Volume 2, Issue 12, December-2015, pp. 1014-1019 ISSN (O): 2349-7084

International Journal of Computer Engineering In Research Trends

Available online at: www.ijcert.org

Hybrid Neural Network Model for Compressive Strength of Reinforced Concrete

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Abstract:- This paper focuses on the procedure of statistical assessment of test results in reference to the strength development of self compacting concrete and normally compacting concrete. A self compacting concrete and a normally compacting concrete (NCC) with similar ultimate compressive strength were developed. The concrete cubes were tested at 7, 28, 60, 90, 120 and 150 days after normal water curing. For each case 10 samples were tested and the test results were recorded for each sample on as obtained basis. To predict strength characteristics four input parameters namely water cement ratio, aggregate cement ratio, percentage of fibers and aspect ratio were identified. The results of the present investigation indicate that Genetic Algorithm based Artificial Neural Network (GANN) has strong potential as a feasible tool for predicting strength characteristics of steel fibre reinforced concrete.

Keywords – Genetic Algorithm , Back Propagation Network , Steel Fibre Reinforced Concrete , Neural Network .

1. INTRODUCTION

Concrete is an essential material in civil engineering, which is widely used all over the world. It is a composite material comprising of key constituents, namely, cement, sand (as fine aggregate), fly ash, coarse aggregate, admixture and water. The properties of concrete, including its compressive strength are a highly nonlinear function of its constituents. Various studies have shown that concretes strength not only depend on water-to-cement ratio, but is also related to the other additive constituents (Oluokun). The lack of standard empirical relationships to judge the compressive strength of concrete based on its constituents has created the interest of the researchers towards soft computing tools. Soft computing harnesses statistical, probabilistic and optimization tools for learning, predicting and classifying new patterns based on the past data. Artificial Neural Networks (ANNs) touted as the next generation of computing forms a sub-set of Soft Computing Tools. FRC is a composite material consisting of cement, sand, metal, water and fibers. In this composite material, short discrete fibers are randomly distributed trough out the concrete mass. The behavioural efficiency of this composite material is far superior to that of plain concrete and many other construction materials of same cost. Due to this benefit, the use of FRC [1]has steadily increased during last two decades and its current field of application includes airport and highway pavements, earthquake resistant and explosive resistant structures, mines and tunnel linigs, bridge deck overlays, hydraulic structures, rock slope stabilization.

Strength properties of fibre reinforced concrete mixes are greatly influenced by several parameters, viz. fibre material, volume of fibre percentage, fibre aspect ratio, ratio of fine aggregate to coarse aggregate, aggregate cement ratio and water cement ratio. Hence development of hybrid neural network model for SFRC requires an extensive understanding of the relation between these parameters and properties of resulting mix.

Development of empirical or semi-empirical formulae for mechanical modeling of SFRC is rather difficult due to highly non-linear interaction among the above parameters and degree of non-linearity and extent of interaction of constituent parameters is also not clearly known. In this paper an alternative method of machine learning genetic algorithm and back propagation network for predicting strength characteristics of SFRC was developed. ANN is a sophisticated technique for modeling behavior of any physical system including structural systems. Neural network takes the data provided as input and tries to adjust itself in such a way that it can adapt to the target values. This process is called training of the network.

The internal adjustment made within the network during training process is in the form of progressive adoption of suitable connection weights and bias values amongst individual neuron. Statistical analysis of test results of concrete is significant to understand if the hardened properties of concrete can be reliably predicted by the existing formulations [2]-[3]. Several researchers have used artificial neural network to predict 28 days compressive strength of self compacting concrete [4].The model was developed from literature data and was applicable to the experimental data, with bottom ash as partial replacement of sand. Similar ANN techniques along with regression analysis were reported for prediction of compressive strength of vacuum processed concretes [5]. Statistical study on the variability of the mechanical properties of hardened self compacting concrete including compressive strength was conducted by a few investigators [6]-[7].

