Predictive Models for Bond Strength of Reinforced Concrete with the Application of ANN

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Abstract. The bond strength of grip b/w steel and concrete can be defined as the resistant to separating concrete or mortar from the reinforced bar. This bond strength is the most critical characteristic of reinforced-cement concrete. Structural performance depends upon this characteristic, especially in the failure phase. Bond strength is primarily dependable on many variables that affect this attribute. These variables include the diameter of the reinforced steel bar, bond extent, length to diameter ratio, cube compressive strength, concrete cover, cover to diameter ratio, volume fraction and most importantly, different temperatures. Up to 150°C, there is no such change in bond strength of reinforcement concrete, but when the temperature rises beyond 150°C, it starts to decrease gradually. We have collected experimental data from the internationally published record. This study will see the change in bond strength at these temperature variations i.e., 200°C, 400°C, and 600°C. This observational study will represent a soft computing tool, i.e., an Artificial Neural network (ANN), to predict and measure the grip strength between concrete and steel bar at elevated temperatures. The bond strength of reinforced concrete has been predicted by using ANN Models. Data set based upon the different factor that affects the bond strength has been used as input for generating ANN model & ultimate bond strength of reinforced concrete has been used as output during the development of the ANN model. This model was then prepared to predict bond strength and affected by many input features and recorded a linear regression analysis. The predicted result then confirmed the accuracy and high estimation capability of the model.

Keyword: Artificial Neural Network (ANN), Bond strength, Regression Analysis

1. Introduction
Cement, aggregate, and water are the main constituent in the composition of Conventional concrete. Concrete has segregation and deformable property. Concrete is based on strength in compression as well as tension zone. It is necessary to ensure that the concrete will gain appropriate strength in 28 days [1,2]. So, concrete compressive strength has become the most reliable property on which a structure's safety will depend. Because concrete is also termed as a compression member means it gains high strength in the compression zone. For several years many researchers are keeping their focus on...
compressive strength of concrete. But in RCC (Reinforced cement concrete), we provide steel bars in their tension zone to make it more feasible; it will also show less deflection in the tension zone [3,4]. So, when we use steel in concrete, the grip by concrete to steel bars will be termed a bond strength. For bond strength, we test the grip of steel with concrete ultimately. RCC structure would have to go through with different environments. So, we know that reinforcement will behave differently at different temperatures. In RCC, the vulnerability of concrete is directly proportional to the temperature. Sudden increases in temperatures make the reinforced structure more vulnerable [5].

In high or elevated temperatures, concrete and steel's physical and mechanical properties are drastically and majorly affected. As well as the bond strength of that concrete also crucially decays with respect to time [6–8]. It became more dangerous when it is over-reinforced concrete. Because in over-reinforced section steel will behave like a rigid, sometimes concrete will deteriorate suddenly. Sometime when a fire leads to a building, the overall structural capacity will reduce because of sudden high temperatures. Because the bond created between concrete and steel will lose, there would be plastic deformation in the structure. Researchers have been setting up the overall concrete member for the last few decades and checking the effect on bond strength due to temperature variation to the standard reinforcement parameters [9–12].

We are using ANN to resolve this difficulty by implementing artificial intelligence in construction. With the supported assistance of ANN, we can reduce so many difficulties which we’ll face to achieve an ideal bond strength. Only the w/c ratio is not only responsible for achieving adequate strength. We need to keep our eyes on all the other aspects and standards of concrete. Because the proportion of every compound in a block of concrete is also significant and relevant to achieve a great bond strength.

For the last several years, our researchers and scientists related to the construction industry are trying to develop a prediction model mathematically and computationally. It will help to predict the composition of concrete. An interdisciplinary zone of artificial intelligence, will tie up with the worldwide infrastructure industry. It will help to lessen the stress of engineers who are trying to achieve adequate bond-slip strength experimentally [6–8,13–16].

