Prediction of the Slump of Fly Ash Blended Concrete Based on Various Numerical Models

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Abstract. Slump is a fundamental engineering property of fly ash blended concrete. This study proposes various numerical models, such as multiple linear regression (MLR), artificial neural network (ANN), and genetic algorithm assisted artificial neural network (GA-ANN) for estimating the slump. First, the concrete slump is regressed as a multiple linear equation of water-to-binder ratio, water content, sand ratio, fly ash replacement ratio, air-entraining agent content, and superplasticizer contents. The correlation coefficient of the MLR method is 0.63. Second, the ANN model is set up, which consists of an input layer, a hidden layer, and output layer. Based on the backpropagation (BP) training method, the optimized network is found. The correlation coefficient between analysis results and experimental results of ANN model is 0.78. Third, GA is used to assist in the optimization process of ANN. The initial value of the hidden layer of ANN is generated by using a genetic algorithm (GA). The correlation coefficient of GA-ANN integrated model is 0.85. GA-ANN integrated model can make more accurate prediction results than MLR model and ANN model.

Keywords. Slump, genetic algorithm, artificial neural network, fly ash blended concrete.

1. Introduction
Fly ash is widely used as mineral admixtures for producing high-performance concrete. Workability is an essential property of fly ash blended concrete. Slump is a frequent index of workability of concrete. Slump can be experimentally measured based on the slump cone test or other rheology tests. However, experimental tests need lots of economic costs and human working. A prediction model of slump can lower these costs and favor the production, transport, and construction process of the concrete industry [1].

Many studies have been done about predicting the slump of concrete. Lim et al. [2] made multiple linear regression of the slump of concrete. The slump was determined as a linear function of components of concrete. Yeh [3] evaluated the slump of concrete by using second-order regression and ANN. Yeh [3] found that the prediction results from ANN were more accurate than those from second-order regression. Jain et al. [4] found that ANN can capture the complex relationships hidden among combined concrete constituents, e.g., paste and mortar and slump in a very efficient manner. Sonebi et al. [5] evaluated the early-age workability parameters, such as L-box test, V-funnel tests, and slump tests based on ANN.

Although ANN is widely used for evaluating properties of fresh concrete, ANN has some weak points. For example, the backpropagation training method in ANN is a local-optimum searching algorithm which may make the optimization process failure [6-8]. To overcome the weak points of ANN, we use a genetic algorithm (GA) to assist in the training process of ANN. We find the correlation coefficient from GA-ANN model is higher than that of the ANN model. GA-ANN integrated model can
make more accurate prediction results than the ANN model.

2. Numerical Models for Concrete Slump
In this study, we evaluated the slump of fly ash blended concrete using various numerical methods, i.e., multiple linear regression (MLR), artificial neural network (ANN), and genetic algorithm assisted artificial neural work (GA-ANN). Experimental results of the slump of fly ash blended concrete from Lim et al. [2] are used to build numerical models. Total 104 experimental results of concrete slump were measured [2]. The effects of water-to-binder ratio, water content, sand ratio, fly ash replacement ratio, air-entraining agent content, and superplasticizer contents on concrete slump were considered in Lim et al. [2] study.

2.1. Multiple Linear Regression (MLR) Model for Concrete Slump
In regression analysis, should there be several independent variables, it's known as multiple regression. A phenomenon is frequently associated with multiple factors. While using optimal mixture of multiple independent variables to calculate or estimate the dependent variable works better and practical than predicting or estimating just one independent variable. Therefore, multiple straight line regression is much more practical than single straight line regression.

In this study, the slump of concrete is regressed as linear equations of water-to-binder ratio, water content, sand ratio, fly ash replacement ratio, air-entraining agent content, and superplasticizer contents. Based on the experimental results of Lim et al. [2], the multiple linear equation of slump is determined as follows:

\[
\text{slump} = (-6.630)\frac{W}{B} + 1.204W + (-1.313)\frac{S}{A} + 0.362FA \\
+ (-2343.973)AE + 5.305SP + 403.250
\]

where \(\frac{W}{B}\) is water to binder ratio, \(W\) is water content, \(\frac{S}{A}\) is sand ratio, \(FA\) is fly ash content, \(AE\) is air-entraining agent content, and \(SP\) is superplasticizer content. The prediction results of multiple linear regression are shown in Figure 1. The correlation coefficient between prediction results and experimental results is 0.63. The accuracy of MLR model is not high. Hence it is necessary to build a more accurate model for estimating the slump of fly ash blended concrete.

