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ANN based prediction of Bond and Impact Strength of Light Weight Self Consolidating Concrete with coconut shell

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***Abstract*—In this experimental investigation, lightweight self-consolidating concrete (LWSCC) was developed with coconut shell as coarse aggregate. The effect of coconut shell aggregate (CSA) on bond strength and impact strength of Rice Husk Ash (RHA) based binary blended and RHA + Silica fume (SF) based ternary blended Self consolidating concrete (SCC) were determined. The bond strength was determined through pull-out test and the impact strength was calculated using falling weight test. The concrete mix was developed with the total powder content of 450 kg/m^3. The coarse aggregate content was replaced by CSA in the gradation of 0%, 25%, 50%, 75% and 100% in the designated SCC. The investigation revealed that the bond and impact strength of CSA based LWSCC were comparable to current code practice and other lightweight concretes. The experimental data obtained was used to develop an ANN model for predicting the strength characteristics of fresh or hardened concrete. The high regression values obtained during training the neural network models reveals high accuracy and were predicting the strength characteristics very similar to the experimental results.**

Keywords*—*Light weight self-consolidating concrete, coconut shell, rice husk ash, silica fume, bond strength, impact strength, ANN

I. INTRODUCTION

Light weight concrete (LWC) has been employed in construction industry since the time of ancient Romans. The major reason for gaining popularity is its lower density and 25 – 35% lighter in weight [1]. The significant reduction of dead load of the structural elements improves the structural response and lowers the foundation costs. LWC is more suitable for long-span structures with high strength to weight ratio and large-scale pre-cast production [2]. It also reduces the transportation and erection costs of pre-cast structural elements.Light weight concrete manufacturing has become possible using lightweight concrete having density ranging from 1560 to 1960 kg/m^3 by using lightweight aggregates. Naturally available lightweight aggregates, like volcanic pumice [3-4] and synthetically produced aggregates from industrial by-products, like sintered fly ash are utilized as an alternate to the conventional aggregates. These aggregates have gained due to its lightweight, lower density and availability [6-7]. The agriculture wastes also exist in this group. In developing countries like India, the rich agriculture wastes are discarded and can be utilized in the construction industry in place of the conventional materials [8].

Self-consolidating concrete (SCC) is a kind of high-performance concrete and can be well thought-out as a futuristic concrete which can flow by means of virtue of its own self weight by keeping the coarse aggregates in the mixture as homogenous[10-12]. One of the major disadvantages of SCC is with the use of high powder content and chemical admixtureswhich are highly cost associated [9]. In order to reduce the cost of preparing SCC, industrial waste products such as CSA, slag etc., are utilized as important alternatives for conventional coarse aggregate. Lightweight self-consolidating concrete (LWSCC) combines the complimentary properties of lightweight aggregate in SCC. Extensive investigations on SCC have been made from the inception of SCC during 1980s and there are few studies on LWSCC so far. In this background, Slag was being considered as coarse aggregate in the light weight self-compacting concrete (LWSCC) [13-15, 18]. With this background, the important objective of the study is to investigate the bond and impact strength of CSA based LWSCC [12].

Many researchers developed models that can predict the strength characteristics of the concrete added with supplementary ingredients. The common methods used were analytical modelling, artificial intelligence and statistical modelling. Among all of these methods artificial neural network, a sub branch of artificial intelligence gained popularity by giving the predictions more accurately compared to other methods. In this study Levenberg-Marquardt algorithm was used for training the neural network model.

II. MATERIALS AND METHODS

A. Materials

Ordinary Portland cement and Rice husk ash (RHA) and silica fume (SF) were used for the experimental investigations. Coarse aggregate used for concrete is blue metal granite of size 12 mm. The specific gravities of the RHA, SF and coarse aggregates were found to be 3.170, 2.15 & 2.78 respectively. The water absorbing capacity of coarse aggregate used in this study was found to be 3.47%. The coconut shells to replace the coarse aggregates were collected from the local fields and allowed to dry in open barren lands for one month before being crushed. The crushed CSA was taken for washing and it was allowed to experience ambient temperature conditions for another one month before it is utilized. The water absorbing capacity of CSA used in this study was found to be 5.88%. The density and specific gravity of CSA were found to be 1683 kg/m3 and 1.71 respectively. The results were lower than the specific gravity of normal weight conventional coarse aggregate (2.5 – 3.0) and therefore CSA can be classified as light weight aggregate. Polycarboxylic based superplasticizer (SP) with a specific gravity of 1.07 was employed to achieve the desired workability [28-30].

