Computing of Optimized Strength for modified Fine Fly Ash binder based High Performance Concrete.

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Abstract: To utilize the benefit of the Computational System for Ready-Mixed-Concrete Plant and to meet the increasing demand in the construction industries, it is vital to validate the Compressive-Strength of Concrete for Design Mix Ratio, before batching the concrete. Fine-Fly-Ash (FFA) is a waste from Coal Industries, which can be mixed partially with concrete to reduce the consumption of cement which ultimately reduces carbon footprint during the production of cement and it is economical in construction. Silica Fume (SF), reduce the porosity of concrete. Both minerals are served to increase in the durability. This work is optimized the method for prediction of robustness of the industry to reduce laboratory time. In this paper, Multiple-Regression (MR) and Artificial-Neural-Networks (ANNs) are developed and analysed. To develop these models, the data are collected from the experimental results. The experiments have been conducted at six levels by increasing the amount of FFA mixture with cement starting from 5 to 30 % with an interval of 5% and by increasing the amount of SF partially mixed with cement from 2.5% to 15 % with an interval of 2.5%. The Water and binder ratio is between 0.38% and 0.55%. 150 samples are observed with M20 and M25 grade of concrete. Observations are made at 2 levels of data for analysis purpose and it is denoted as MR1, MR2 and ANNS1, ANNS2 for MR and ANNS respectively and compared. Among the two models, ANNS is more reliable and possess higher degree of adoption than MR model.

1. Introduction
Versatile nature of concrete is the reason that it is the most widely used modern infrastructure material. These days mineral admixtures, which are squander side-effects of other assembling businesses are being utilized in making High-Performance Concrete (HPC) a substitute for either concrete or fine total and making eco-accommodating and maintainability of the Environment [1 - 4]. Fine powdered Fly-Ash (FFA) and Silica Fume (SF) are discarded by-product obtained from Coal Industry. These products can be mixed with concrete to increase the recital of concrete and also to improve the economy of concrete [5,6]. Its common in practice that micro fillers are nano fillers are used in modifying the mechanical properties of the materials. UFFA is a finely divided siliceous reactive mineral admixture having the property of pozzolanic and cementitious while SF is an inert mineral, which is added as filler having no pozzolanic or cementitious properties [7 – 10].
In model generation methods is Multiple Regression, which is the simple predictions. The precision of the model can be accomplished by Multiple-regressions (MRS). For complex data prediction are done by Artificial Neural Networks(ANNS) adaptive neuro fuzzy inference systems factorial design genetic based algorithms, model tree [11 – 14]. In above mentioned methods MRS and ANNS are employed in this research paper. ANNS is used to find out the strength of the experimental results. In this study, the materials of mix are the separate variables and while the 28 days compressive strength(CS) of Concrete is dependent variable [15,16].

2. Materials for Experiments
In this experiments the materials Cement(C) , Fine Fly ash(FFA), Silica Fume(SF),Fineaggregate(FA), Coarse aggregate(CA) and water (W) are used with Indian specifications.

3. Data collection
Totally 150 samples of data arrived from experimental with different mix ratio. Here Cement is replaced with 0%, 5%,10%,15%,20%,25% and 30% FFA at different levels. Also cement in concrete is replaced partially with 0%, 2.5%,5%,7.5%,10%,12.5% and 15% of SF at different levels for M20 and M25 concrete. The ratio of W and C, 0.43,0.45 and 0.47 are used for M 25 of concrete and ratio 0.50,0.525,0.55 are used for M 20 of concrete. All the cubes are casted with 53 Grade of cement, Zone III FA and rounded CA. The potable water is used to mix the concrete and then curing is done for 28 days and then finally they are tested. The raw data for model generation includes the quantizes of C, FFA, SF, FA, CA and W and CS.

