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Research Paper

A Review on Prediction of Strength of Concrete Using Artificial Neural Networks And Machine Learning

Vajji Karthikeya[1]; Pusarla Geetha[1]; Shaik Firoj Vali[1]; Venkumahanti Tanusha[1]
Department of Civil Engineering, GMRIT.
Rajam, 532127.

ABSTRACT:
From several decades research has been going on to develop prediction models for predicting strength of concrete. The prediction models developed well and giving accurate results with minimum error when compared to past models. This study works on prediction of concrete strength using various models of Artificial Neural Networks (ANN) and Machine Learning (ML). Various algorithms/methods are used for prediction of concrete strength like Response Surface Method, Gene Expression, linear Regression, etc. The input data used is mix proportion, water-cement ratio, aggregate type, curing time, etc. By using Neural Networks and Machine Learning algorithms we can predict concrete strength more accurately and maximum average error did not exceeds 10% of test results.

KEYWORDS: *compressive strength, neural networks, machine learning, Fire fly algorithm.*

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I. INTRODUCTION:

Concrete play vital role in construction field in terms of constructing variety of structures and providing various strength parameters to the structure. Before going to construct any structure it's necessary to predict the strength parameters of concrete in order to get more safety. For prediction of strength properties concrete accurately we have to replace with the new methods in place of conventional methods. So, we adopt new models of Artificial Neural Networks (ANN) and Machine Learning (ML) such as Linear regression, Non-linear regression, Response Surface Method,Gene Expression and so on. These models are developed using MATLAB, Kubeflow, Python Programming, R-Programming, etc.The models used for prediction are explained below

Linear Regression:

Also called simple regression ,linear regression establish the relationship between two variables. Linear regresson is graphically depicted using a straight line with the slope defining how the change in one variable impact a change in other [10].

Non Linear Regression:

The non-linear regression is a form of regression analysis in which data is fit to model and then expressed as a mathematical model. If a regression of equation doesn't follow the rules for a non-linear model [10].

The best multiple regression model was deemed to be the Linear Regression Model because it has the highest AIC and a fairly low R^2.

1.$y = a + \sum_{i=1}^{k} \beta_i x_i$

2.y=$a + b(c)^c + \partial(FA) + F\left(\frac{\omega}{b}\right)^g + h(Fagg)^i + +j(c \cdot agg)^k + l(SP)^m + n(Days)$

Where, a is constant,

βi and (b-0) are coefficients

Xi (i=1,2, 3, . . .) represent a input parameters and y is output.

Response Surface Method:

The surface methodology explores the relationships between several explanatory variables and one or more responses variable. Response surface plots such as a contour and surface plots are useful for establishing desirable response values and operating conditions. The RSM is a sequential procedure, however the RSM is not the all and end all of optimisation [10].

$$Y = \beta + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} \beta_{ij} x_i x_j$$

Where, Y=is the response(output)

$\beta, \beta_i . \beta_{ii}\, and \beta_{ji}$ = are the constant, linear, quadratic and intersection coefficient

$x_i = are\ the\ independent\ variabl$e

Gene Expression:

Another name of Gene expression is Hyponym Gene expression is the process by which information from a Gene. Gene is used in the synthesis of a functional gene product that enable it to produce the product of proteins. Gene expression is tightly regulated process that allows a cell to respond to its changing environment [10].

$$\Delta CT = \Delta CT(a\ target\ sample) - \Delta CT(a\ reference\ sample)$$

$= (CT_D - CT_B) - (CT_C - CT_A)$

$$(C * FA) + (0.5 - sP)$$

Size Effect Model:

The size effect defined as a relationship between strength properties of the material and specimen cross-section and size effect mainly shows the failure loads permanent effect size. These means that the nominal strength tends to decrease with an increase in size for the concrete structure having identical geometric shape [2].

$$\sigma_{Nc} = B\sigma_0 (1 + d/d_0)^{-1/2}$$

$$\sigma_{Nc} = c_N \left(\frac{P_u}{bd}\right)$$

Where, d=characteristic dimensions,σ_0 =strength parameters

$B\ and\ d_0$=empirical constants

P_u =ultimate load

c_n=convenience coefficient related to loading

b=beam width

d=beam depth

Sensitivity and Parametric Analysis:

Sensitivity is a financial model that determines how target variables are effected based on changes in other variables is known as input variables. Then the mainly sensitivity analysis is find out the relative contribution of independent variable on dependent variables.

In addition of parametric analysis allow you to nominate parameters for evaluation, define the parameter range, specify the design constrain and analyse the result of each parameter variation [10].

$$N_i = F\, max(x_i) - F\, min(x_i)$$

$$s_i = \frac{N_i}{\sum_{j=1}^{n} N_i} \times 100$$

Where, $f_{max}\ and\ f_{min}$ =minimum and maximum predict output based on ith input variable

Stacking and Super Learner:

Stacking is to arrange things in an ordered pile, and also the stacking is a combined multiple classifiers or regression generated by different algorithms and it works at layers or levels. This stacking ensemble model can produce many different combinations using the various ML algorithms, and this study limited to super learner ensemble method [9].

$$Q_i = (xi, y_i)$$

I=1,2, 3….