The variability study was done in the same range than the expected for normally compacting concrete with in a confidence level of 95%. Ramadoss and Nagamani applied statistical methods on compressive strength of high performance steel fiber reinforce concrete to develop model for quantification of the effect of fiber content on compressive strength [8]. It was reported that the estimated strength from the models differed from the actual values within + 3.2 % and -3.2 %. Equation was also proposed to estimate the effect of size of the concrete specimens.

Genetic algorithm on the other hand, is adoptive search and optimization algorithm that mimic the principal of genetics. Genetic algorithms are quite different from traditional search and optimization techniques used in engineering design problems but at the same time exhibits simplicity, ease of operation, minimal requirement and global perspective.

The purpose of I-PreConS was to provide in-place strength information of concrete to facilitate concrete form work removal and scheduling for construction. Five different ANN architectures were used having four categories of input neurons and seven output neurons designated as compressive strength at 16 h, 20 h, 24 h, 2 days, 3 days, 7 days and 28 days respectively. The training patterns were created experimentally by performing cylinder tests. The concrete compressive strength prediction of ANN was compared with that of traditional maturity method. The study showed that ANN-based model prediction is better than the maturity method and modular neural networks solved the problem conveniently and efficiently in comparison to a single neural network.

2. LITERAURE REVIEW

Yeh has developed ANN model for strength of high performance concrete. Wang et al. developed NN based model for design of concrete mix. Hayalioglu developed a genetic algorithm for the optimum design of geometrically non-linear elastic-plastic steel frame with discrete design variables. Nehdi et al. Presented NN model for performance of cellular concrete mixtures. Raghunath reddy developed Macro mechanical model for steel fibre reinforced concrete using ANN. Cengiz Toklu developed a multi- objective optimization problem and solved by using Genetic algorithm. Noorzai et al. developed an ANN model for predicting 28days compressive strength. Sudarsana Rao et al. have developed hybrid ANN model for the design of beam subjected to bending and shear. Sudarsana Rao et al. have developed ANN model for slurry infiltrated concrete. Sudasana Rao et al. have developed genetic algorithm based hybrid neural network model for predicting the flexural strength of ferro-cement elements .Vaishali et al have developed

GA/ANN model for predicting strength of high performance concrete.

3. MATERIAL

Ordinary Portland cement of 43 grade was used throughout the course of the investigation. The physical property of the cement conformed to Indian Standard code of practice [9]. A low calcium fly ash obtained from combined fields of the electrostatic precipitator of a thermal power plant was used. The 45 micron passing fraction in the unprocessed fly ash was more than 90 percent. Micro silica of grade 920 U with silica content of more than 92 percent was used. The normally compacting concrete (NCC) had a cement content of 490 kg/m3 with water cement ratio of 0.35. A fine aggregate content of 690 kg/m3 and a total coarse aggregate content of 1000.6 kg/m3 were adopted for the mix. A super-plasticizer dose of 2 kg/m3 was used. In the mix of self compacting concrete (SCC) a total powder content of 582.4 kg/m3 was used, 50 percent of which was cement content and the remaining portion was fly ash content.

The mix had a fine aggregate content of 1062.4 kg/m3 against a total coarse aggregate content of 455 kg/m3. A limited amount of silica fume (14.6 kg/m3) was mixed in the mix which had a water powder ratio of 0.32. A poly-carboxylic ether based super plasticizer of 1.67 percent of total powder content was applied to get the desired flow ability of SCC mix. The compressive strength test was performed on 150 mm standard size cubes after the desired curing period. The specimens were demoulded after 24 hours of casting and were placed in a fixed temperature tank at 27+ 20 C. The specimens were removed from water at 7, 28, 60, 90, 120 & 150 days and were tested in surface dried condition.

Cement: The cement used in this experimentation work was 53 grade cement and having a specific gravity of 3.12 which satisfies the requirement of IS:12269-1987 specifications.

Coarse aggregates: The Crushed granite aggregates were collected from the local quarry. The aggregates used in this work were of 20mm and down size and tested as per IS:2386-1963.

Fine aggregates: Locally available river sand collected from river bed of river Tungabhadra was used as fine aggregate .The sand having fineness modulus of 2.34 and confirmed to grading zone -II as per IS:383-1970 specifications.