B. Mix Proportions

Recently, Su and Miao proposed a new method to design the mix proportion for self compacting light weight concrete. Shi & Wu and Su et al., have adopted the modified method to predict the mix proportioning of self compacting light weight concrete [16-17]. In order to develop the SCC in this experimental investigation, Rice Husk Ash (RHA), another agricultural waste product, was used as cementitious material for developing binary blended SCC and Silica Fume (SF) along with RHA to develop ternary blended concrete [19, 22-24]. A concrete mix was considered with the total powder content of 450 kg/m^3. To develop the mix concrete, the cement and mineral admixture ingredients (RHA and SF) were assorted. After several trials with reference to the previous literature evidences [18-21, 31-32], the final combination was arrived and designated as LWSCC450. The mix proportions were given in Table 1. The investigation was carried out with granular coconut shell as a replacement for coarse aggregate in the gradation of 25%, 50%, 75% and 100%.

C. Testing methods

1. Impact Resistance Test

The impact resistance of concrete specimen can be determined by using the method of drop-weights as per the guidelines of ACI committee 544.1R-82. The number of blows required for causing prescribed levels of distress in the test specimen was determined using this test. The concrete specimens of 152 mm in diameter and 64 mm thick disc were employed within four positioning lugs welded on a base plate for the impact resistance test. The disc undergoes continuous impact blows and the compaction hammer was dropped on test specimen from a height of 457 mm repeatedly as shown in Fig 1. The number of blows for the first visible crack (N1) appeared on the top of the specimen and the number of blows till broken the specimen (N2) into number of pieces were recorded. The surface of the test specimen was white washing in order to facilitate the identification of crack. The impact resistance was determined at 28 days and 90 days cured specimen.

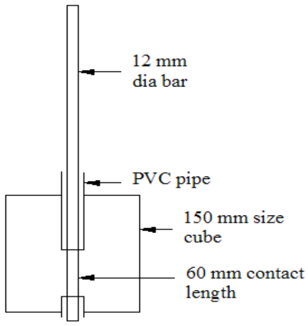
(a)Drop weight test setup

(b) Specimens after failure

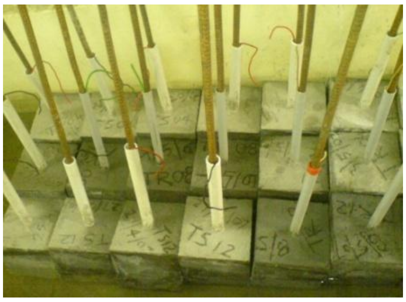
Fig.1. Impact resistance test

2. Pull out Test

The bond strength of concrete was determined using pull-out test. The pullout specimens were prepared as per the guidelines of IS: 2770 (Part-I)-1967. Concrete cubes of size 150 x 150 x 150 mm were prepared and 12 mm diameter reinforcement was embedded in the cubes. Thermo mechanically treated (TMT) low carbon steel rebar with yield strength 433.6 MPa (average of five specimens) was adopted for this investigation. The average rib height and width of rebar was measured as 0.98 and 0.6mm respectively. The reinforcement samples were cleaned properly before casting in to the concrete specimens. The embedded length of reinforcement was calculated as five times the diameter (60mm) of the rebar. The remaining length of reinforcement was covered by poly vinyl chloride (PVC) pipes to maintain the embedded length. A 10 mm projection of reinforcement at the bottom of the specimens was providing to meet the requirement during the measurement of slip of the reinforcement effectively. Mild steel of 6mm diameter was used as transverse reinforcement with a pitch of 25mm and provided in the cubes just adjacent to outer periphery of the cubes. The PVC ends were properly sealed. The details of pullout specimen are shown in Fig.2.