![Figure 1](image)

**Figure 1.** Prediction results of multiple linear regression.

2.2. ANN Model for Concrete Slump
Artificial neural systems happen to be an investigation focus in the area of artificial intelligence because the 1980s. In the outlook during information processing, a person's brain neural network is abstracted, some simple models are in place, and various systems are created based on different connection methods. A neural network is definitely an operation model made up of a lot of interconnected nodes (or neurons). Each node represents a particular kind of output function known as an activation function. The bond in between each node represents the weighted worth of the signal with the connection, known as the load, which is equivalent to the memory from the artificial neural network. The creation of the network varies...
based on the connection method, weights, and excitation functions. The network itself almost always is an approximation of the formula or function, or perhaps an expression of the logical strategy.

The neural networks toolbox in Matlab is used for prediction slump [8]. The illustration of the ANN model is shown in figure 2. The input parameter consists of six parameters (water-to-binder ratio, water content, sand ratio, fly ash replacement ratio, air-entraining agent content, and superplasticizer contents), the hidden layer consists of seven neurons, and the output layer is slump of concrete. Backpropagation method is selected as a training method. The total experimental results are divided into three groups, i.e., training set, validation set, and test set. The percentages of training, validation, and test are 70%, 15%, and 15%, respectively. In the ANN model, the initial values of the hidden layer are random numbers. Figure 3 shows the evolution of mean squared error (MSE) as a function of training epochs. The MSE decreases as the proceedings of the training process. The training process will stop once the best validation performance reaches.

Table 1 shows the results of the weight matrix and bias vector of the hidden layer. Because the input layer consists of six parameters, and the hidden layer consists of seven neurons, the weight matrix is 7×6 matrix and bias vector is 7×1 vector. Based on the trained neural networks, the prediction results of ANN model are calculated (shown in figure 4). The correlation coefficient between prediction results and experimental results is 0.78. Generally, the prediction results agree with experimental results. However, this correlation coefficient of slump model is lower than that of strength model [9-10]. This may because the experimental results of the slump of concrete are more irregular than those of concrete strength.

2.3. GA Assisted ANN Model

Backpropagation method of ANN is sensitive with local optimum. When the training process falls into the optimum local region, the accuracy of ANN will be lowered. To overcome the weak points of the ANN model, we use a genetic algorithm (GA) to assist in the training process of ANN. The global optimization toolbox in Matlab is used for GA [8]. In GA-ANN model, the initial values of the weight matrix and bias vector are initially calculated by using GA toolbox. Then the output results from GA is used as input parameters of ANN.

![Image](image_url)

Figure 2. ANN model.

![Image](image_url)

Figure 3. Training process with BP method.

| Weight matrix    | bias   |
|------------------|--------|
| 0.115            | 0.343  |
| 0.293            | -0.036 |
| 1.412            | 1.026  |
| -1.412           | -0.236 |
| 0.024            | 0.194  |
| 0.574            | -0.201 |
| -0.787           | 0.191  |

Table 1. Weight matrix and bias vector of ANN.
Figure 4. ANN model: correlation coefficient between prediction results and experimental results.

Based on GA-ANN model, the weight matrix and bias vector are determined and shown in table 2. These values are different from those of table 1. The calculated results of GA-ANN integrated model are shown in figure 5. The correlation coefficient between prediction results and experimental results is 0.85. In other words, the calculation results from the GA assisted ANN model is more accurate than those from the ANN model.

Table 2. Weight matrix and bias vector of GA-ANN integrated model.

| Weight matrix  | bias    |
|----------------|---------|
| -1.030         | 0.121   |
| 0.413          | -0.459  |
| 0.869          | -1.310  |
| 1.763          | -0.241  |
| -1.353         | 0.694   |
| -1.788         | -0.699  |
| -0.541         | -0.628  |
Figure 5. GA-ANN model: correlation coefficient between prediction results and experimental results.

3. Conclusions
This research proposes multiple statistical models for example multiple linear regression (MLR), artificial neural network (ANN), and artificial neural network (GA-ANN)-aided genetic algorithm to estimate slump. First, the slump of concrete is expressed like a multivariate straight line equation water-to-binder ratio, water content, sand ratio, fly ash substitute ratio, air content, and water reducing agent content. The correlation coefficient of the technique is 0.63. Second, the neural network model is split into an input layer, a hidden layer, as well as an output layer. The correlation coefficient between analysis results and also the experimental outcomes of the neural network model is 0.78. Third, the genetic algorithm can be used to optimize the neural network. The genetic algorithm(GA) can be used to create the first worth of the hidden layer from the neural network. The correlation coefficient from the GA-ANN composite model is 0.85. In contrast to the MLR model and also the ANN model, the GA-ANN integration model can acquire better conjecture results.

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