Nowadays, ANN has become such a feasible and efficient way to resolve complexity in every field of engineering discipline. it can easily solve and analysis the data acquisition. The prediction of reinforced-cement-concrete bond strength has great implications. It is brisk and compatible because it would help to do an identical important modification in a parameter. The concrete would be unable to conquer the ultimate bond strength. Concrete is the material mainly used for the solidification of the structure. In today's time, ANN will become the prominent source to examine and predict the different properties of concrete without wasting any material and precious time. We have simple raw data of their previous instances of that compound. After that, we can do MLR and NT, by which we can well enough get the ideal equation for compressive strength, which properties we want to find out.

In this analytical paper, we trained ANN and FL to compute the prediction instance. In ANN and FL, we use a regression method to compute and predict the dependent variable (bond strength) of concrete. This paper will enlarge and spread the ANN techniques to determine the ultimate bond strength of steel-reinforced concrete.

Objective:

1. The utmost important aspect & aim of this independent study is to connect our vast civil industry with the IT industry by applying Artificial Neural networks.
2. To observe and detect the changes of bond strength due to abrupt variation of different temperatures.
3. With the support of regression analysis, we will determine an ideal equation to get ideal bond strength of reinforcement concrete at extreme temperatures [17–19].

2. Modelling and interpretation technique
2.1. Ann (artificial neural network)

In this study, the prominent move for feeding & interpretation of instances of data to generate archetypal for the bond strength to determine the network web or architecture better. ANN is perfectly competent for such analysis and prediction. ANN is also called the multi-layer neural network. It says that they used feed forwarding to embody all the different layers. First was the input layer which certainly put in predilection for the data interpretation to localize the data in the network. Second, the hidden layer, which is stationed between the algorithm of input and output layer. The hidden layer is known to execute the non-linear transformation of provided input from the data lexicon. At last, the output layer is prominently responsible and executes the algorithm to get the desired result.

In today's world, to perform the analysis more conveniently, many previous data have been compiled in this ANN model, which has become a significant step. ANN has been discovered and established after getting inspired by the human brain. Only the difference is ANN entail of artificial neuron and the human brain consists of a biological neuron. The programmer read about the natural neuron how it works in the human brain. Then they made an algorithm to set and implement the layers. These layers consist of artificial neurons, which are later called Artificial Neural networks, see figure 1

Figure 1. Artificial Neural Network Diagram

In the mathematical expression of the neuron, which is artificially developed, the association b/w the input and output is shown in fig - 1. The result could be linear or nonlinear; it will further depend on the data provided. To make it more accurate, several neurons could be used and connect to engender the neural network, see figure – 2.
2.2. Data interpretation and processing

In this independent study, we have used a data set of different parameters for the implication of the ANN network and to get the desirable prediction rate. We have used significant data on the bond strength of concrete compiled and placed together from the present journals. A pull test is conducted to get the bond strength result, i.e., the grip strength between reinforcing steel and concrete. The concern is about the instant rise and fall of temperature.

The data has been collected based on the effect of temperature variation on concrete. In these certain instances, there are different standard parameters. We will check the result when the concrete will bear the temperature variation having different composition/standards of the concrete.

These are data instances which we are using for proceeding to organize prediction analysis. For the exquisite prediction rate,, see table 1

| s.no. | Standard input parameters | Min. | Max. |
|-------|---------------------------|------|------|
| 1.    | $F_{C, \text{cube}} \ 20^\circ \text{C} \  \text{[Mpa]}$ | 19   | 52   |
| 3.    | Diameter [mm]              | 8    | 20   |
| 4.    | Bond length [mm]           | 32   | 250  |
| 5.    | Length to diameter [ l/d]  | 2    | 20.83|
| 6.    | Concrete cover [mm]        | 40   | 90   |
| 7.    | Cover to diameter [ c/d]   | 2.86 | 5.75 |
| 8.    | Age at testing [ days]     |      | 28   |
| 9.    | Max. $T \ [^\circ \text{C}]$ |      | 800  |

Figure 2. Artificial neuron (perceptron)
Here we have used three different temperatures to perform the analytical study with the help of various instances collected by training and testing experimental research. By the competent researchers, we compiled all the data of this temperature. After that, Predict the expression for the given parameter. These expressions will make the bond strength and the reinforcement capable to withstand in the high temperature. And it will not cause the sudden failure. So, every temperature will go through from the regression analysis.

