Artificial Neural Network for Prediction of Compressive Strength of Concrete using MATLAB

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ABSTRACT The world's most used building material is concrete because of its exceptional durability and compressive strength. These characteristics are tested and evaluated using time- and money-consuming standard methods on both fresh and hardened concrete. In the current study, the compressive strength of concrete was predicted using an Artificial Neural Network (ANN). The ANN was built using various input parameters related to the design of the concrete mix, such as the properties of the coarse and fine aggregates, the cement content, the water/cement (W/C) ratio, the type and dosage of admixtures, etc.The experimentally obtained real compressive strength data received from RMC Plant was compared with the projected strength. Using the MATLAB neural network toolkit, an ANN model has been created. Regression values of 0.93 and 0.95 for strength and slump indicate a good correlation. It is concluded that the ANN method can gain acceptable predictions for compressive strength.

Keywords: Artificial Neural Network (ANN), Compressive strength, Mix design, Modelling, Regression, Slump.

1. Introduction

The procedure of obtaining concrete mix design is delicate and challenging. Numerous factors influence it, however a single combination design is only useful for a single compressive strength. Every manufacturing that uses somewhat varied material properties necessitates the creation of new mixing designs. As a result, the results of the traditional mixed design were unreliable. Ultimately, it demonstrates that manual mixed design is only an approximation[1].

Mix design techniques can be divided into two categories: artificial intelligence (AI)-based techniques and empirical techniques. The American Concrete Institute (ACI) and the British Department of Environment (DoE) are two examples of experimentally established approaches based on experience in the former category. They involve determining quantities of ingredients by different ways.

The most popular artificial intelligence techniques are computer-based and based on the principles of machine learning. ANN, fuzzy analysis, and genetic algorithms are examples of these approaches[2]. The artificial neural networks (ANNs) are computational models that use a training method to identify the connections between a set of causal input factors and the conclusions that are drawn from them. After being trained, ANNs can forecast outcomes based just on the input parameters for an unknown situation that was not used during training.

In this paper, an artificial neural network (ANN) model has been built to forecast the compressive strength of concrete using data from various mix designs. The model has been verified, validated, and regression analysis has been performed to evaluate the accuracy of the model. At first the data has been collected, then preprocessed (i.e. reviewing, validating data, standardization and normalization …etc.). And then the model is constructed.

2. CONTENT

An alternative to mathematical modeling is provided by ANN. The neural network's basic idea is to feed it input and target output data so that it may figure out how to relate the two. The trained network can then be used to forecast the results of further input sets for which the solution is unknown. Refer to the introductory textbooks on the topic in references [3] or [4] for a more thorough explanation of the ANN approach.

Using ANN has many advantages. includes solving complex problems for which doesn't exist any sequential algorithms. Instead there are only examples of solutions. The ability of the ANNs to adapt to a changing environment; deterioration of some neurons does not involve a steep deterioration in performance, but degrades network performance. The ANNs exhibit opportunity to work with imprecise data; ability to modify the internal structure in order to perform the desired action. They generate their own rules of learned examples and are used to model the nonlinear systems. Creating a well-trained ANN lead to the removal experimental phase; inexpensive and fast to a slow and expensive program structural analysis. They may be used for real-time applications; ability to approximate a nonlinear continuous function with the desired degree of accuracy; easily modeled neural networks multivariable systems (due to the large number of inputs and outputs).

One of the ANNs' drawbacks is that selecting the training set can be challenging, which complicates the learning process. Training takes a lot of computational power and might take a long time, depending on the training method and size of the training set. A very large volume of data is needed for training; setting up a training base is a challenging task that requires covering every searchable solution[2].

The ANN has the same weakness as the mathematical model. Because it is also based on empirical data. But the advantage over the mathematical model is that the programmer making the model doesn't have to declare every action of the program. When using ANN applications for problem solving, it is needed to understand the problem to such a level that relevant parameters can be chosen as input. But when the network is trained, then learning about the problem is achieved by studying the way the network generalizes. In other words, the neural network summarizes the experience hidden in the input-output relationship.

According to some, the ANN is the second-best method for doing almost anything [1]. Naturally, the best approach is to fully comprehend the issue at hand before determining the appropriate formula or method to solve it. This could not always be feasible, though, and there would still be many issues that could be resolved by using a less-than-ideal strategy[5].

3. COMPUTER IMPLEMENTATION OF THE NEURAL NETWORK MODEL

A. *Data description*

Data used in model has been tabulated, organized, filtered and published by researchers [6]. The data includes mix designs according to the British DoE, the parameters used are illustrated in Table I.

