cement' ratio (qs/c). The ANN model developed is tested for the 12 mix proportions randomly selected from experimental data for which the experimental compressive strengths were available. The compressive strength given by the model when compared with the experimental values showed an average error of only 3.99 %. **Novelty/Improvement:** The model developed has coefficient of determination R^2 equal to 0.9066 which indicates a significant enough correlation.

Keywords: Artificial Neural Network, Concrete Mix Design, Reactive Powder Concrete

1. Introduction

Reactive Powder Concrete (RPC) is a material with high strength and durability characteristics as compared to normal conventional concrete and even high-performance concrete. This concrete will satisfy the present need of highly developed infrastructural development.

RPC uses a combination of constituent materials *viz.* fine quartz, silica fume and cement to form a cementitious matrix. Conventional aggregate is completely substituted by fine quartz sand with a particle size of between 150 and 600 μm and therefore it more closely approximates a mortar. High compressive strengths of 200 to 800 MPa have been reported to be achieved with RPC, with special curing and setting conditions. Along with the high strength, other mechanical properties also shows enhancement, such as; Young's modulus: 50 to 60 GPa, tensile strength: 6-13 MPa which is maintained even in the inelastic stage after first cracking and fracture energies: 15,000 J/m^2 to 40,000 J/m^2. These values depend on the amount of steel fibre added to the mix and these characteristics have been achieved for RPC by P. Richard[1]. Development of RPC was made possible by the application of a certain number of basic principles relating to the composition, improved micro-structure and ductility by adopting special curing methods including presetting.

In the case of RPC, special constituent materials are used and as many of the material properties cannot be assessed truly quantitatively, the process of selecting proportions for RPC for finding the optimal mixture of these

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constituents on the basis of the compressive strength is difficult. The compressive strength of RPC which is the primary characteristic of any concrete can be considered to be an index of its other mechanical properties. The currently used mix proportioning methods of conventional concrete cannot be directly used for RPC as these methods cannot effectively account for the large variations in the properties of constituents of RPC. Even in the normal concrete, if the concrete is made with more than four components and if the number of its properties incorporated in design is also increased, the empirical methods currently used are no longer sufficient in concrete mix design. Also, the empirical methods have limitations because several blends of the components, their proportions, mixing and curing methods have never been explored or published[2-4].

Mix design of Reactive powder concrete is more complicated as it excludes the coarse aggregates and includes materials like super-plasticizer and supplementary cementitious materials like silica fume. In addition, maintaining a low w/c ratio with adequate workability makes the design process more complicated. There is paucity of the research done on modeling the strength of Reactive powder concrete. Trial mixes is one of the option for RPC. Further, Artificial Neural Network (ANN), which is a system identification procedure based can be used to predict the compressive strength of concrete based on proportions of ingredients used.

2. ANN in Mix Design

Empirical relationships are the best tools to adopt to estimate engineering properties in engineering systems having intricate complexity. Generally, this complexity is virtue of a number of interacting factors of that system, wherein the relationship between these governing factors is not exactly known. In statistics, the empirical relations can be build using conventional traditional methods such as multi-variable linear regression, but these methods have their own limitations. They cannot be easily applied in a complex non-linear system. Artificial Neural Network (ANN) approach is an alternative solution for this[2]. An ANN model is a model developed in computer whose features of working and functioning essentially imitates the learning and improvising characteristics of the human brain. Basically, the main element of a neural network are analogous to the neurons in the human brain. There are many such simple elements which are arranged in layers which have the computational capabilities. The ANN tool is a good computational tool to model the complex systems involving non-linearity[5].

Earlier work reports the use of a standard multilayer feed forward ANN to predict the compressive strength of concrete. Back-propagation algorithm is used to train the network existing datasets in this method[5-13]. Jain[14] implemented these methods and discussed regarding the efficiency of different neural network models for concrete mix. Adaptive neuro-fuzzy inference system to train a fuzzy model and estimate concrete strength was developed by S. Tesfamariam and H. Najjaran[15].