Adoption of those data has been done based on temperature variation selection in which max. temperature is 800°C. The already taken data of temperature has been shortlisted based on temperature instances. There were very few researchers who studied the temperature variation effect on the bond strength. So, the instance we have collected from the journals and conferences will be very dignified work. It will be very effective because the prediction would help specific industries working on the fire safety structure. And also, who are trying to organize the implementation of such work on the most effective structure and has stand-in high temperature.

In this research, we establish a specified objective to achieve an ideal equation with the help of ANN. In this ANN part, we are willing to perform a regression analysis to predict the bond strength of steel concrete by keeping temperature variation in our minds.

So, onwards completion of all processes specified in the chart, we got the result. This prediction of ideal expression strengthens the bond strength help to make it more reliable. It also helps to improve endurance in normal conditions as well with the change of temperature. So, moving forward, we would show and discuss the result in the next section of the report.

3. Result and discussion.

The data set has been collected from several researcher's experimental works and fed to the ANN model. ANN predicted the bond strength of reinforcement concrete at different temperatures. The variables used as input are termed independent variables & those used for evaluating are called dependent variables. In this ANN model, the dependent variable is bond strength. The independent variables are compressive strength (MPa), dia. of the reinforcing bar(mm), bond length(mm), length to diameter ratio, concrete cover(mm), cover to diameter ratio, maximum temperature(°C) and the time duration(hrs). At 200°C, 400°C, and 600°C temperatures, the analysis has been done.

The normal probability of the Residuals to test the normal distribution hypothesis has been plotted. The Residual against the fits plot confirms that the Residuals have constant variance. A Residual histogram is used to estimate data distortion and the existence of an outlier in the data. Verify the expected bond strength rate after model analysis to check the accuracy of its estimated error.

For 200°C temperature, we get an R-square prediction value of 84.03%. For 400°C temperature, we get an R-square prediction value 83.61%, 600°C temperature, we get an R-square prediction value 76.65%.

| 10. Time at max T [hrs] | 0.75 | 3 |
Table 2. The coefficient Value for 200°C

Table 2 and 3 Represented coefficient value which has been adopted from the dataset. These values measure specific properties of a component that has been used to obtain ideal Reinforcement concrete.

| Term                        | Coef | SE Coef | T-Value | P-Value | VIF |
|-----------------------------|------|---------|---------|---------|-----|
| Constant                    | -190 | 162     | -1.17   | 0.255   |     |
| fc,cube,20 °C [MPa]         | 0.160| 0.178   | 0.90    | 0.380   | 1.47|
| Diameter [mm]               | 3.17 | 5.44    | 0.58    | 0.567   | 268.25|
| Bond length [mm]            | -0.2760| 0.0863  | -3.20   | 0.005   | 20.69|
| Length to diameter [l/d]    | 2.54 | 1.10    | 2.31    | 0.032   | 17.78|
| Concrete cover [mm]         | -0.78| 1.16    | -0.67   | 0.510   | 113.55|
| Cover to diameter [c/d]     | 9.4 | 18.7    | 0.50    | 0.620   | 100.03|
| Max. T [°C]                 | 0.314| 0.106   | 2.96    | 0.008   | 10.62|

Table 3. Model Summary and Analysis of Variance

The present table - 3 summarizes the model that will use the R- square method to evaluate the value of R-square prediction. R-squared is a static measurement, where it shows that the number of fitted values close to the Regression line. In this 200°C temperature, we get an R-square prediction value 84.03% which is a good prediction value.
Figure 3. Pareto chart of the Standardized Effect

Figure 4. Residual plots for Bond Strength

Regression Equation: Bond strength at 200°C = -190 + 0.160 fc, cube,20 °C [MPa] + 3.17 Diameter [mm] - 0.2760 Bond length [mm] + 2.54 Length to diameter [l/d] - 0.78 Concrete cover [mm] + 9.4 Cover to diameter [c/d] + 0.314 Max. T [°C] + 0.23 Time
Using the available data, we obtain the predicted bond strength and the ideal regression equation to achieve adequate strength, see figure 3, 4 and 5.

