

# Determination of Concrete Compressive Strength from Non Destructive Test Results using Artificial Neural Network

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**Abstract:** The paper deals with the neural identification of the compressive strength of artificially(steel slag) replaced aggregate concrete on the basis of non destructively determined parameters. Basic information on artificial neural networks and its analysis of experimental results are given. A set of experimental data for the training and validation of neural networks is described. The data set covers a bulk density, ultrasonic pulse velocity and rebound number as input and compressive strength for M20, M30, M40 as output. The methodology of the neural identification of compressive strength is presented. The result show that Artificial Neural Network are highly suitable for computing the compressive strength of artificial(steel slag) replaced aggregate concrete.

**Keywords:** artificial (steel slag) replaced aggregate concrete, compressive strength, non destructive testing( Ultrasonic Pulse Velocity and Rebound hammer),Artificial Neural Networks

## I.INTRODUCTION

### 1.1 GENERAL

Concrete is essentially a mixture of paste and aggregate. The paste, comprised of cement and water, binds the aggregate into a hard mass, the paste hardens because of the chemical reaction of the cement and water called hydration. In concrete mix design and quality control, the uniaxial compressive strength of concrete is considered as the most valuable property, which in turn is influenced by a number of factors.

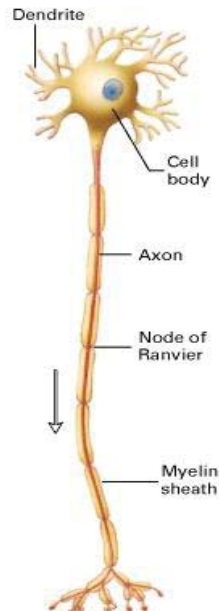
### 1.2 NON DESTRUCTIVE TEST

NDT is the test widely employed for inspecting the condition of structure without creates any destruction to the structure. Non destructive techniques, which are less time consuming and relatively inexpensive, can be used for the following purposes such as test on actual structures, test at several locations, test at various stages, assess the quality control of actual structures, assess the uniformity of concrete , etc.

### 1.3 FACTORS AFFECTING THE NON DESTRUCTIVE TEST

- Size and age of concrete
- Surface texture
- Concrete mix characteristics
- Stress state and temperature
- Carbonation level in concrete
- Moisture content.
- Reinforcement.

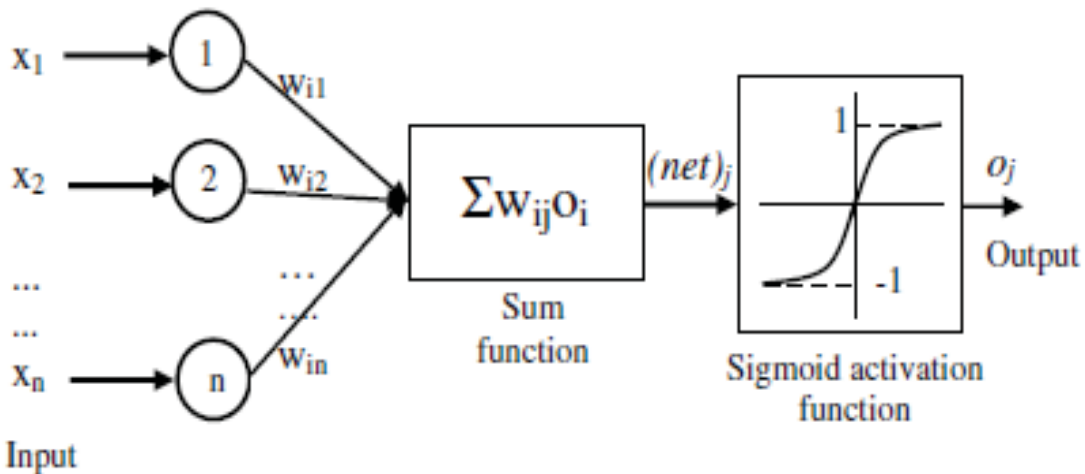
## II. EXPERIMENTAL INVESTIGATION



- Receives input through dendrites.
- Dendrites meet at synapses.
- Input from the all neurons is summed up in the cell body.
- If the sum is above a threshold value, then neuron fires.

