Prediction of Concrete Mix Proportion using ANN Technique

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Abstract – ***Concrete mix design is carried out based on some empirical relationships and the experience of the engineer. To arrive at a satisfactory mix proportion a number of trial mixes are to be prepared and tested to check the various design parameters. Thus it is a time consuming task. An artificial neural network (ANN) can overcome these difficulties by predicting the mix proportions based on experimental mix design data. The use of ANN technique in the prediction of concrete mix proportions can be efficient and economical as it would reduce the need of preparing a large number of trial mixes. The learning processes in artificial neural networks use previous experimental mix design data to predict mix proportions specified by various input parameters. To train the ANN model a database of large number of mix proportions of M25 grade of concrete is prepared using PPC cement. To get the output as mix proportion of various ingredients, input parameters are Target Mean Strength, Workability in terms of slump, W/C Ratio, Specific Gravity of Cement, Sand & Coarse Aggregate and Grading Zone of Fine Aggregate. The trained network is validated with a set of five mix proportions which were not used in the training process. The average percentage error is observed as 0.193%. On comparison with linear regression analysis the ANN model is found to be more efficient.***

Key Words: *Concrete Mix Design, Grade of Concrete, ANN Technique, Feed Forward Neural Network, Regression Analysis.*

1. INTRODUCTION

Concrete is the second most consumed material in the world after water. Concrete is commonly made by mixing cement with fine aggregate, coarse aggregate and water. Except cement all other ingredients are locally available, because of which it is popular among the engineers as well as common people. One more reason of its popularity is the ease with which concrete can be poured into desired shape and size. This is because of the property of plasticity to flow into prefabricated formwork. Once it hardens and attains the specified strength, it can sustain huge amount of compressive load.

Concrete mix design refers to the process of appropriate selection and proportioning of constituents to produce a concrete with predefined characteristics in plastic as well as in solid state. Compressive strength is the most important requirement of concrete mix design. Concrete, when specified as a structural material in any construction activity, it primarily has to satisfy the required compressive strength criteria. However, durability is one more property which has almost equal importance as that of compressive strength. Environmental conditions which may adversely affect the quality of concrete should be taken into consideration. To achieve a dense and impervious concrete, proper gradation of fine and coarse aggregate has to be ensured. Workability is another design requirement which helps in easy handling and proper compaction of concrete.

There are several mix design procedures which are carried out using certain empirical relationships developed from past experience. Various assumptions and equations in the theoretical calculation of mix design make it cumbersome as well as time taking. To obtain a mix proportion of required strength and workability, a no. of trial mixes have to be prepared. Thus it takes a lot of time to arrive at a satisfactory mix proportion.

Artificial neural network (ANN) can efficiently overcome these difficulties faced during design of concrete mixes. ANN derives its origin from the human brain or the nervous system. A neural network is composed of many artificial neurons that are linked together according to a specific network architecture. Similar to the human brain these networks have the capacity to learn from examples. ANN tries to map some relationship between input and target data that is to be provided to the network. Once the network is trained it can predict mix proportions from various predefined design parameters of concrete. Thus Artificial Neural Network can reduce the requirement of large number of mix trials and subsequently the process of mix design will be economic as well as time efficient. To train the neural network, sufficient set of concrete mix proportions are required. Therefore, a large no of cubes of

M25 grade of concrete were cast and a database was prepared for the training of the ANN.