Jong-In Kim et. al applied for the first time ANN system identification procedure to predict the compressive strength of concrete based on proportions of the ingredients[16]. Mohammad Iqbal Khan has used ANN for the determination of concrete strength and permeability of concrete and thereby established the applicability of the model. The model proposed by him takes the account of both secondary and tertiary binding constituents with a wide range of different w/c ratio and compressive strength. The model incorporates the effects due to wide range the binding materials like silica fume and pulverized fly ash, which heavily influences the properties of concrete. With the developed model, and general knowledge of concrete mix details along with the influencing characteristics, the compressive strength and perviousness aspects of any concrete can be determined. No empirical relations or equations are required which are generally used in customary models for prediction of compressive strength[17].

In current scenario, with the development of various high performance concrete, the Artificial Neural Network tool has come up exceptionally as an effective regression tool in prediction of the compressive strength. The primary strategy in these tools is that they can capture multifaceted interactions among input and output variables in a system, though the nature of these interactions is unknown. Considering this feature, to take care of the intricacy of high performance concrete behaviors and their mix proportions, ANN technique has been adopted in reactive powder concrete mix proportion design in the work presented here.

3. Materials and Experimental Work

The primary basis for developing an ANN model for understanding material behavior is to train a neural network based data. Here the data is obtained in the form of the results of an exhaustive experimentation carried on RPC for different mix proportions. Extensive experimentation for compressive strength of RPC was carried out in order to create the exhaustive data required for the training of ANN. The RPC considered here is prepared by mixing Ordinary Portland Cement (OPC) of 53 grade, quartz sand with maximum particle size limited to 600 µm and silica fume with the particle size less than 1µm in diameter, the average being about 0.15 µm. Particle sizes below 150 µm in quartz sand are avoided, in order to prevent interface with the largest cement particles (80 - 100 µm). The very low water cement ratios are used in RPC and it necessitates the fluidizing power of high-quality third generation super-plasticizing agent. Some important specifications of the material used are:

The quartz sand has SiO_2 of 99.9 % with a specific gravity of 2.6-2.7 and pH neutral. Silica fume of Silica Grade 920-D is used having minimum 90% SiO_2 and with coarse particles greater than 45 microns limited to maximum 1%. The specific surface is 18 m^2/g with a bulk density of 500 - 700/m^3. The super plasticizer is polycarboxylate based with minimum pH 6.0 and volumetric mass @ 20°C equal to 1.09 Kg/Litre.

Mixes having different proportions of ingredients have been made and specimens have been cast with those mixes to have sufficient data. These proportions are based on research studies carried by the previous researchers: P. Richard[1], A. S. Dilli[18], Halit Y[19]. Based on the proportions selected by them, the upper and lower limit of each constituent is decided and accordingly the variation is done. The silica fume to cement ratios are taken as 0.15, 0.20, 0.25 and 0.30. The quartz sand to cement ratios are taken as 1.1, 1.2, 1.3, 1.4, 1.5, and 1.6. Water to cement ratios are taken as 0.20, 0.25, 0.30, and 0.35.

The combination of the above different ratios resulted in 112 proportions. Four cube specimens of size 70.6 mm are cast for each proportion. The concrete is mixed in a bucket mixer. Concrete is filled in the prepared mould in three layers and is compacted on a vibrating machine. It is moist cured for 24 hours, de-molded, and then cured in water at 27°C until testing at 28 days. All the cube specimens are tested on a 2000 kN capacity compressive testing machine to determine the compressive strengths and are given in Table 1.

Out of the 112 results obtained for compressive strengths, random100 values are used to train the ANN model. Remaining 12 values of compressive strengths for the corresponding mixes are used to evaluate the accuracy of the model built.

4. ANN based Analytical Model for RPC Mix Design

The aim of the methodology is to find the desired compressive strength for a particular mix proportion. Application of the procedure of ANN for finding strengths, necessitates formulating the problem statement, to prepare the input data consisting of experimental results in a desired format and input the data in the program in an apt way and finally run the program. MATLAB software is used here for developing the neural network model.

For the proposed work, the compressive strength of concrete in this model is chosen as a function of three input parameters *viz*. 'Water/Cement' ratio (w/c), 'Silica Fume/Cement' ratio (sf/c), and 'Quartz Sand/Cement' ratio (qs/c) as input features.

