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Soft Computing and Regression Models for Compressive Strength of BFS and SP Mixed Concrete

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Abstract––*This research is prepared with a notion that it will encourage the use of soft computing methods in the field of concrete technology since these methods are being extensively used in many field of engineering now a days. Concrete mix design calculation was carried out for blast furnace slag and super plasticizer mixed concrete. Compressive strength was determined by casting cubes in the laboratory. Hence, the mix design calculations and experimental set up yielded set of variables viz. cement content, water content, super plasticizer, coarse aggregate, fine aggregate and curing period. Using these variables as inputs and compressive strength as target, two different soft computing methods, Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) were employed to understand the nonlinear pattern between concrete mix design data and corresponding compressive strength. Later on, multiple linear and nonlinear regression analysis was also carried out for comparative performance. Compressive strength was satisfactorily modeled with given set of variables using ANN technique.*

Keywords -Blast Furnace Slag, Super Plasticizer, Artificial Neural Network, Adaptive Neuro Fuzzy Inference System, Regression Analysis.

1. INTRODUCTION

A suitable value of compressive strength of concrete is the primary and most important requirement of hardened concrete to ensure satisfactory performance under service load. However, binding capacity, strength and workability of conventional concrete is often below expectations. To overcome this problemuse of admixtures in concrete are encouraged. Mineral admixtures increases the binding capacity of concrete (Huang et. al, 2013 and Nath&Sarker, 2011). In addition, chemical admixture are used to increase the workability of concrete (Elsageer et. al., 2009 andJatale et. al., 2013**)**. Hence, this study takes into account the use of Blast Furnace Slag (BFS) and Super Plasticizer (SP) into concrete mix.

Variation in behavior of conventional concrete materials and admixturein different places, vagueness in design parameters like workability, shrinkage of cement and shape of aggregate causes substantial imprecision in the design strength even though quite a lot of care had taken in the calculation of design mixes and subsequent preparation of laboratory samples. Casted cubes takes several days in curing. Soft computing methods can offer a ground to overcome the difficulties involved in standard design mix process and save time involved in curing.

This research paper is prepared to examine the feasibilityArtificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) in determining the concrete compressive strength. Two regression analysis were also carried out to compare the results of ANN and ANFIS models with the regression models.

2. ARTIFICIAL NEURAL NETWORK

A large number of interconnected processing units (also called as neuron) working on the principle of biological neuronal cell is called as Artificial Neural Network (Goh, 2002).Function and structural aspects of ANN is same as a bunch of biological neurons. ANN is advanced and standard tools to find solutions to a wide variety of non-linear statistical data complications (Hanna et. al., 2007).Interconnections among neurons are established by weights. The ANNs are arranged in three or more layers (depending on number of hidden layers). The very first layer is input layer, second layer is hidden layers and last layer is target layer. Each layer of neurons has connections to all the neurons in next layer. Each neuron receives an input signals from the previous neuron. Each of these connections has numeric weights associated with it. Figure 1 shows the simplest form of ANN.

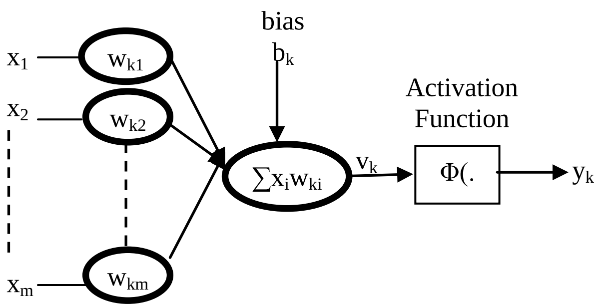

Figure 1 simplest form of ANN

Where x_1, x_2, …,x_m are input signals; w_{k1}, w_{k2}, …., w_{km} are synaptic weights of neuron k; u_k is the linear combiner output; b_k is the bias ;φ (.) is the activation function; v_k is the induced local field or activation potential; and y_k is the output signal (Haykin, 2006).