2. CONCRETE MIX DESIGN

The first objective of concrete mix design is to achieve required strength and durability. The second objective is to make the concrete economical. Performance of concrete depends on plastic as well as hardened state. If the plastic concrete is not workable, it cannot be properly placed and compacted. Thus it is a challenge for the concrete engineer to design the right mix proportion considering the best available quality of ingredients. Rich mixes may lead to high shrinkage and cracking in the structural concrete, and the evolution of high heat of hydration in mass concrete which may cause cracking. Thus proportioning of the ingredients of concrete is an important part of concrete technology as it ensures the quality and economy.
An essential part of mix design is to minimize voids in order to produce an impervious structure. It is assumed that any voids (micro- not entrapped air) within the concrete will be filled with water. By minimizing these voids, lower water content and cement content, for a given w/c ratio, are ensured. However, the concrete must contain enough fine material so that the voids become filled with hydration products from the cement, additions, admixture and water combination. Inadequate fines will lead to harsh concrete that has a tendency to entrap air. In comparison, high levels of fines can lead to cohesive mixes which can entrap air.
There have been many methods developed from the simple volumetric batching. In all the cases, some or all of the following parameters need to be specified i.e. maximum water-cement (w/c) ratio, minimum cement content, slump, maximum size of aggregate, and strength requirement. Estimating the required mix proportion for the concrete involves a sequence of logical straightforward steps whether based on a series of trial mixes, sound rule of thumb advice, experience or a combination of all three.

2.1 Experimental Study

The methods of design followed all over the world are essentially similar, except that each country has its own set of tables and graphs for the calculation of density, water requirement for workability and strength, etc., based on the type of aggregates and cement available locally.
The BIS method of mix design is based on some empirical relations which are developed after substantial experiments in national laboratories on locally available material. The design procedures given in IS 10262:2009[1] are applicable to ordinary and standard concrete grades only. The durability requirements, limitations on w/c ratio and maximum cement contents are adopted as per IS 456:2000[2]. Air content is not considered as in case of normal concrete air content is not significant.

The design mix of M25 grade of concrete has been proportioned by BIS recommended mix design method (IS 10262:2009). Material properties of all the ingredients required for mix calculations are examined in the laboratory. Aggregates of 20mm and 10mm are used in the ratio of 3:2 of total coarse aggregate volume. PPC cement is used as binding material. For each mix proportion six cubes of 150 mm size were casted in the laboratory and tested in Compression Testing Machine at the age of 7 and 28 days. Mix proportioning satisfying the compressive strength criteria for M25 grade of concrete are used as input for the training of ANN model.

3. ARTIFICIAL NEURAL NETWORK

The artificial neural network (ANN) is a computational model inspired by the structure and functions of the human brain. ANNs are able to learn past data, just like the human brain. The network learns the past data by repeating the learning process for a number of iterations. Once ANN has been well taught the historical data, it can predict the outputs from unknown inputs with quite high precision.

An artificial neural network is composed of many artificial neurons that are linked together according to a specific network architecture. Neuron is the basic processing units, which operates in a highly parallel manner. Each neuron does some amount of information processing. It derives inputs from some other neuron and in return gives its output to other neurons for further processing. This layer-by-layer processing of the information results in great computational capability. Figure-1 shows the general architecture of the ANN.

Computational complexity is decided by the number of layers present in the architecture of ANN. In general, every ANN has at least three layers: the input layer, the hidden layer, and the output layer. Although there is only one input layer and one output layer, there can be multiple hidden layers. All the connections in the neural network are associated with some weight. Weights corresponding to each input are multiplied by the inputs during the aggregation, or weighted addition. The only way to control the system's output is to change the weights of the various connections. The training or learning in an ANN corresponds to the change in their weights. The different combinations of weights for any ANN determine the effectiveness or performance of the ANN. Many researchers have used artificial neural networks to predict the compressive strength of concrete [3-5].

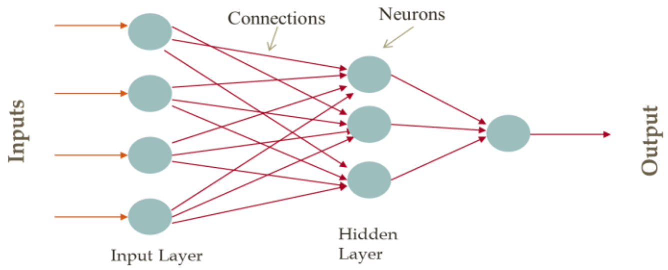

Figure-1: The Architecture of Artificial Neural

3.1 Modelling of ANN

In the present study Back Propagation Neural Network is used to develop the ANN model by using MATLAB program to predict the mix proportions of concrete. A data set of sixty samples which satisfies the compressive strength criteria for M25 grade of concrete is used to train the ANN model. Seven parameters such as target mean strength, workability in terms of slump, water-cement ratio, specific gravity of cement, specific gravity of fine aggregate, specific gravity of coarse aggregate and grading zone of fine aggregate are used as input to predict the mix proportions of all the four ingredients as output. One hidden layer is used in the network architecture. All the input and output data have been normalized by using the input-output processing function 'mapstd'. This function will return the inputs and targets with zero means and unity standard deviation. The following command is used for normalization.

```
[pn,ps]=mapstd(p);
[tn,ts]=mapstd(t).
```