Table I: Mix design parameters

	Parameter	Type	Designation
1	Type of coarse Aggregates	Input	X1
2	Type of Fine Aggregates	Input	X2
3	Max. Size of Coarse Aggregate (mm)	Input	X3
4	Sand Passing 0.6 mm Sieve (%)	Input	X4
5	Ordinary Portland Cement (OPC) (kg/m^3)	Input	X5
6	W/C Ratio	Input	X6
7	Water Content (kg/m^3)	Input	X7
8	Admixture class	Input	X8
9	Admixture dosage (Litre)	Input	X9
10	Fine Aggregate (kg/m^3)	Input	X10
11	Coarse Aggregate (kg/m^3)	Input	X11

B. Construction of Neural Network model:

For a feed-forward back-propagation network structure and training process, the important internal parameters include data preprocessing and presentation and initial synaptic weights. Furthermore they include learning rate, number of hidden layers and number of neurons in each hidden layer, activation functions for hidden layers and output layers and the number of training epochs [7].

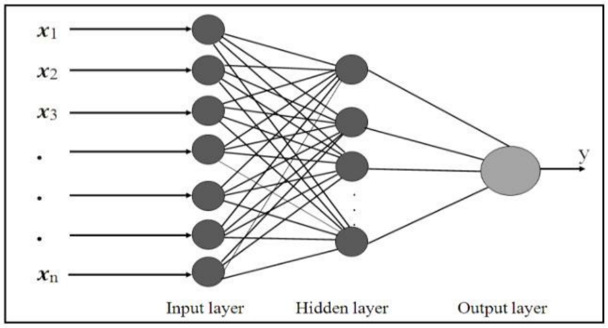

Fig. 1: ANN structure

In this work, a three-layer feed-forward back-propagation neural network is developed through experimental investigation of various internal parameters to predict the compressive strength of concrete.

In Fig. 1: X1, X2, X3,….., Xn are the input variables, where for the problem in hand, the values is defined as in Table I.

The model is constructed to predict the properties of fresh concrete, and also to predict the properties of hardened concrete (i.e. strength in 7 days). With the same input data and modelling parameters.

B. Modelling parameters:

Selection of activation function, Number of neurons in hidden layer, training algorithm and type of networks can influence the effective functioning of the ANNS approach [8].

According to literature [9], the most used types of activation functions are: Sigmoid functions (tan sigmoid and log sigmoid) and Purelin function (linear function).

Number of hidden neurons: The hidden layer and nodes play very important roles for many successful applications of neural networks. It is the hidden nodes in the hidden layer that allow neural networks to detect the feature, to capture the pattern in the data, and to perform complicated nonlinear mapping between input and output variables. There is no theoretical basis for selecting this parameter although, so optimization is carried out by selecting different numbers of hidden neurons (from 10 to 100 hidden neurons) and choosing the optimum number that has the smallest mean squared error (MSE), and the largest regression coefficient.

Division of data: The issue of data division into training, validation and test sets is one of most affecting factors. There is no general solution to this problem, several factors such as the problem characteristics, the data type and the size of the available data should be considered in making the decision. It is critical to have both the training, validation and test sets representative of the population or underlying mechanism.

Inappropriate separation of the training and test sets will affect the selection of optimal ANN structure and the evaluation of ANN forecasting performance. The literature offers little guidance in selecting the training and the test sample. Most authors select them based on the rule of 70% for training, 20% for validation and 10% for testing.

The architecture of the two developed ANNs in this paper are abbreviated as (STR-11-n-1) with STR denoting strength.

The MSE was used as the ANN stop training criterion. In this regard, lower values are corresponding to more idealized network performance. Regression values (R-values) are utilized to measure the correlation between outputs and targets in the networks wherein an R-value of unity indicate strong relationships. The MSE and R- values were applied as the criteria for evaluation of the generated networks performance.

4. Results & Discussion

A. Implementation results:

The eleven input parameters (X1~X11) as shown in Table I, are utilized as the input layer with one hidden layer in the architecture of the ANN model (Fig. 1). All nodes in the ANN model utilize the log-sigmoid function as their activation. Two ANNs were constructed, one for predicting the strength at 7 days, and the other for predicting the consistence as slump.

For training the ANNs, 180 samples were randomly divided into training, validation and test sets. The training set was used to teach the network. Training had continued as long as the network improved on the validation set. The test set provided a completely independent measure of network accuracy[10].

The network type utilized in this study was the Back-propagation ANN. A typical neuron in the network contains biases, a sigmoid activation function and a linear output layer. It is capable of

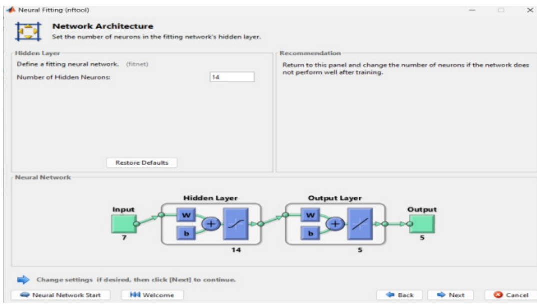

Fig. 2: General layout of the ANN

approximating any function having a finite number of discontinuities as illustrated in Fig. 2. The results of training were as shown in Figs 3.