3. NEUROFUZZY INFERENCE SYSTEM

There are various categories of neurofuzzy system which is essentially an integration of ANN and Fuzzy logic. However Adaptive Neuro-Fuzzy Inference System (ANFIS) which was originally proposed by Jhang, 1993 is frequently used due to its simplicity and vast applicability. Fuzzy inference systems are mainly composed of a rule base, a database and a decision making unit(Habibagahi, 2002). The steps of FIS consist of fuzzification, allotment of membership grade, rule base development by employing if, then reasoning and finally defuzzification i.e. fuzzy set into crisp set. This is how an input variable x is fuzzified to be a partial member of the fuzzy set A by transforming it into a degree of membership of function $\mu\ _A(x)$ *of interval (0, 1)(Shahin et.Al., 2003).* A typical ANFIS structure containing zero order and first order Takagi-Sugeno-Kang (TSK) model are shown below (Figure 2 & 3).

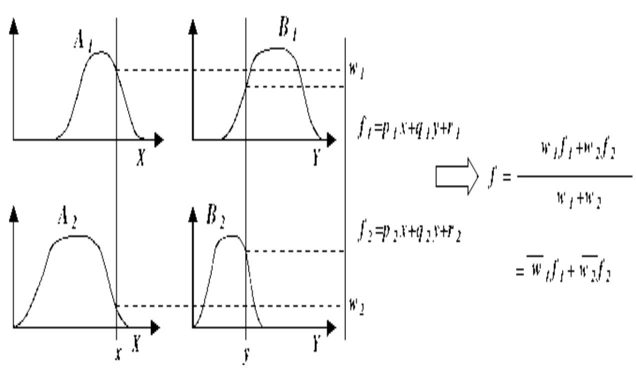

Figure 2: Sugeno method of fuzzy inference system

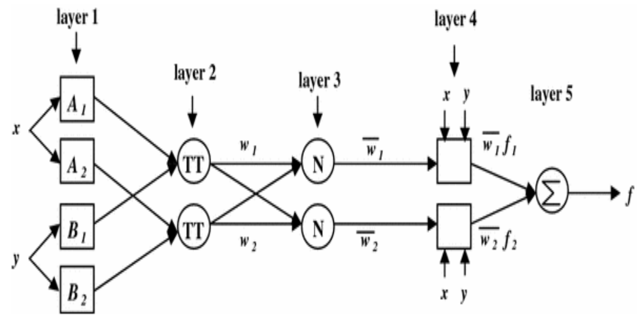

Figure 3 Architecture of ANFIS model in conjunction with Sugeno FIS

A typical rule in a Sugeno fuzzy model has the form, if input $x = A_1$ and input $y = B_1$, then output is given as $f_1 = p_1x + q_1\ y+ r_1$. For a zero-order Sugeno model, the output level $f_1$is a constant *(p_1= q_1 =0).Likewise*,If input $x = A_2$ and input $y = B_2$, then output is given as $f_2 = p_2x + q_2\,y+ r_1$. For a zero-order Sugeno model, the output level $f_2$is a constant *(p_2= q_2 =0). But if output f_1,f_2* are linear then we have first order TSK fuzzy inference system. The output level f_i of each rule is weighted by the firing strength w_i of the rule. For example, for an AND rule with input $x = A_i$ and input $y = B_i$, the firing strength is

$$w_i = \textit{And Method } \{\mu\ A_i(x),\ \mu\ B_i(y)\},\ i=1,2 \quad (8)$$

Where, $\mu\ A_i\ (.)$ *and* $\mu\ B_i\ (.)$ are the membership functions for inputs 1 and 2. The final output of the system is the weighted average of all rule outputs, computed as shown in Equation 1 below

$$\text{Overall output} = \sum_i \bar{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (9)$$

4. DEVELOPMENT OF CONCRETE MIX DESIGN DATA

The concrete mix data used in this research paper was developed in laboratory by casting cubes of Blast Furnace Slag (BFS) and Super Plasticizer (SP) mix concrete. BFS and SP were used as partial replacement of cement and water respectively. Total 170 samples of cubes were casted to carry out compression test. The discussion on properties of BFS and design mix calculations are avoided here due to limitation of space. The compression testing machine was used to break the casted cubes of concrete for curing period of 3, 7, 28, 56, and 91 days. In this manner,seven variable data matrix was prepared from BFS and SP mixed concrete. These variables were cement content (CC), water content (w), coarse aggregate (CA), fine aggregate (FA), BFS, SP and curing period (CP).These seven variable were taken as input in both soft computing methods. The concrete compressive strength (CCS) obtained from compression test was taken as target parameter in both methods.