The original network inputs and targets are given in the matrices p and t. Normalized input and targets are returned as pn and tn. The settings structures ps and ts contain the means and standard deviations of the original inputs and original targets. After the network is trained, these settings are used to transform any future inputs that are applied to the network. They effectively become a part of the network, just like the network weights and biases.

If 'mapstd' is used to scale the targets, then the output of the network is trained to produce outputs with zero mean and unity standard deviation. The following code applies the same setting 'ps' to the new set of samples and after simulating these outputs are converted back into the same units which are used for the original targets.

```
snew=mapstd('apply',sample_new,ps);
pred_new=sim(net1,snew);
pred=mapstd('reverse',pred_new,ts)
```

To create the network, 'feedforwardnet' command is used. The network creation function 'feedforwardnet' automatically assign process function and transfer function to the network. These functions transform the input and target values provided into values that are better suited for network training. The default transfer function is 'tansig'. The default process function 'mapminmax' is overridden with 'mapstd' and 'removeconstantrows' as these are found to be best suited for training data set.

4. RESULTS AND DISCUSSIONS

Feed forward back propagation technique is used to train the neural network for predicting the concrete mix proportions. With one number of hidden layer, the optimum number of neuron is decided by trial and error. Initially an ANN model is created with two no of neurons in the hidden layer and gradually the number of neuron is increased up to twenty. Various performance parameters are calculated against each model to determine the best suitable ANN model.

Table -1: Selection of ANN Model with optimum number of neurons

no of neurons	RMSE	R	ME_{Nash}	MAE
2	3.6978	0.9683	0.9360	0.0539
3	3.0465	0.9737	0.9477	0.0665
4	2.7392	0.9781	0.9560	0.0444
5	1.4990	0.9938	0.9872	0.0385
6	2.5961	0.9804	0.9614	0.0226
7	1.8036	0.9899	0.9795	0.0032
8	1.0970	0.9968	0.9934	0.0141
9	1.5404	0.9932	0.9860	0.0220
10	2.9125	0.9728	0.9434	0.0049
11	1.7228	0.9913	0.9819	0.0235
12	1.2858	0.9959	0.9915	0.0261
13	1.0143	0.9975	0.9945	0.0087
14	0.9556	0.9978	0.9955	0.0018
15	2.4344	0.9824	0.9648	0.0144
16	2.5895	0.9836	0.9658	0.0282
17	2.5522	0.9807	0.9597	0.0113
18	3.1422	0.9759	0.9463	0.0239
19	3.3713	0.9655	0.9306	0.0089
20	2.9184	0.9817	0.9627	0.1383

The following parameters are calculated to determine the performance of the ANN models.

Correlation Coefficient (R)

The correlation coefficient measures the statistical correlation between the predicted and actual values.

Correlation coefficients are expressed as values between +1 and -1. A coefficient of +1 indicates a perfect positive correlation. A coefficient of zero indicates that there is no distinguishable relationship between the variables. It is computed as

$$R = \frac{\sum_{i=1}^{n}(Xai - \overline{X}ai)\,(Xpi - \overline{X}pi)}{\sqrt{\sum_{i=1}^{n}(Xai - \overline{X}ai)^2\ \sum_{i=1}^{n}(Xpi - \overline{X}pi)^2}}$$

where Xai and Xpi are actual and predicted values respectively, and $\overline{X}ai$ and $\overline{X}pi$ are average values of Xai and Xpi respectively.