(a)Details of pull out specimen



(b) Pull out specimens for testing

Fig. 2. Pull out specimens

For each concrete batch, the bond strength was determined as an average of three tests in each case. A 200kN capacity universal testing machine was considered for conducting the pullout test. The free end slip was recorded with a high precision dial gauge and the movement of the concrete specimen was also measured with another high precision dial gauge. As per IS 2770, the pullout force corresponding to 0.25mm slip was considered and then the corresponding bond strength was determined[19]. The bond strength was calculated from the applied loads on the bars and the total surface area of the embedded portion of the bar using the equation.

$$f_b = \frac{P}{\pi d_b l_b} \qquad (1)$$

Where,

f_b = bond strength in MPa

P = pullout force in Newtons

d_b = effective diameter of bar in mm

l_b = embedded length of bar in mm

D. Artificial Neural Network

Artificial Neural Networks (ANNs) is a computational and physical cellular system where it can acquire, store and utilize the experimental knowledge acquired by the method of structure processing [25]. ANNs are a set of parallel and distributed computational elements classified and characterized according to topologies, learning paradigms, at the way information flows within the network and by the change in Architecture, learning paradigm, activation functions [27]. The Characteristics also includes a large number of very simple processing neuron-like processing elements, a large number of weighted connections between the elements, Distributed representation of knowledge over the connections, Knowledge is acquired by network through a learning process [25-27]. The usage of ANN is of Massive parallelism, distributed representation, learning ability, generalisation ability and fault tolerance [17]. There are vast and different techniques which can be used in ANN where they are named as 1. single-layer NN such as Hopfield network, 2. Multi-layer feedforward NNs such as backpropagation, functional link, 3. Temporal NNs and 4. Radial basis function networks [25].

1. ANN architectures

Artificial neural network is generally consist of three layers, input layers, hidden layer and output layers. Input layer is generalized by the input parameters given to the network. It consist of passive nodes, which do not take part in any function and it only sends the signal to the next layer. Hidden layer is an arbitrary layer consisting of arbitrary neurons which takes part in modification or activation function, hence they are active. Based on the weights, two types of supervised algoritms are available. One is delta or stochastic, in which weights are updated after every pattern presentation. Second one is Batch training weights are accumulated to changed only after all patters are presented. The number of neurons indicates the number of output parameters of the given inputs of the network. The nodes are active.

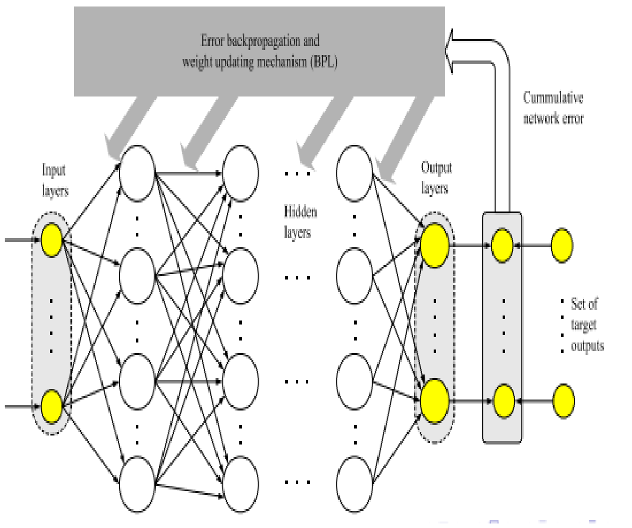


Fig. 3. Schematic Representation of the network illustrating the notion of error back-propagation