A typical representationof above discussed variables is given in Table 1. Serial no. 1 – 6 in this table illustrates the ranges of each components of concrete in Kilograms in one m^3 mixture of concrete.Serial no. 7 (curing periods) and 8 (Concrete Compressive Strength) are in days and MPa respectively. 145 datasets were used to develop the soft computing and regression models and remaining 25 datasets were reserved to validate the models.

Table1-Range of input and target parameters

Sr. No	Input Parameters	Min	Max
1	Cement Content (CC)	133.00	475.00
2	Blast Furnace Slag (BFS)	50.00	282.80
3	Water content (w)	126.60	214.00
4	Super Plasticizer (SP)	2.00	32.20
5	Coarse Aggregate (CA)	811.00	1134.30
6	Fine Aggregate (FA)	605.00	992.60
7	Curing Period (CP)	3.00	91.00
8	Concrete Compressive Strength (CCS)	18.28	82.60

5. ANN ATTRIBUTE AND ARCHITECTURE

As discussed in previous articlesback-propagation neural network (BPNN) was employed for all kind of operations. Training in BPNN is carried out through the minimization of the defined error function using the gradient descent approach (Chua and Goh, 2003). There exists many ways to improve the rate of convergence one of them is normalization, therefore datasets were normalized using following equation (Rafiq et. Al., 2001,Kayadelen, 2008 and, Gunaydım, 2009).

$$U_{normalized} = \frac{U_{actual} - U_{min}}{U_{max} - U_{min}} \quad (10)$$

The ANN toolbox inMATLAB (R2010a)computer added software was utilized to perform the necessary computation in which learning rate (LR) and momentum term kept constant whereas connection weights kept adjustable for all the models. ANN network architecture with a hidden layer (ten number of neurons in hidden layer) is shown in Figure 4. It describes the way the network was treated from given set of input and target parameters.

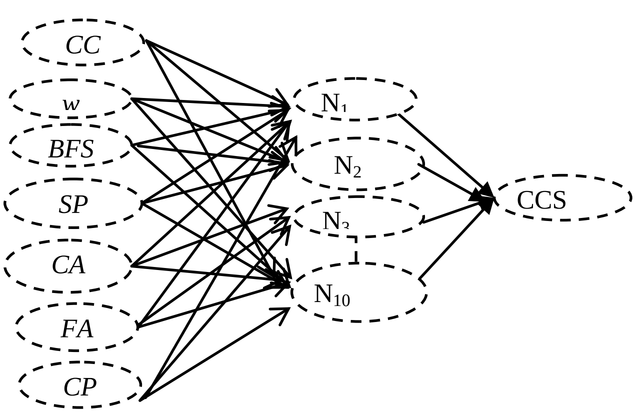

Figure 4 ANN network architecture

6. ANFIS ATTRIBUTES

Subtractive clustering was used with hybrid optimization to generate ANFIS models. Hybrid optimization is a combination of least-squares and back propagation gradient descent method. Training was carried out for fifty iterations only since more iterations results over-fitting in training output and FIS out.

7. RESULTS AND DISCUSSION

The best validation performance was obtained at MSE of 0.0043939 at second number of cycle(Figure 5).

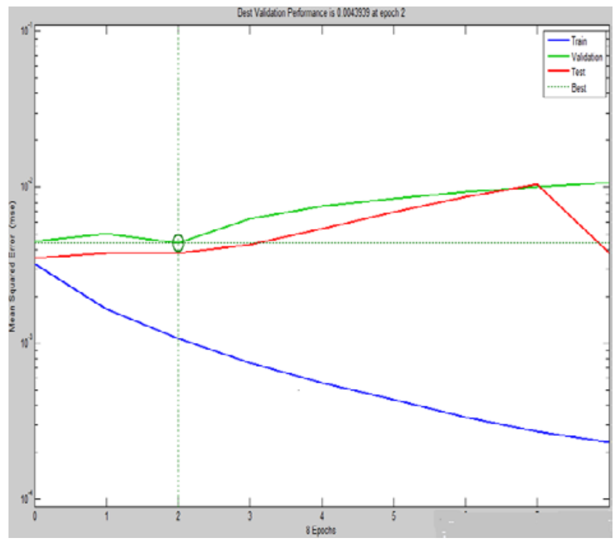

Figure 5 MSE plot from ANN model

Figure6 shows continuously decreasing trend of mean squared error in ANFIS model. Error was decreased to a value of 0.0182393 which is highercompared to ANN. This indicates improper training and it may yield in poor predictability. Total sixteen number of fuzzy rules were developed after minimization of error.