Root Mean Square Error (RMSE)

Root-Mean-Square Error (RMSE) is a frequently used measure of the differences between actual values and values predicted by a model. RMSE index ranges from 0 to infinity, with 0 corresponding to a perfect fit.

$$RMSE = \sqrt{\frac{1}{n}\left(\sum_{i=1}^{n}(Xai - Xpi)^2\right)}$$

where Xai and Xpi are actual and predicted values, respectively.

Model Efficiency (Nash-Sutcliffe Coefficient)

The model efficiency (ME_{Nash}) is an evaluation criteria proposed by Nash and Sutcliffe (1970)[6] to evaluate the efficiency of hydrological models. The Nash–Sutcliffe efficiency is a widely used and potentially reliable statistic for assessing the goodness of a fit. Nash–Sutcliffe efficiencies can range from −∞ to 1. An efficiency of 1 corresponds to a perfect match of predicted data with actual data.

$$ME_{Nash} = 1.0 - \frac{\sum_{i=1}^{n}(Xai - Xpi)^2}{\sum_{i=1}^{n}(Xai - \overline{X}ai)^2}$$

where Xai and Xpi are actual and predicted values respectively, and $\overline{X}ai$ is the average values of Xai.

Mean Absolute Error (MAE)

Mean absolute error is a quantity which is very commonly used to measure the accuracy of predicted values. The MAE measures the average magnitude of the errors in a set of forecasts, without considering their direction. It is defined as

$$MAE = \frac{1}{n}\left(\sum_{i=1}^{n}(Xai - Xpi)\right)$$

From Table-1 it is found that ANN model having 14 nos. of neuron with one hidden layer gives the best performance, which are also shown in Figures-2 & 3 and this model is selected for further validation.

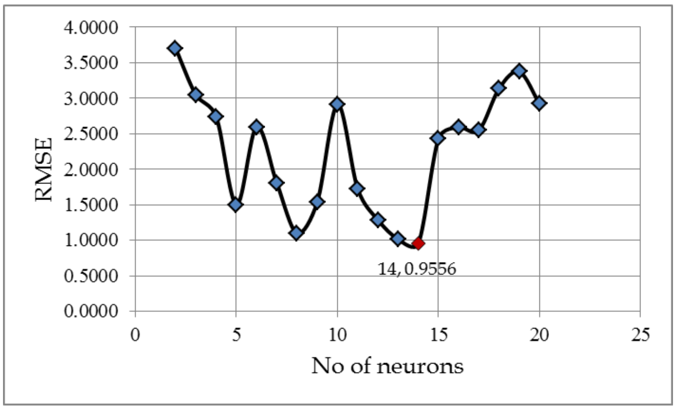

Figure -2: Variation of RMSE with Number of Neurons

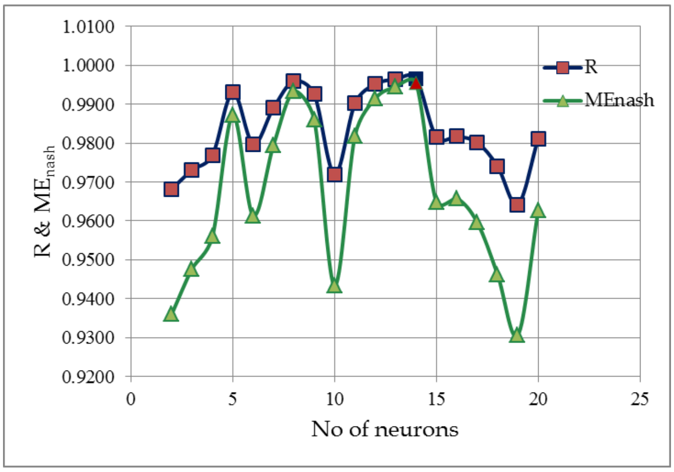

Figure -3: Variation of R & ME_{Nash} with no. of Neurons

4.1 Validation of the ANN Model

The results obtained from the selected ANN model with 14 numbers of neurons is validated with a data set which is different from training data. The validation data consists of five set of mix proportions which are set aside for the validation purpose and is not used for the training purpose. These five data sets are presented in Table-2.