TABLE I. IMPACT TEST AND PULL OUT TEST RESULTS OF LWSCC 450 MIX

Cement (Kg/m^3)	RHA (Kg/m^3)	SF (Kg/m^3)	Sand (Kg/m^3)	CA (Kg/m^3)	CSA (Kg/m^3)	w/p	SP (l)	Impact resistance (MPa)		Bond strength MS(MPa)		Bond strength RTS(MPa)	
								28 days	90 days	28 days	90 days	28 days	90 days
330	120	0	850	940	0	0.35	2.61	29.07	34.06	5.84	6.13	6.9	7.55
330	120	0	850	705	90.5	0.35	2.61	25.81	31.06	5.83	6.24	6.96	7.43
330	120	0	850	470	181	0.35	2.61	23.03	29.31	5.81	6.27	6.9	7.43
330	120	0	850	235	271.5	0.35	2.61	21.72	27.27	5.79	6.31	6.89	7.55
330	120	0	850	0	362	0.35	2.61	19.33	24.53	5.66	6.29	6.84	7.37
318	100	32	850	940	0	0.37	2.68	31.15	37.73	6.13	7.01	7.78	8.57
318	100	32	850	705	90.5	0.37	2.68	28.73	35.77	6.25	7.13	7.9	8.43
318	100	32	850	470	181	0.37	2.68	26.16	32.07	6.25	7.07	7.67	8.47
318	100	32	850	235	271.5	0.37	2.68	24.51	30.26	6.07	6.91	7.53	8.37
318	100	32	850	0	362	0.37	2.68	21.33	28.15	6.02	6.79	7.31	8.24

Using the sigmoid function as the activation function for all the neurons of the network, we define Ec as

$$E_C = \sum_{k=1}^{n} = \frac{1}{2}\sum_{k=1}^{n} x \sum_{i=1}^{q} [t_i(k) - O_i(k)]^2 \quad (2)$$

The formulation of the optimization problem can now be stated as finding the set of the network weights that minimizes Ec or E(k).

The very first back propogation algorithm was developed by Paul Webros in 1974 and then rediscovered by many researchers. As it is a rediscovery, this has been utilized in many learning algorithms of multilayer neural networks.

Back propogation assorted ANN models will perform simultanious training for improving the efficiency of the network of Multilayer Perceptron (MLP).

It is an easy and effective model in terms of accuracy and speed for complex multilayered networks. Back propogation is mainly depends on gradient descent method which tries to minimize the error of the network by heading downwards in the error curve.The weight error correction rules in the architecture of supervised learning is most popular in ANN. The generalization of delta rule is taken into account for multilayer networks and nonlinear activation functions. ANN applications are gaining more popularity and they are being utilized in everyday services, products and applications.Eventhough latest softwares enable comparitively very easy handling with ANN, The creation, optimization and the utilization in real life problems makes it essential to learn and understand the theory behind the Artificial neural networks.

III. RESULTS AND DISCUSSION

The concrete with varying mix proportions were tested after curing for 28 days and 90 days. The tests done were impact test and pull out tests for mild steel bars and rounded tampered bars. The test results were shown in table 1.

A. Impact resistance

Impact resistance is an important property of concrete the experimental results were obtained from the experimental investigations conducted on concrete with varying mix design proportions the data was divided as 70% for training 15% for validation and 15% for testing Levenberg-Marquardt algorithm was used for training the network the regression values for training, validation and testing were found to be 0.98938, 0.97697, 0.97095 respectively the best performance was observed as 3.1224 at epoch 2. The overall regression value was found to be 0.9683. Interestingly the predicted values are very nearer to the experimental results. The performance and regression plots were shown in fig 4 and fig 5 respectively.

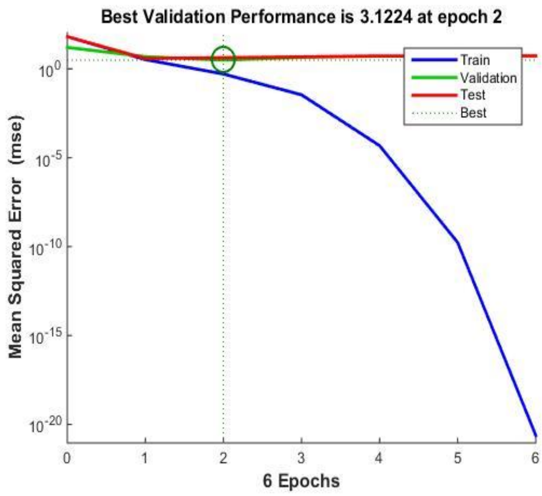


Fig. 4. Variation of MSE against the various epochs for training, testing and, validation data sets obtained for impact resistance tests along with best validation performance

