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Prediction of Compressive Strength of Conventional Concrete using Various Correlation Techniques between Destructive and Non Destructive Test Results on Concrete

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Abstract: To calibrate material properties destructive techniques as well as non destructive techniques mainly ultrasound pulse velocity (UPV), rebound hammer (RN), combined use of ultrasonic pulse velocity tester and rebound hammer (SonReb), Windsor probe penetration test etc. are frequently used to combine. For these purpose different mathematical models designed with the combination of NDT techniques. From last few decades data training method such as response surface, artificial neural network, least square method, fuzzy logic, M5 methods are popular. This review work presents the regression techniques proposed by various authors to estimate compressive strength by correlating destructive and non destructive test results on concrete.

Keywords: Correlation techniques, NDT, Response Surface, Artificial Neural Network, Least Square Method, Fuzzy Logic

INTRODUCTION

Non destructive tests have been in use for many years now for estimating the compressive strength, concrete quality and other parameters of concrete. The proximity of their results to values obtained by destructive tests shows the reliability of these methods. In absence of destructive test values, the values of compressive strength of concrete are obtained from available correlations between the destructive and non-destructive test results. Various methods have been used for the correlation work by several researchers. Some methods are described below.

1. Polynomial Response Surface Methodology (PRSM)

PRSM observed non linear theoretical assumption among the variables.
The output parameter (response y) is a function of input parameter (x); which is defined as $y= x.\beta+\varepsilon_y$ …… (1) Where β is unknown coefficient vector and ε_y is error vector.
The quadratic polynomial as follows
$Y= \beta_0 +\sum_{i=1}^{k}\beta_i x_i + \sum_{i=1}^{k}\left(\sum_{j=1}^{k}\beta_i x_i x_j\right)$……….(2)
Errors minimize by using least square method (LSM)
$e(\beta)= \sum_{i=1}^{n}\left[yi - \beta 0 \sum_{i=1}^{k}\beta_i x_i - \sum_{i=1}^{k}\left(\sum_{j=1}^{k}\beta_i x_i x_j\right)\right]^2$ ………(3)
$= (y=x\beta)^T (y\text{-}x\beta)$
Values of unknown coefficients can find by equation 3
$\beta= [x^T x]^{-1} \{x^T y\}$
The success of this approach is based on proper selection of initial input data (x, y).
Box and Wilson were the first to propose polynomial response surface methodology (PRSM) based on mathematical and statistical approach. Bucher, C.G. & Bourgund, U., (1990) suggested interpolation technique with basic variable mean values and standard deviation in response surface (RS) method to increase efficiency and accuracy.
Rajashekhar, M.R. & Ellingwood, B.R. (1993) with the help of numerical examples showed the methodology of response surface (RS) method, and applied polynomial approximation instead of high computational cost acquired in structural analysis.

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Kim, S.H.& Na, S.W. (1997) proposed sequential response surface method. The control range of sampling points was selected and reduces error in approximating appeared by non linear limit state with help of linear response surface.
Moodi, Y. et al. (2018) used response surface methodology with modified model based on whale algorithm for determining the compressive strength of confined column by fiber reinforced polymer (FRP).
Poorarbabi, A. et al. (2020) used response surface methodology (RSM) to determine the compressive strength and provide the correlation between rebound hammer (RN) and UPV from the proposed equation and response surface model. The models provided on the experimental data at different ages for estimating compressive strength using UPV and RN tests. The accuracy of response surface model is not influenced by age of concrete specimen. The proposed model are listed below in Table 1.

Table 1: Models establishing correlations between UPV and RN
Source: Poorarbabi, A. et al. (2020)

Models	**Equations**
Power- power	$F_c= a(UPV)^b (RN)^c$
Bilinear	$F_c = a+ b(UPV)+ c(RN)$
Double exponential	$F_c= a \exp (b(UPV)) \exp(c(RN))$
Linear logarithmic	$F_c= aLn(UPV)+ bLn(RN)+c$

2. ARTIFICIAL NEURAL NETWORK (ANN)

ANN Process is based on principal of biological neuron connect to brain. It is simple analogy between the biological and artificial neuron. And the neural network is composed of connection of layers (consisting nodes). It is a multi-layer model in which each layer is connected to next layer. Its layers have interneuron (processing element) connection that stores the input knowledge. Each node of processing element is nonlinear function except input node. The performance of ANN is chain process, input layers get the information from input data and the hidden layers perform necessary calculation to achieve desired output. Useful properties of ANN are multi-layer input output mapping, non linear activation function, flexible and automatic adoption of complex data for their training.