Table -2: Experimental data for validation of ANN model

Slump (mm)	W/C ratio	Cement (kg/m³)	F.A. (kg/m³)	C.A. (kg/m³)	Water (kg/m³)
65	0.48	393	641	1170	189
75	0.50	382	641	1173	192
80	0.47	411	614	1170	193
95	0.48	408	629	1149	196
115	0.50	401	627	1145	201

The predicted output of the ANN model corresponding to the input given for validation is presented in Table-3. It is observed that the predicted quantities are very close to the values obtained experimentally. The maximum percentage error is obtained as 0.7281%, (presented in Table-4) which can be considered as very accurate for the predicted model.

Table -3: Predicted mix proportions from ANN model

	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
Cement kg/m^3	392.3316	380.7456	410.5354	408.1037	399.9354
F.A. kg/m^3	641.6368	642.3792	615.3060	629.0788	628.9370
C.A. kg/m^3	1171.0550	1174.9290	1169.2340	1149.3300	1146.0290
Water kg/m^3	188.4612	190.6021	192.8449	195.9101	199.9185

Table -4: Percentage errors of predicted ANN output

	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	
Cement kg/m^3	0.1701	0.3284	0.1130	0.0254	0.2655	Max. percent -age error is 0.7281
F.A. kg/m^3	0.0993	0.2152	0.2127	0.0125	0.3089	
C.A. kg/m^3	0.0902	0.1645	0.0655	0.0288	0.0899	
Water kg/m^3	0.2851	0.7281	0.0804	0.0459	0.5380	

4.2 Comparison of ANN Model with Statistical Model

The mix proportion values obtained using ANN model is compared with linear Regression Analysis using MS Excel. Mix proportions are calculated based on a set of five data (Table-2) and using the equations obtained from regression analysis. The obtained mix proportions from regression analysis are presented in Table-5.

Table -5: Predicted mix proportions from Regression Analysis

	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
Cement kg/m^3	393.9783	380.1109	410.3964	408.3351	399.4713
F.A. kg/m^3	634.4940	644.4554	622.2305	623.2706	628.9904
C.A. kg/m^3	1175.7770	1173.2060	1163.3350	1155.3450	1146.2280
Water kg/m^3	188.7869	190.6935	192.4694	195.7455	199.9799

The various performance parameters such as correlation coefficient, root-mean-square error, Nash-Sutcliffe coefficient and mean absolute error are calculated for predicting the output of ANN model as well as Regression Analysis corresponding to the input set of validation data. These performance parameters obtained are presented in Table-6. It is observed that the predicted output of ANN model is much better compared to regression analysis output. Thus the ANN model is more efficient than regression analysis.

Table -6: Comparison of performance parameters

Parameters	ANN Model	Regression Analysis
RMSE	1.0118	3.1326
R	0.9971	0.9346
ME_{Nash}	0.9819	0.8665
MAE	0.1152	0.1150

The variation of predicted output of various models as compared to experimental values are shown in Figure-4 to Figure-6.