4. Methodology
Present study, MR and ANNS models are created. The description of each model is shown in Table 1.

| Type id | parameters | Samples Counts |
|---------|------------|----------------|
| TI      | Concrete Mix Contains FFA 0,15,20 & 25% and SF 0 to 15 % for M20 | 75 |
| TII     | Concrete Mix Contains FFA 0,15,20 & 25% and SF 0 to 15 % for M25 | 75 |

4.1. Multiple Regression (MR)
The MR has been carried out using MS Excel. According to the validation is based on the following methods (a) Determination coefficient ($R^2$), (b) Root Mean Squared Error (RMSE) , (c) Mean Absolute Percentage Error (MAPE)and (d) Durbin–Watson statistic(DWS) and the $R^2$ is calculated by Eq.(1) [15 -17].

$$R^2 = 1 - \frac{\text{Sum of squares of residuals}}{\text{Sum of squares of predicted value}} \quad \text{Eq. (1)}$$

In order to obtain a model which is not influenced by multi-co linearity the Durbin-Watson statistic should be between 1.5 and 2.5. Root Mean Squared Error (RMSE) (Eq. (2)) should be nearest zero to better result [17,18].
where, \( n = \text{count of samples} \).

MAPE is calculated by the Eq. (3):

\[
MAPE = \left( \frac{1}{n} \sum_{i=1}^{n} \left| \frac{ACST - PCST}{ACST} \right| \right) \times 100 \%
\]

Eq. (3)

The results are shown in Table 2.

### Table 2. Multiple Regression Analysis Result of Models

| Model id | \( R^2 \) | \( p \)-value | F-value | F-significance | DW-Statistic | RMSE | MAPE |
|----------|----------|--------------|--------|----------------|--------------|------|------|
| MR1      | 0.786    | 0.000        | 87.286 | 0.000          | 1.13         | 2.09 | 4.41 |
| MR2      | 0.752    | 0.000        | 71.744 | 0.000          | 1.15         | 2.81 | 6.55 |

4.2. Artificial Neural Network(ANNS)

ANNS has various algorithms to predict the artificial neural network [19 - 21]. In this Levenberg-Marquardt Algorithm and feed-forward networks are used to create ANNS models and results are shown in Table 3.

### Table 3 Result of ANNS models

| Model id | R    | \( R^2 \) | RMSE | MAPE | DW Statistic | Epoch |
|----------|------|----------|------|------|--------------|-------|
| ANNT1    | 0.99 | 0.980    | 0.64 | 1.14 | 1.89         | 36    |
| ANNT2    | 0.99 | 0.977    | 0.84 | 1.89 | 2.24         | 41    |

5. Result and discussion

In this study 150 data are used to predict the MR and ANNS. It was noticed that, in contrast to the regression models, the \( R^2 \) obtained for all ANNS models are more than 0.96. This shows that these models can be acceptable in adoption. In this study, the RMSE values of those developed ANNS are 0.64, 0.84, while their MAPE values are 1.14 and 1.89. The Epoch are 36 and 41. And also ANNS Models satisfy the DWS as their values are 1.89, 2.24 which are in acceptable range of 1.5 to 2.5.

Fig. 1 shows that the comparison of \( R^2 \) MARTs and ANNTs. The \( R^2 \) of ANNT1 is maximum and it displays that the compressive strength prediction is good. The RMSE value and MAPE is must be minimum for correct prediction of the compressive strength. The Fig. 2 and Fig. 3 clearly shows that the RSME and MAPE minimum for ANNT1. The comparison of DW-statistic value is shown in Fig.4 and the optimum value for this statistic is 2 for correct prediction. SO, the DW-statistic of ANNT1 is near by 2 and it is the correct prediction of the compressive strength.
6. Conclusion

The experiments have been conducted at six levels by increasing the amount of FFA mixture with cement starting from 5 to 30% with an interval of 5% and by increasing the amount of SF partially mixed with cement from 2.5% to 15% with an interval of 2.5%. The Water and binder ratio is between 0.38% and 0.55%. 150 samples are observed with M20 and M25 grade of concrete. Observations are made at 2 levels of data for analysis purpose and it is denoted as MR1, MR2 and ANNS1, ANNS2 for MR and ANNS respectively and compared. Among the two models, ANNS is more reliable and possess higher degree of adoption than MR model. From the results observed from different types of MR and ANNS, every combination of two levels with different ratio of FFA and SF data have been computing and analysed with experimental results. Among two ANNS is better than the MR for this High Performance Concrete.
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