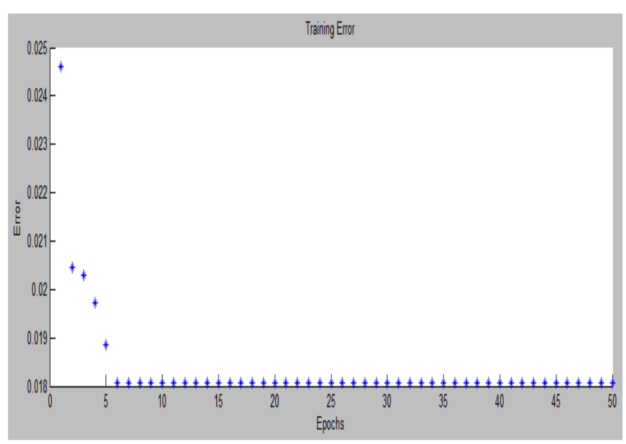

Figure 6Training error in concrete ANFIS model

Figure 8a & b shows coefficient of determination obtained fromANN and ANFIS models respectively. The R^2 was 0.8275 for ANN model. Contrary to ANN models, the performance of ANFIS model got declined giving R^2 = 0.4886. The higher performance of ANN model may be attributed to higher number of inputs. However, same could be the cause of underperformance of ANFIS that is it don't work well with higher number of inputs. Poor predictability also depends on several other factors also like nature of input and validation data, optimization of fuzzy rule bases and training parameters.

Concrete compressive strength (CCS) of BFS and SP mixed concrete was selected as dependent variable in multiple linear regression (MLR) and multiple nonlinear regression (MNR) analysis. Dependent variables were same as input in case of soft computing models. The SPSS 20 statistical software was used for developing regression models.

The multiple linear equation obtained from MLR analysis is gives as:

CCS = 0.696+ (0.439**cc**) + (0.296**BFS**) - (0.636**w**) - (0.375**SP**) - (0.378**CA**) - (0.434**FA**) + (0.499**CP**) (11)

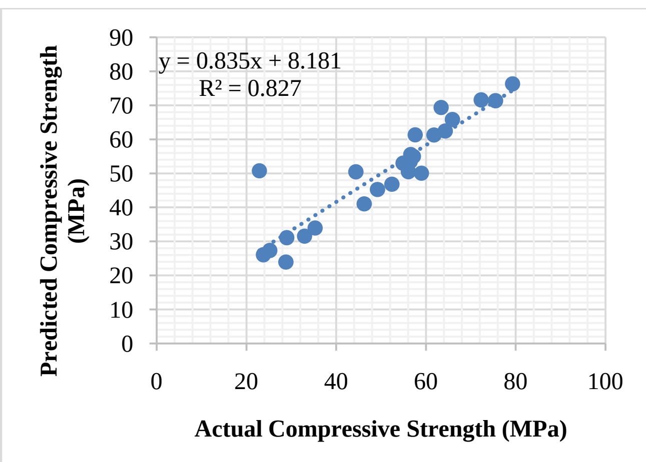

Figure 8a ANN Prediction for BFS & SP Mixed Concrete

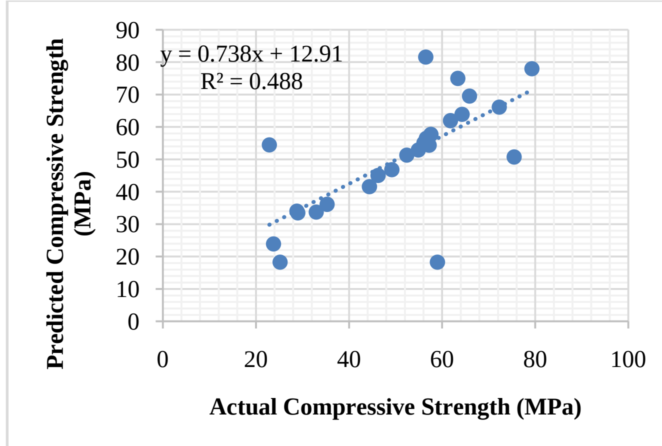

Figure 8b ANFIS Prediction for BFS & SP Mixed Concrete

The values of gradients and intercept obtained from regression analysis are shown in above equation. The R^2 obtained from compressive strength yielded by this multiple linear equation and actual compressive strength was 0.5885 (Figure 9a). Multivariate power equation was adopted for MNR analysis. Same set of independent and dependent variable yielded following multivariate power function