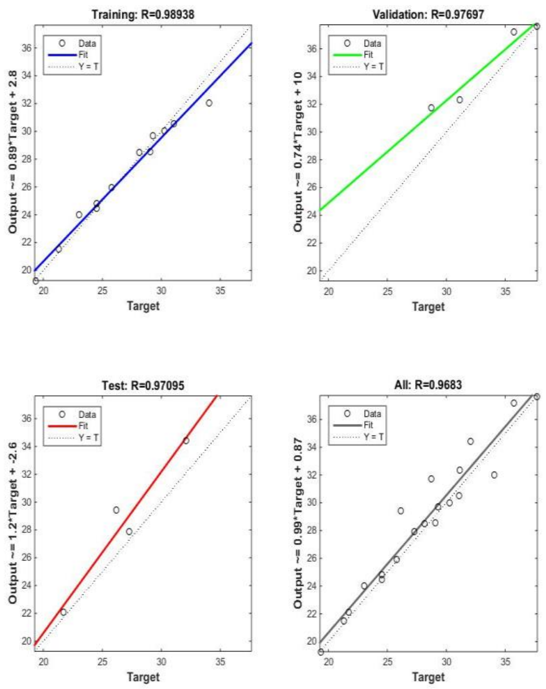


Fig.5. Plot showing the performance of ANN for training data, testing data, validation data, and all data obtained for impact resistance test

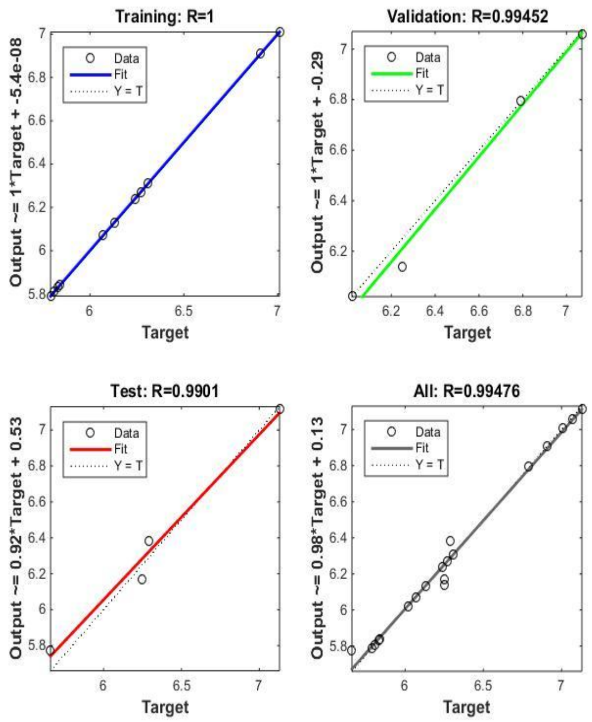


Fig. 7. Plot showing the performance of ANN for training data, testing data, validation data, and all data obtained for pull out tests of MS bars

B. Bond strength MS

The bond strength of the concrete also an important mechanical property of concrete. The experimental results were obtained from the experimental investigations conducted on concrete with varying mix design proportions the data was divided as 70% for training 15% for validation and 15% for testing Levenberg-Marquardt algorithm was used for training the network the regression values for training, validation and testing were found to be 1, 0.99452 and 0.9901 respectively the best performance was observed as 0.0031937 at epoch 5. The overall regression value was found to be 0.99476. Interestingly the predicted values are very nearer to the experimental results. The performance and regression plots were shown in fig 6 and fig 7 respectively.