At the same time, two more regression analyses have been done for 400°C and 600°C temperature and got two more ideal regression equations.

**Table 4. Coefficient value for 400°C**

| Term                   | Coef  | SE Coef | T-Value | P-Value | VIF |
|------------------------|-------|---------|---------|---------|-----|
| Constant               | -154  | 145     | -1.06   | 0.301   |     |
| fc,cube,20 °C [MPa]    | 0.357 | 0.185   | 1.93    | 0.068   | 1.47|
| Diameter [mm]          | 1.54  | 5.70    | 0.27    | 0.789   | 282.01|
| Bond length [mm]       | -0.332| 0.104   | -3.18   | 0.005   | 30.94|
| Length to diameter [l/d]| 4.40  | 1.16    | 3.79    | 0.001   | 21.66|
| Concrete cover [mm]    | -0.19 | 1.17    | -0.17   | 0.870   | 105.91|
| Cover to diameter [c/d]| -3.7  | 18.3    | -0.20   | 0.841   | 109.56|
| Max. T [°C]            | 0.287 | 0.101   | 2.84    | 0.010   | 8.81 |
| Time                   | 0.45  | 4.29    | 0.11    | 0.917   | 7.41 |

**Table 5. Model Summary and Analysis of Variance**

| Source                  | DF | Adj SS       | Adj MS  | F-Value | P-Value |
|-------------------------|----|--------------|---------|---------|---------|
| Regression              | 8  | 2736.02      | 342.00  | 4.44    | 0.003   |
| fc,cube,20 °C [MPa]     | 1  | 286.21       | 286.21  | 3.72    | 0.068   |
| Diameter [mm]           | 1  | 5.66         | 5.66    | 0.07    | 0.789   |
| Bond length [mm]        | 1  | 778.20       | 778.20  | 10.10   | 0.005   |
| Length to diameter [l/d]| 1  | 1106.46      | 1106.46 | 14.37   | 0.001   |
| Concrete cover [mm]     | 1  | 2.11         | 2.11    | 0.03    | 0.870   |
| Cover to diameter [c/d] | 1  | 3.19         | 3.19    | 0.04    | 0.841   |
| Max. T [°C]             | 1  | 621.56       | 621.56  | 8.07    | 0.010   |
| Time                    | 1  | 0.86         | 0.86    | 0.01    | 0.917   |
| Error                   | 20 | 1540.43      | 77.02   |
| Lack-of-Fit             | 9  | 664.88       | 73.88   | 0.93    | 0.537   |
| Pure Error              | 11 | 875.54       | 79.59   |
| Total                   | 28 | 4276.45      |         |
In this 400°C temperature, we get an R-square prediction value 83.61%, which is a good prediction value.

**Figure 5.** Pareto chart for 400°C Temperature

**Figure 6.** Residual plots for 400°C

Regression Equation of Bond strength at 400°C = -154 + 0.357 $f_{c,\text{cube,20°C}}$ [MPa] + 1.54 Diameter [mm] - 0.332 Bond length [mm] + 4.40 Length to diameter [l/d] - 0.19 Concrete cover [mm] - 3.7 Cover to diameter [c/d] + 0.287 Max. T [°C] + 0.45 Time, see table 4 & 5 and figure 6.
Therefore, the ideal composition for bond strength at 400°C temperature has been obtained with the help of regression analysis.