$$\mathbf{CCS} = 2.032895\,\mathbf{cc}^{0.864565}\,\mathbf{BFS}^{0.476152}\,\mathbf{w}^{-72.328}\,\mathbf{SP}^{-0.06611}\,\mathbf{CA}^{-0.1991}\,\mathbf{FA}^{-0.048406}\,\mathbf{CP}^{0.215445} \quad (12)$$

This MNR model yielded R^2 = 0.7354 (Figure 9b) which is higher than R^2 obtained from MLR analysis. It shows that multivariate power equation can model concrete compressive strength better than multiple linear equation. Overall it can be observed that soft computing method may satisfactorily model concrete compressive strength by offering favorable conditions to them.

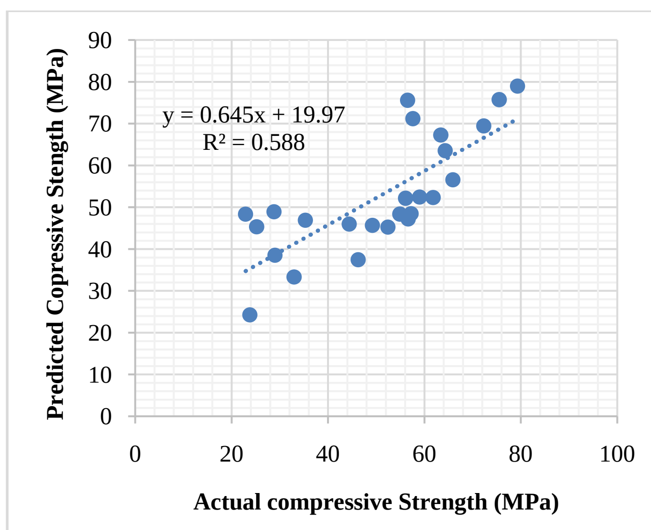

Figure 9a MLR Prediction for BFS & SP Mixed Concrete

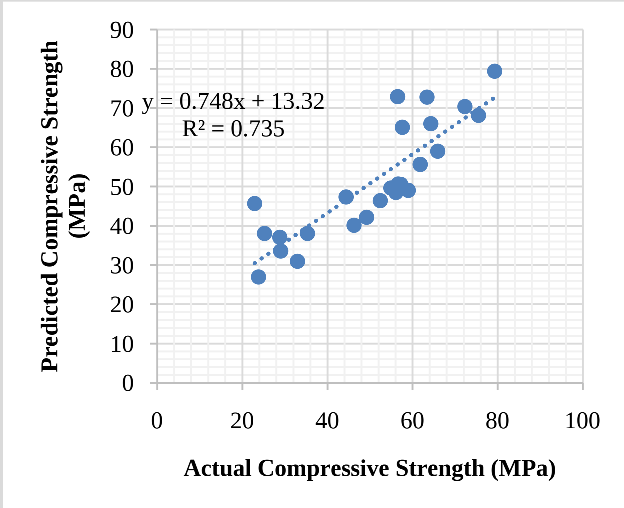

Figure 9b MNR Prediction for BFS & SP Mixed Concrete

8. CONCLUSIONS

The study was carried out to test the ability of soft computing methods in determining concrete compressive strength. Based on obtained results it was concluded that higher number of inputs decreased training error considerably in ANN modeling. Hence, ANN models with seven input variables gave good performance evaluation measure. Contrary to ANN model, performance of ANFIS was severely affected due to higher number of inputs. Hence, ANFIS model can be further examined when number of inputs are less. Another important conclusion drawn from regression analysis is that multivariate power regression equations have far greater ability to work with higher number of data matrix. However, multiple linear regression was not found suitable for modeling compressive strength.

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