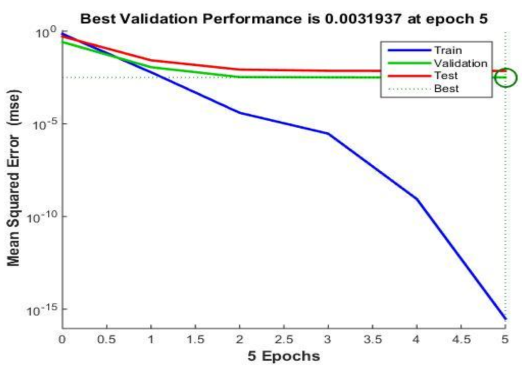


Fig. 6. Variation of MSE against the various epochs for training, testing and, validation data sets obtained for pull out tests for MS bars along with best validation performance

C. Bond strength RTS

The bond strength of the concrete also an important mechanical property of concrete. The experimental results were obtained from the experimental investigations conducted on concrete with varying mix design proportions the data was divided as 70% for training 15% for validation and 15% for testing Levenberg-Marquardt algorithm was used for training the network the regression values for training, validation and testing were found to be 0.9996, 0.99734 and 0.99031 respectively the best performance was observed as 0.013723 at epoch 2. The overall regression value was found to be 0.99395. Interestingly the predicted values are very nearer to the experimental results. The performance and regression plots were shown in fig 8 and fig 9 respectively.

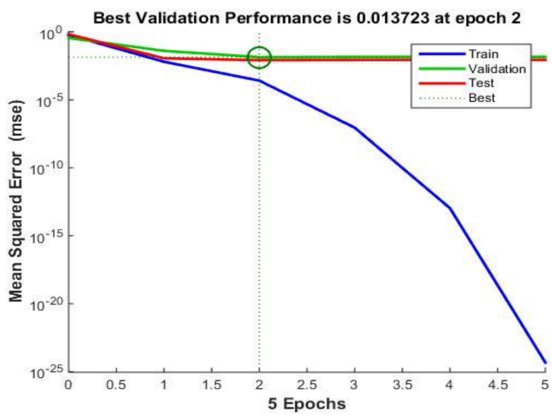


Fig.8. Variation of MSE against the various epochs for training, testing and, validation data sets obtained for pull out tests for RTS bars along with best validation performance

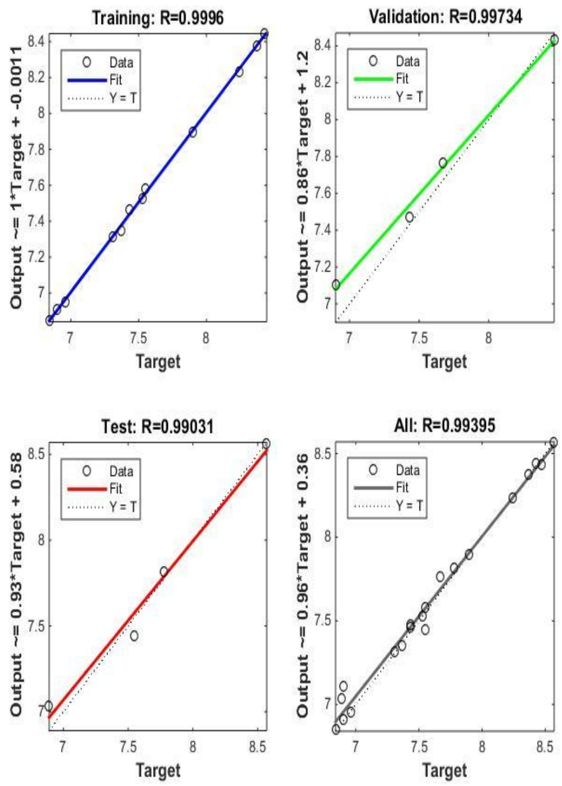


Fig. 9. Plot showing the performance of ANN for training data, testing data, validation data, and all data obtained for pull out test of RTS bars

IV. Conclusions

Based on this experimental investigation, it is practicable to use CSA as aggregate to produce light weight concrete with satisfactory performance. The developed ANN network by using Levenberg-Marquardt algorithm was giving good results. The ANN architecture was found to be 8-12-2, which consists of 8 input layers, 12 hidden layers and 2 output layers. The coefficient of regression values for impact resistance, bond strength of mild steel and bond strength of round tapered bars were found to be 0.9683, 0.99476 and 0.99395 respectively. The best performance was observed as 03.1224 at epoch 2 for impact resistance, 0.00319 at epoch 5 for bond strength of MS and 0.0137 at epoch 2 for bond strength RTS. Interestingly the predicted strength characteristics from the developed network are very nearer to the experimental results.

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