Table 6. Coefficient Value for 600°C

| Term                  | Coef | SE Coef | T-Value | P-Value | VIF  |
|-----------------------|------|---------|---------|---------|------|
| Constant              | -1240| 315     | -3.93   | 0.001   |      |
| fc,cube,20 °C [MPa]   | 0.323| 0.128   | 2.53    | 0.020   | 1.64 |
| Diameter [mm]         | 1.22 | 3.99    | 0.31    | 0.763   | 277.39|
| Bond length [mm]      | 1.402| 0.398   | 3.52    | 0.002   | 928.85|
| Length to diameter [l/d]| -8.83| 3.24    | -2.73   | 0.013   | 339.74|
| Concrete cover [mm]   | -2.226| 0.908  | -2.45   | 0.024   | 134.86|
| Cover to diameter [c/d]| 40.4 | 14.9    | 2.71    | 0.013   | 125.99|
| Max. T [°C]           | 1.182| 0.309   | 3.83    | 0.001   | 182.06|
| Time                  | 92.1 | 22.2    | 4.15    | 0.000   | 382.94|

Table 7. Model Summary and Analysis of Variance

Analysis of Variance

| Source                  | DF | Adj SS   | Adj MS   | F-Value | P-Value |
|-------------------------|----|----------|----------|---------|---------|
| Regression              | 8  | 5255.25  | 656.906  | 17.86   | 0.000   |
| fc,cube,20 °C [MPa]     | 1  | 235.90   | 235.898  | 6.41    | 0.020   |
| Diameter [mm]           | 1  | 3.45     | 3.447    | 0.09    | 0.763   |
| Bond length [mm]        | 1  | 455.67   | 455.666  | 12.39   | 0.002   |
| Length to diameter [l/d]| 1  | 273.26   | 273.264  | 7.43    | 0.013   |
| Concrete cover [mm]     | 1  | 220.75   | 220.753  | 6.00    | 0.024   |
| Cover to diameter [c/d] | 1  | 270.61   | 270.615  | 7.36    | 0.013   |
| Max. T [°C]             | 1  | 540.06   | 540.058  | 14.68   | 0.001   |
| Time                    | 1  | 633.22   | 633.222  | 17.21   | 0.000   |
| Error                   | 20 | 735.72   | 36.786   |         |         |
| Lack-of-Fit            | 10 | 649.84   | 64.984   | 7.57    | 0.002   |
| Pure Error              | 10 | 85.88    | 8.588    |         |         |
| Total                   | 28 | 5990.96  |          |         |         |

In this 600°C temperature, we get an R-square prediction value 76.65%, which is a good prediction value, see table 6 and 7.
Figure 7. Pareto Chart for 600°C Temperature

Regression Equation of Bond Strength at 600°C = -1240 + 0.323 \( f_{c,\text{cube},20} \) [MPa] + 1.22 Diameter [mm] + 1.402 Bond length [mm] - 8.83 Length to diameter \( l/d \) - 2.226 Concrete cover [mm] + 40.4 Cover to diameter \( c/d \) + 1.182 Max. T [°C] + 92.1 Time, see figure 7 and 8.
The graphs have been plotted based on instances provided to predict the response value. In the Residual graph, the percentage of normal probability and the Residual value are on the fitted line. This fitted line has been sketched based on the provided instances explained by the software used. The Pareto chart shows which components have more effect on bond strength at higher temperatures and which components have less effect.

4. Conclusion

In this observational study, three different models have evolved from the collected database by engaging ANN & linear regression models. The evolved model with its input value for different benchmarks has been examined to predict bond strength for the regression equation. The residual plots of bond strength have been drawn for different instance sets of input databases to get appropriate regression. It could help to determine whether the ordinary least square hypothesis of holds. The least-square regression provides an unbiased estimate of the coefficient with the lowest value of variance.

The followings are the conclusion of the study:
- The bond strength of reinforcement concrete at different temperatures is predicted with the application of the ANN model.
- This study also provides a regression equation that can help any structure prevent failure at very high temperatures.
- Without attempting any critical experimental complexity, ANN can help predict bond strength in a very short period. So, this model will help in saving the wastage of time and material.

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