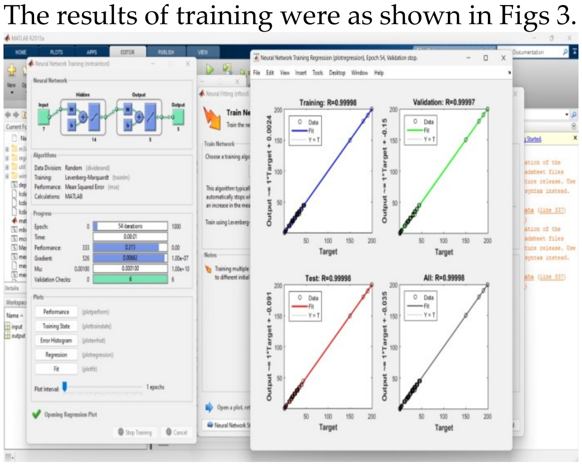

Fig. 3: Regression of training, validation and test simulated by STR11–60–1.

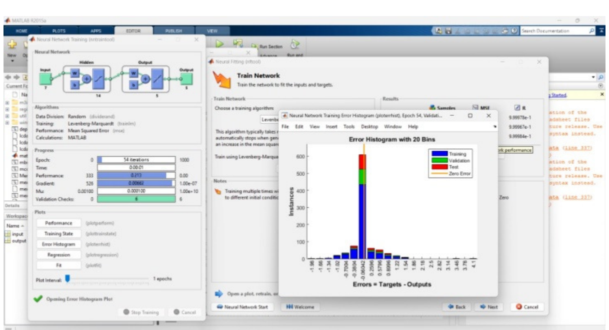

Fig. 4: Error histogram for STR11-60-1

B. Optimization

The optimization was carried out by implementing 10 networks with different number of hidden neurons in each time, the number of hidden neurons is plotted against regression coefficient in(fig 5)that show R-values of the networks having various numbers of hidden nodes.

For STR11-n-1 the highest R-value for training data was obtained with 100 hidden neurons and 60 hidden neurons, (they are 0.99 and 0.99 respectively).

C. Results of optimized ANNs

Generally, the error reduces after more epochs of training, but might start to increase on the validation data set as the network starts overfitting the training data. In the default setup, the training stops after six consecutive increases in validation error, and the best performance is taken from the epoch with the lowest validation errors.

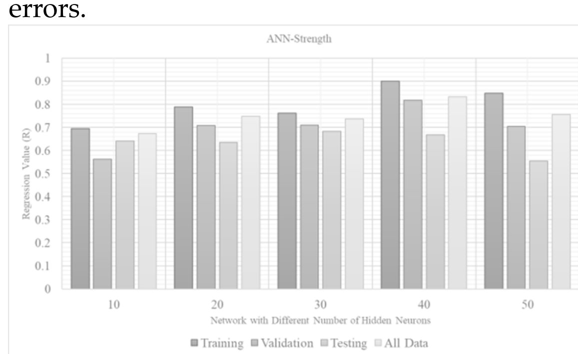

Fig. 5 Effect of number of hidden neurons on regression coefficient for
STR 11-n-1.

Another measure of how well the neural network has fit the data is the regression plot (Fig. 3). Here the regression is plotted across all samples, the regression plot shows the actual network outputs plotted in terms of the associated target values. If the network has learned to fit the data well, the linear fit to this output-target relationship should closely intersect the bottom-left and top-right corners of the plot[10].

Another third measure of how well the neural network has fit data is the error histogram (fig.4). This shows how the error sizes are distributed. Typically, most errors are near zero, with very few errors far from that.

As it can be seen, it may be concluded that the ANN model learnt and predicted the experimental data with acceptable degree of precision for strength in 7 days and slump, but there is low precision and high errors in some cases. This can be interpreted by the effect of admixture, probably because of the different types of admixtures with different specifications and manufacturers, which led to variability in some results.

5. SUMMARY

There are not enough investigations dealing with development of fundamental knowledge which leads to understand the nature of the internal representations generated by an ANN in response to a given problem. More than often, an ANN is presented to its users as a black box with complicated internals which work to convert inputs into desirable outputs.

6. Recommendations

- Further research in this field should be carried out to study the effect and importance of each parameter in the results of the ANN model.
- Many important factors like, fineness modulus of aggregates, shape of aggregates, absorption

and specific gravity which have great effect in strength of concrete, further studies should take into account the variability of these factors.

- The admixtures used in the data sets are variable in types and manufacturers, the dose of each product differs from company to company, but in this study, it is assumed that all the admixtures fall in the same ASTM classification, have the same properties. This assumption affected the slump prediction accuracy of the model, because the majority of the admixtures are related to consistence.
- The package used in this study is MATLAB Neural Network toolbox, further research may use other packages to compare the results and increase their reliability.

7 .Acknowledgment

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