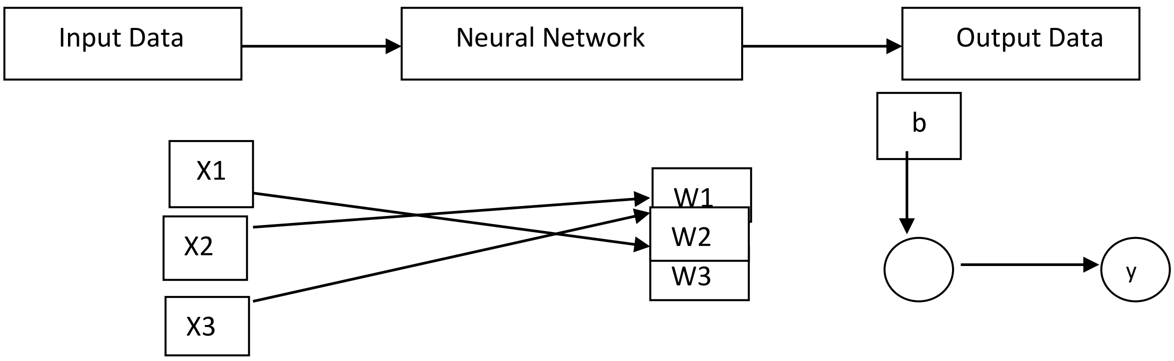

Fig: 1 Architecture of single layer Artificial Neural Network

Source: Faruqui N. (2017)
Suppose x_1, x_2, x_3 input signals with w_1, w_2, w_3 their corresponding weights are entering to the node. And 'b' bias is associated with storage data. The input signals are multiplied by their corresponding weight before entering the node.
$v= w_1 x_1+ w_2 x_2+ w_3 x_3+ b$
$= w*x+b$ ……………..(4)
Or we can write the equation in matrix form

$W= [w_1\ w_2\ w_3];\quad x= \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$ ………………(5)

output $y= \varphi(v) = \varphi(w+b)$………………..(6)
We can say that neural network stores the information in the terms of weights. If desired to enter additional information weight has to be modify. This way of modifying the weights is called learning rule.
Error e_i = corrected output (d_i) - output $(y)_i$……………(7)
Updated weight
$w_{ij} \leftarrow w_{ij} + \alpha e_i x_j$ …………(8)

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where x_j output from jth node , e_i error of node 'i', α is learning rate value between 0 and 1.

$w_{ij} \leftarrow w_{ij} + \alpha\delta_i x_j$ ………………(9)

e_i is replaced by delta 'delta i' this is called generalize delta rule.

$\delta_i = \varphi'(v_i)\, e_i$............................(10)

v_i= sum of output weights at 'i' node.

$\varphi' = \frac{d(\text{activation function})}{dx}$ ……………(11)

'S' shape sigmoid curve is produce by mathematical logistic function used as activation function.

$\varphi(x) = 1/(1+e^{-x})$ ……………………….(12)

from the equation 11

$\varphi' = \varphi(x)(1- \varphi(x))$…………………..(13)

put φ' value in equation 10

$\delta_i = \varphi(v_i)(1- \varphi(v_i))\, e_i$....................(14)

Twomey, J.M. and Smith, A.E. (1999) reviewed the theory of artificial neural network is based on one or more error matrices such as root mean square error, mean absolute error, mean square error. ANN model constructed from trained data and validation of this data based on one or more selected error matrices.

Prasad, R. et al. (2009) applied ANN for finding the regression between 28 days compressive strength and slump value of both SCC and HSC.

Erdal, M. (2009) developed correlations between rebound number R and UPV (V) to determine compressive strength of concrete, for vacuum processed concrete under 40 MPa by using artificial neural networks. He gave polynomial equations for the same.