Fibres: Black binding wire (mild steel) of diameter 0.944 mm was used as fibers in this work. The strength of fibre found as 364N/mm2 .

Water: Ordinary potable water free from organic content, turbidity and salts was used for mixing and for curing throughout the experimentation work.

4.Modeling Compressive Strength of Concrete using Artificial Neural Networks

Concrete compressive strength is its most important characteristic and has a strong relationship with quality. The key constituents of concrete, namely, cement, aggregate and water influence the behavior of the concrete as they impart strength and durability. The composite nature of concrete and nonlinear relationship among its ingredients and compressive strength has diverted the attention of the researchers towards nature inspired computational tools. ANN through its learning ability is used to model the compressive strength, which gives an insight into the factors affecting its strength. The following paragraphs give a detailed literature review on the application of ANN in modeling the compressive strength[10] of various types of concrete.

4.1 Applications in Modeling Compressive Strength of Self Compacting Concrete

Self Compacting Concrete (SCC) is a type of High Performance Concrete (HPC). Self-compacting concrete can be defined as the concrete which requires no vibrations and can flow around obstructions, encloses the reinforcement and fills up the formwork completely under its self weight . Used back-propagation neural networks for developing two neural network models ANN-I and ANN-II based on data taken from the literature and experimental data for Self Compacting Concrete[11] (SCC) containing bottom ash as partial replacement of fine aggregates respectively. The data were randomized and divided into training, validation and testing data sets.

The SCC mix proportions namely, cement, coarse aggregate, fine aggregate, fly ash, chemical admixture and water-cement ratio formed the neural network inputs and 28 days compressive strength was treated as neural network output. The ANN predicted compressive strength of SCC was compared with the experimental results. The error between the predicted and observed strength was found to less than 10%, thereby proving effectiveness of ANN modeling. The ANN model with ten inputs, namely, the amount of cement, amount of fly ash, amount of limestone, amount of marble powder, amount of fly ash, amount of natural aggregates I and II, the amount of super-plasticizer, unit weight and water absorption and one output variable viz., compressive strength of concrete was developed with one hidden layer containing fourteen and fifteen neurons.

4.2 Applications in Modeling Compressive of High Performance Concrete

High Performance Concrete (HPC)[12]has certain distinct features that distinguish it from an ordinary Portland cement concrete. These features can be categorized as high strength, high frost and abrasion resistance, early strength etc. (Yeh)was the first to model the compressive strength of HPC using neural networks by drawing a relationship between the compressive strength and eight input parameters namely, cement, fly-ash, blast furnace slag, water, super plasticizer, coarse aggregate, fine aggregate and age of testing. The results of the study showed that the neural network models are supported better by experimental data than the regression analysis. However the neural network models cannot be used for extrapolation beyond the domain of the collected data. Fibre-reinforced polymer (FRP) made from carbon, glass, aramid, or other high performance materials embedded in polymeric matrices in the form of bars, tendons, and strands are being produced and used.

4.3 Applications in Modeling Compressive Strength of Rubberized Concrete

The waste material rubber from scrap tyres is used in rubberized concrete. This can affect the unit weight and compressive strength of concrete and is used in pavements, sidewalks and sound barriers. The results indicate that back-propagation neural network have the ability to predict the strength of rubberized concrete with an acceptable degree of accuracy in comparison to Multiple Linear Regression (MLR) model. The ANN methodology proved to be an accurate and quick tool for estimating the compressive strength of rubberized concrete.

4.4 Applications in Modeling Compressive Strength of Concrete containing Meta Kaolin and Silica Fume

Meta kaolin (MK) is a thermally activated alumino-silicate materials obtained by calcining kaolin clay within the temperature range 650-800ºC. Silica fume is a byproduct of manufacture of silicon and ferrosilicon alloys. MK and FK act as mineral admixtures in combination with a super plasticizer and produce a high performance, high strength, dense and impermeable concrete and reduce the cement content in concrete production. The ANN predicted values were found to be very close to the experimental results and therefore proved the complex, non-linear functional modeling ability of neural networks. Conventional concrete can be designed for achieving strength upto 50 MPa. In contrast High strength concrete (HSC) having compressive strength up to 100 MPa can be design to cater to specific construction requirement. The main advantages achieved using HSC are high performance and uniformity in comparison to conventional concrete. The concrete is characterized by a superior level of workability and strength and uses chemical and mineral admixtures that reduce the water cement, thereby reducing porosity.