Table 1. Compressive Strength (MPa) of RPC for various mix proportions

Quartz sand/ cement ratio	Silica fume/Cement ratio: 0.15				Silica fume/Cement ratio: 0.2				Silica fume/Cement ratio: 0.25				Silica fume/Cement ratio: 0.3			
	Water/Cement ratio				Water/Cement ratio				Water/Cement ratio				Water/Cement ratio			
	0.2	**0.25**	**0.3**	**0.35**	**0.2**	**0.25**	**0.3**	**0.35**	**0.2**	**0.25**	**0.3**	**0.35**	**0.2**	**0.25**	**0.3**	**0.35**
1	62.09	58.62	59.32	57.75	67.43	65.59	65.04	65.04	68.22	67.66	66.15	77.5	75	80.75	66.25	63.75
1.1	63.5	60	60.15	68	69.36	71.82	70.42	70.5	70.71	73.66	75.32	81.5	74.77	77.09	76	84
1.2	65.92	62.6	62.37	62.37	70.05	71.94	67.86	74.25	76.66	75.55	73.9	84.25	81.25	80.35	80	80.25
1.3	64	66.25	70.5	67.25	77.25	73.2	74.08	78.75	78.02	77.37	76.21	80.75	79.93	81.55	91.36	72.75
1.4	69.78	70.11	77.75	77	78.57	77.21	81.5	80	81.17	80.64	85.55	85.55	82.5	85.25	94.3	66
1.5	75	80	77.75	82.25	80.1	89.32	91.15	79.75	88.67	89.84	93.41	81	91.8	98.09	95.21	54
1.6	79.94	81.99	94.66	79.75	80.09	78.97	78.32	74.75	87.46	85.41	82.59	76.74	62.25	65.25	72.75	50

Table 2. Result of 'Testing of ANN model'

Mix No.	w/c	sf/c	qs/c	Compressive Strength by Experiment (MPa)	Compressive Strength by ANN Model (MPa)	% Error
1	0.35	0.3	1.5	54	53.05	-1.75
2	0.35	0.25	1.4	85.55	84.32	-1.43
3	0.35	0.2	1.0	65.04	62.97	-3.18
4	0.35	0.15	1.2	62.37	59.79	-4.33
5	0.3	0.2	1.1	70.42	68.66	-2.50
6	0.3	0.15	1.5	77.75	81.84	5.26
7	0.25	0.25	1.1	73.66	80.08	8.72
8	0.25	0.2	1.2	71.94	72.97	1.43
9	0.25	0.15	1.4	70.11	67.60	-3.57
10	0.2	0.3	1.0	75	75.17	0.24
11	0.2	0.25	1.6	87.46	97.08	11.00
12	0.2	0.15	1.6	79.94	83.46	4.42

Model used is one output model

Compressive Strength = f(w/c, sf/c and qs/c)

4.1 Architecture of Neural Network

Artificial neural networks consists of large parallel layers which are interconnected with each other via artificial neurons. These artificial neurons are simple computational elements in the architecture of ANN. In ANN most of the models developed are based on back-propagation neural networks (BPNN)[3]. Each layer is identified and associated with weight. While training, these weights of connections can be modified as the process of learning takes place along with the information it has gather. Depending on the output obtain at the end of each cycle, comparison of the output with the targeted output for the particular input pattern is made. The network further learns from this process. The network calculates the error between the targeted and obtain values. It then disseminates an error function backwards again to the network. The process is continued till the error reaches a permissible limit defined by the user. Once the network is trained, it is run, the input values of the experimental work are provided to the network as input parameters. Output parameters are generated considering the associated weights as well as the thresholds prescribed in the network.

In the process of the training of the network, the input as well as the output data are to be normalized. Normalize data ensures the allocation of minimum value of the output variable to a minimum anticipated value. It also allocates the maximum value of the output variable into the maximum anticipated value.

4.2 Network Parameters

The network structure and parameters need to be selected so that the RMS error of the testing data is minimized. These are selected as follows. Number of hidden layers = 1; Number of input neurons = 4; Number of hidden neurons = 3; Learning cycles = 5,000; Goal = 0.000001. This is selected after a number of trials[20].