$$\Psi 0(x) = E\left({}^{y}/_{x}\right)$$

$$x(x \in \dot{x})$$

$$\psi_0(k) = argminE[L(0, \Psi)]$$

Where, Y=vector input variable and outcome of variable
L=loss of function

Effective Crack Model (ECM):
The main thing is effective crack model for the determination of fracture and toughness of concrete. The effective crack refers to the mechanics of the solids containing planes of displacement discontinuities with this is attention to the special growth from cracks [6].

$$\delta_{\cup}=\frac{p_u}{4bE_{\mathbb{C}}}\left(\frac{s}{\sigma}\right)^3\left[1+\frac{5qS}{8Pu}+\left(\frac{d}{s}\right)^{2\left\{2.7+1.35\left(\frac{qS}{Pu}\right)\right\}}-0.84\left(\frac{d}{s}\right)^3\right]+\left(\frac{9Pu}{2bEc}\right)\left(1+\left(\frac{qS}{2Pu}\right)\right)\left(\frac{S}{d}\right)^2(F\alpha_e)$$

Where, Pu=peak load
δu=measurement displacement at the peak load

II. LITERATURE REVIEW:

The specimen was measured at 3,7,28 and120 days. Meanwhile the measurements of the ultrasonic pulse velocity (UPV) of the reference concrete and admixture concrete was conducted the same ages in keeping with ASTM C597. The propagation velocity of compressional waves in concrete was also measured as part of this test approach. The compressive strength of input and output parameters and range of actual values day-d actual value 3-120, cement (c)kg -minimum value 245-max 350-average 289.6 etc. Compressive strength was diminished due to fly ash (FA)substitution although at an early age there was significance of compressive strength, the gap diminished as curing period increased. The FA substitution level of 30% was associated with maximum decrease the BFS substitution PC at 15% level achieved the highest compressive strength and UPV at day 120. At early age compressive strength and ultrasonic pulse velocity (UPV) are minimal for every mineral admixture level, particularly in the case of Fly Ash (FA) sample. However, they both increased in every sample as a curing period increase.in other hand, the same mixture enhanced compressive strength and ultrasonic pulse velocity (UPV) values at the day 28 and 120 of the curing period [1]. And the compression strength tree visualised that is produced by the MP5.the compressive strength is predicted by using LM formula .in the compressive strength predict a calculated as 19.4Mpa by using of tables, and this result gives the 97% prediction success so the calculate compressive strength result can be calculated with$\pm$3% error rate. This prediction result, this prediction performance is also very high. In addition, this RAE value is about 23% and this value indicates that the average error is low. if MAE of compressive strength and ultrasonic pulse velocity (UPV) are compared, it Is seen that the RAE of UPV higher than the compressive strength [3, 10].

The compressive strength of concrete including PA decreased, that the reduction were 14,19,25, and 34% for 25,50,75 and 100% of PA respectively the concrete specimen heated to 100 to 700 degrees range lost some their initial strength by the increase temperature, but less strength loss was observed in the group that include more PA. The result indicates 400 degree temperature, all concrete specimens lost significance part of their compressive strength. the strength loss because of the dehydration of the hydrated calcium silicate and the thermal expansion of aggregate increase internal stresses and from 300 degree c. microcracks are induced through the material. if the target temperature is the most important parameter that the affects of compressive strength [5, 9].

And the flexural strength decrease with the increase of PA ratio. Evaluated temperature caused more significant decrease at 400degree c and above. The reason of the decrease after temperature can be explained with in the crack evolution by the effect of decrease is less in the high volume of PA group. This result shows the that PA is more resistant to evaluated temperature compared with normal aggregate, the artificial neural network (ANN) model, pumice aggregate ratio(%) and target temperature (degree c)symbolized input, and flexural strength symbolized the output [6].

The modulus of elasticity is used in the numerical analysis of concrete structures under dynamic loading conditions. they are static modulus(E_s) dynamic modulus is(E_d)and sustained modulus that accounts for the long-term creep effect of concrete. Among them the most commonly used is the static(E_s)that defines the stress -strain relationship for concrete under static load. this static(E_s)can also be referred to as the chord or instantaneous modulus of elasticity, by the comparison of dynamic modulus of elasticity (E_d) is the ratio of stress to strain under vibratory conditions and its key parameter of structural analysis of dynamic conditions like seismic loadings [3, 9].

The shear known as shear adhesion it refers to the ability of an adhesive to shear stress, the units that the newton per square meter, strengthening reinforced concrete (RC) elements critical to shear with prestressed transversal reinforcement be an efficient method to increase shear resistance [9]. When the shear failure occurs the where the beam has shear resistance lower than flexural strength and the shear force exceeds the shear capacity of different materials of the beam. artificial neural network (ANN), XGBoost (XB), Adaboost (AB), k-nearest nighbor (KNN) and cat-boost (CA) the input data was taken in the shear span to effective depth ratio, longitudinal reinforcement, fiber factor, fiber volume fiber aspect ratio concrete compressive strength the mainly validating boosts gives the experience than the other models [9].

III. CONCLUSION:

Nonlinear Machine Learning Algorithms can be useful tools for reliable prediction of different properties of concrete and reduce the number of such physical experiments.

Sensitivity analysis is technique to identify the contribution of input variables to the network performance. input variables are considered as the most important by the network and also the RMSE value can be calculated as 0.11.

The dynamic elastic modulus (DEM) optimal network was observed to have two inputs: one hidden layer with three neurons and one output layer.

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