4.5 Miscellaneous Applications in Modeling Compressive Strength of Concrete

The neural networks consisted of eight input neurons namely, class of cement, fine sand/m3, coarse sand/m3, fine aggregate/m3, coarse aggregate/m3, cement/m3, water-cement ratio and plasticizer. The compressive strength was modeled as the output neuron. The fineness modulus of sand should prominent effect on compressive strength of concrete in comparison to the sand/aggregate ratio. It was presumed that this quick method of predicting 28 day compressive strength can be helpful to a vast community associated with concrete and construction activity.

The ready mix concrete (RMC)[13] mix proportion data from two companies were used for the study. The validity of the neural network model was proved by comparing the predicted values with experimental compressive strength.

The inputs to the neural networks comprised of cement, water, silica fume, super-plasticizer, fine aggregate and coarse aggregates and 28 day concrete strength formed the neural network output.

The results showed that trained ANN can recognize the concrete strength with a confidence level of about 95%, which denotes significant accuracy of the network.

5. CONVENTIONAL STATISTICS

5.1 Analysis of variance

The analysis of variance method deals with multiple sample averages. It is a statistical hypothesis test with desired risk factor for comparison of multiple distinct data sets. A confidence level of 95% was adopted for the present experimental programme. The least squares approach is adopted in the ANOVA [14]method. The ANOVA method is applied to the test results of normally compacting concrete (NCC) and self compacting concrete (SCC) for different curing periods. The F-ratio highlights existence of any significant difference of sample averages of two sets of test results for different curing ages and concretes. In the present analysis ANOVA provides significant insight into the comparative strength development pattern of NCC and SCC.

5.2 Signal to noise ratio

Signal to noise ratio is a measure of variation present in a set of test results. By evaluating the amount of variation present in a response quantity, factors contributing to variation can be diagnosed. Thus control factors can be identified for further improvement of quality.

5.3 Monte Carlo Simulation

In any physical experimentation the availability of test samples is limited. This is due to the inaccessibility of test location or the robustness of the testing procedure or the cost involved. Success of any statistical procedure depends on the adequate sample size without which the output of any statistical process is unreliable. Thus a practical way to apply any statistical procedure on a set of test results with low sample size is to expand the set for generating adequate sample size without compromising basic physical properties [15]of the test results. A suitable approach is the expansion of the set of test results to larger sample size following the experimental distribution pattern.

The Monte Carlo simulation technique is employed here to generate simulated data of higher sample size for further statistical analysis. The simulation technique adopted does not require the knowledge of the type of distribution followed by the experiment results. But the simulated data set follows the same distribution pattern (known or unknown) as that of the test results. This can be achieved by inverse transformation of uniform random variants on the experimental numerical cumulative probability density curve. The simulated test results follow the same probability distribution as that of the experimental distribution. Statistical analysis performed on this simulated results provides reliable performance parameters.

6. CONCLUSION

Cement Concretes composite nature has always been a challenge to the researcher with regard to modeling its properties, namely, compressive strength, tensile strength, slump etc., based on its mix proportions. The solution to such unstructured problems lies with nature inspired soft computing tools.

ANN inspired by the working of a human brain, can learn from past examples and derive meaningful explanations to the unstructured problems. The review paper has extensively dealt with the ANNs ability to model the compressive strength of concrete.

The network model has been trained using 87 sets of examples obtained from experimental results. The training examples are so chosen that they will cover all variables involved in the problem. The weights for network have been obtained using genetic algorithm. The network could learn the prediction of strength properties with just 1400 iterations .After successful training GANN model is able to predict the outputs of SFRC satisfactorily for new problems with an accuracy of about 95%. Thus it is concluded the neural network model can serve as macro mechanical model for predicting strength properties of SFRC.

The new method has further potential to design more accurate testing programme for better test results. The method can be tested further before widespread application in scientific experimentation.

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