4.3 Modeling of Network

Programming is done to create a neural network for the defined work. Program modeling work is divided into three parts viz.: create a network and train, find the error, and find compressive strength for defined mix proportion.

The input data in the form of excel sheet is loaded into the program, in a matrix format. The loaded data is normalized with an appropriate operation. The training parameters are defined and the defined input data, the percentage of data required for training, testing and validation of the network, training parameters are applied to the network. Out of the total input data available, 70% is used for training, 15% is used for validation and rest 15% is used for testing of the network.

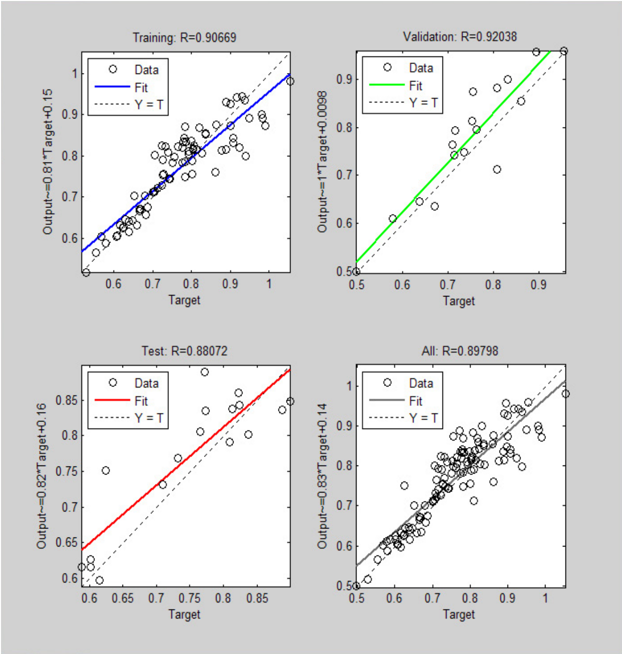

Figure 1. Regression plot of network.

The program is then made to run. The number of neurons in input and hidden layer is provided through the interactive window. The first process of training of the network takes place. The input configuration creates a forward flow of signals from neurons in the input layer to the output layer. The error between output generated (Computed values from each output artificial neuron) and targeted values (experimental values) is then determined by calculating the difference between them.

The regression plot which gives the error between output values and targeted values of various processes as training, validation, testing and average of the all input data is shown in Figure 1. The values of 'R' which is mean squared error of all the processes for the created network, is found to be 0.90669, 0.92038, 0.88072 and 0.89798 for training, validation, testing and overall average respectively.

A program which gives the error between the targeted values and output values from the trained network for a particular pair number from loaded input data is loaded and run. The pair number of which we want to find error between the output value and targeted value is entered through the interactive window and it shows the result in terms of error in percentage.

Finally, the program to find the approximate compressive strength of RPC for the desired mix proportion is loaded and run. The proportion in terms of ratios i.e. w/cratio, sf/cratio and qs/cratio, respectively of the mix whose strength is desired can be entered through the interactive window and the trained network gives the approximate compressive strength.

5. Results

The Artificial Neural Network model developed for the prediction of the compressive strength of Reactive Powder concrete was tested for the 12 mix proportions for which the experimental compressive strength was available. Table 2 shows the results of compressive strength obtained by ANN model and corresponding value obtained experimentally. The compressive strength given by the model when compared with the experimental values shows an average error of 3.99 %.

6. Conclusions

Based upon the results it can be concluded that the developed model of ANN-technique gives effective results in estimating the compressive strength of Reactive Powder Concrete given the mix proportion of constituents.

- It can be seen from the above table that the data used for testing the network gives an average error of 3.99%. Hence, the ANN-based model developed is satisfactory and precisely predicts the experimental results for the testing data.
- The coefficient of determination R^2 for training, validation and test of model was 0.9066, 0.92038 and 0.88072 respectively. Combined value of R^2 for all data is 0.89798. These values of coefficient of determination indicates a significant enough correlation. The developed model shows a guideline to select appropriate constituents and their proportions for starting a trial batch of RPC and thereby reduce the number of trial mixes required for the desired strength.
- As more data is compiled over a period of time, the ANN models trained using this added data will become more valid and the estimation from these models will increasingly become more precise and reliable.

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