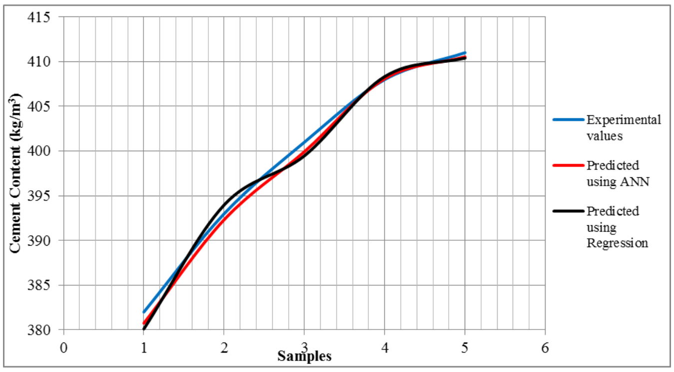

Figure -4: Variation of predicted cement content from experimental values

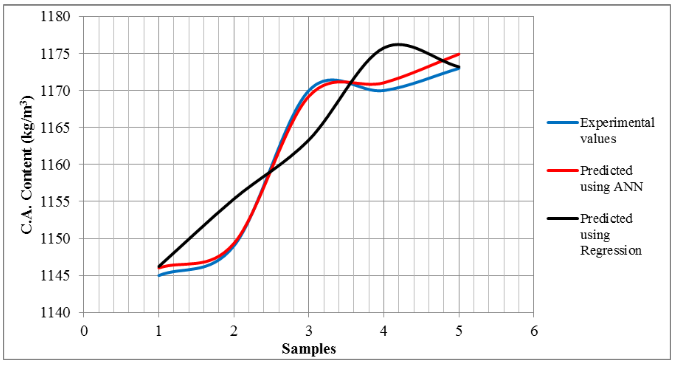

Figure-5: Variation of predicted C.A. content from experimental values

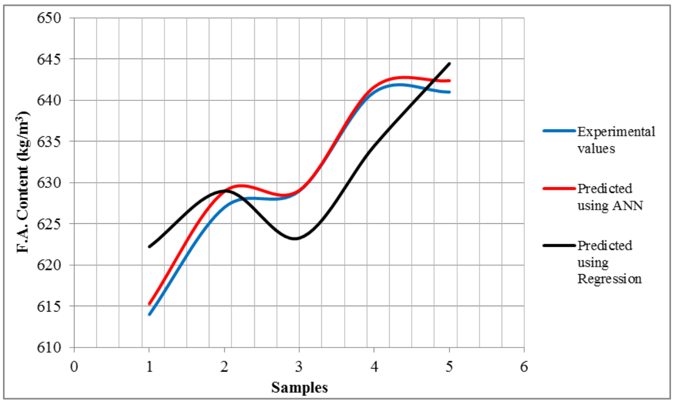

Figure-6: Variation of predicted F.A. content from experimental values

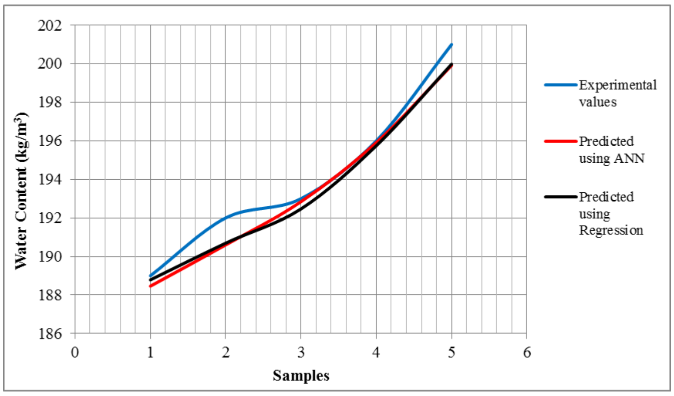

Figure-7: Variation of predicted water content from experimental values

It can be seen from the figures that the deviation of predicted values of cement content and water content from the experimental values are negligible. Whereas quantities of fine and coarse aggregate predicted using regression analysis are deviating much from the experimental values. Thus regression model is not efficient in predicting the fine aggregate and coarse aggregate content.

5. CONCLUSIONS

This paper demonstrates that ANN technique can be used effectively for predicting concrete mix proportions. Predicted mix proportions using the developed ANN model shows maximum percentage error of 0.7281%. The comparison of output results between ANN model and Regression Analysis shows that prediction of fine and coarse aggregate quantity is more difficult as compared to prediction of cement content and water content. The ANN model is found to be more efficient than regression analysis. The developed ANN model uses seven mix design parameters as input (viz. compressive strength, water-cement ratio, slump, specific gravity of cement & aggregates) to predict the quantities of cement, F.A., C.A. and water as output. However, the present ANN model can predict mix proportions for M25 grade of concrete only. This is because the data used for training of the model comprised of mix proportions of M25 grade of concrete which were tested in the laboratory. Similar models can be prepared for other grades of concrete if sufficient input data is available.

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BIOGRAPHIES

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