Gupta, S. (2013) used artificial neural network (ANN) back propogation technique to determine compressive strength of conventional concrete with nano- silica. She collected 32 data samples for large variety of input and output data. With the ANN algorithm, 28 days compressive strength was developed. Statistical values (correlation coefficient, root mean square and mean absolute error) were also calculated.

Shih, Y.F., Wang, Y.R., Lin, K.L. and Chen, C.W., (2015) provided an alternative regression approach to improve concrete compressive strength; this research is incorporated with an artificial intelligence method i.e. support vector machines (SVMs), linear regression with two variables is also obtained to compare SVMs values and values obtained from mean absolute percentage error (MAPE).

Huatangari, L.Q. et al. (2021) proposed five artificial neural network models with feedforward, multilayered architechture methedology and back propogation to determine compressive strength for three mixes. The success of ANN is effecting by selection of data, learning, training and validation. Excel software used collections of data and MatlabR2017 used for learning, training and validation. Result showed that ANN05 was close to real result, R-square value 0.968 with significance of 4%.

3. ORDINARY LEAST SQUARE REGRESSION (LSR)

The principal of LSR depends on residual value and dependency of variable on each other. If there is no relationship between two variables than variability of residual value to the original variance is equal to 1. If variables are perfectly related then no residue will be found and ratio of residual variability to the original variance would be 0. Coefficient of determination or R^2 defines as 1 minus ratio of variance. R^2 value shows compatibility of model with data.

Nash't (2005) developed the correlation for M15 to M25 grade concrete between rebound number and compressive strength using a power equation; for UPV and the compressive strength using exponential equation. The regression analysis process was done by using STATIATICA version 5.5 pc software depends on least square theory.

Mulik Nikhil V., Balki Minal R., Chhabria Deep S., Ghare Vijay D., Tele Vishal S., Patil S., (2015) applied the exponential SonReb equation for concrete grades M15-M40, with the help of MS Excel, for calculating compressive strength from ultrasonic pulse velocity and rebound number values.

Uniyal, S. and Sethy, S., (2017) expressed separate polynomial correlation equations for M20, M25, M30 and M35 between rebound number and compressive strength at 7, 14 and 28 days.

Kolay, P. (2020) casted cylindrical samples of three design mixes with their target strength of 41, 55 and 83 MPa. Samples were cured under laboratory condition and tested after 28 days of curing. The effect of moisture on UPV and RH readings were also studied. The correlation curve and multiple regression equation were obtained by combining the results from UPV and RH using spread sheet. The linear equations developed relationship between compressive strength, UPV and RH readings using nomogram (3 D figure).

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4.FUZZY LOGIC

Fuzzy logic (FL) divided data into two sets that are fuzzy sets and subsets. This process is carried out in three stages. First stage is fuzzification in which input data converted into linguistic value. In next stage membership degree is determine by using membership function and in last stage output is produced by rule "if and then.. else" with the connection of input output data.

Erdal, M. et al. (2009) developed fuzzy logic model to determine compressive strength non destructively and results obtained by model compared with multi-linear (ML) regression model and experimental data. The statistical values R^2 =0.942, 0.912, RMSE= 0.590, 0.637, MAPE= 1.592, 1.726 from FL model and for ML respectively these values showed that FL performed better than the ML.

Golashani, E.M., Rahai, A., Sebt, M.H., Akbarpour, H. (2012) developed the fuzzy logic and artificial neural network model to determine bond strength of spliced steel bar in concrete and compared the results of proposed model.

CONCLUSIONS

Correlations of non destructive and destructive test results have been used for estimation of compressive strength by means of application of Artificial Neural Network (ANN) through single and multilayered perception, RS, FL and other models. In ANN, results obtained from equation with more number of variables performed better than single variable equation. ANN has better predictive results than regression equations. The success of ANN is affected by selection of data, learning, training and validation. If we compare both response surface (RS) and ANN models methodology in terms of errors, the results reflect that trained ANN model predicts more accurate results than the RS. RS is not influenced by age of concrete specimen while other models are sensitive to age. The past researches showed that error is minimized by selecting proper error matrices. Percentage of R square is a representative of variability around regression line. As we implement ANN, RS and FL model on same data and determine R square values, researchers graded the performance of ANN to be highest in comparison to FL and RS methods of correlation.

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