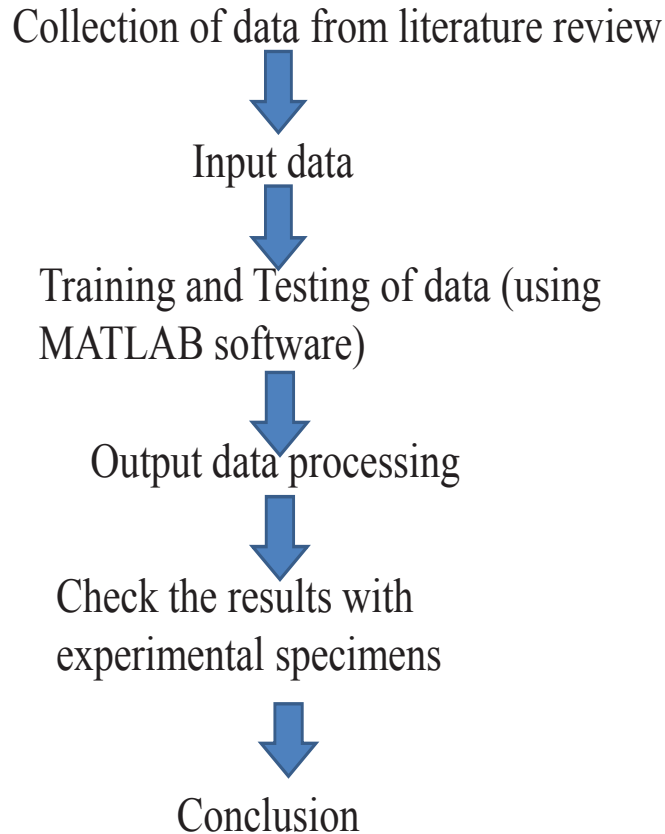
### OUTLINE OF THE PROJECT

- The network function is determined largely by the connections between elements.
- It can be trained to perform a particular function by adjusting the values of the connections (weights) between elements.
- It is adjusted, or trained, so that a particular input leads to a specific target output.
- There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target.
- Typically many such input/target pairs are needed to train a network.



The

traditional approach used in modelling the effects of these parameters on the compressive strength of concrete starts with an assumed form of analytical equation and is followed by a regression analysis using experimental data.

3) *METHODOLOGY*

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## III. DATASET AND SELECTED NEURAL NETWORK

*NEURAL NETWORKS PROCESS**ANN PHASES:**TRAINING*

In the training stage the ANN is presented pairs of several input and output and the corresponding desired target output data.. The rate of learning( 'q' ) plays an important role in this stage.

$$\Delta = q * \text{error signal} * \text{input signal}$$

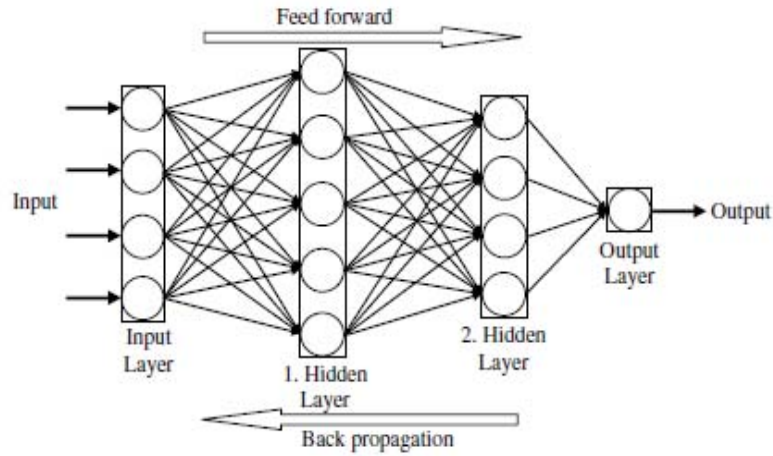
*TESTING*

A fresh set of input, whose output are already known in past records is fed to the network. The response from the network is compared with the target output and it should provide an exact model with minimum prediction error

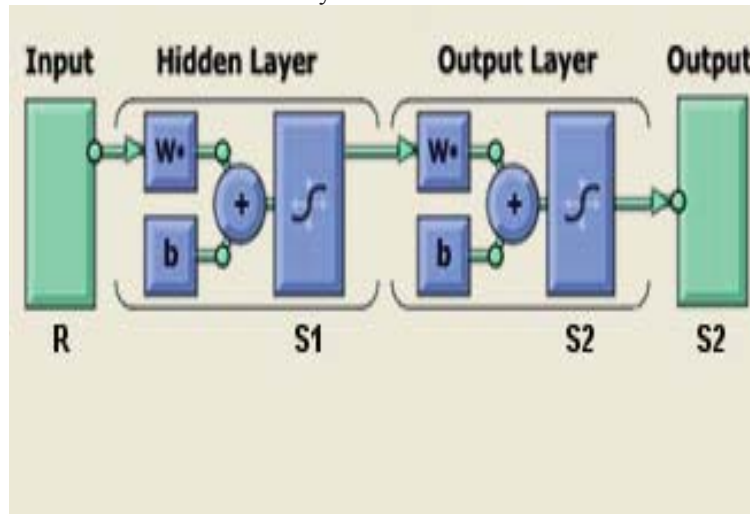
*BACK PROPOGATION ALGORITHM*

Back propagation algorithm, as one of the most well-known training algorithms for the multilayer perceptron a gradient descent technique to minimize the error for a particular training pattern in which it adjusts the weights by a small amount at a time. The network error is passed backwards from the output layer to the input layer, and the weights are adjusted based on some learning strategies

FEED --> FORWARD & <-- BACKWARD PROPAGATION NETWORK



Layers between the input and output layers are called hidden layers and may contain a large number of hidden processing units. All problems, which can be solved by a perceptron can be solved with only one hidden layer, but it is sometimes more efficient to use two or three hidden layers.



Finally, the output layer neurons produce the network predictions to the outside world. Each neuron of a layer other than the input layer computes first a linear combination of the outputs of the neurons of the previous layer, plus a bias. The coefficients of the linear combinations plus the biases are called weights. Neurons in the hidden layer then compute a nonlinear function of their input. Generally, the nonlinear function is the sigmoid function.

TABLE 5.1 RANGE OF PARAMETERS IN DATABASE FOR ANN

PARAMETERS	DATA BASE RANGE (ANN)
Bulk density (kg / m <sup>3</sup> )	2636-3043
UPV(μs)	33.9-25.1
Rebound number	27-42..2

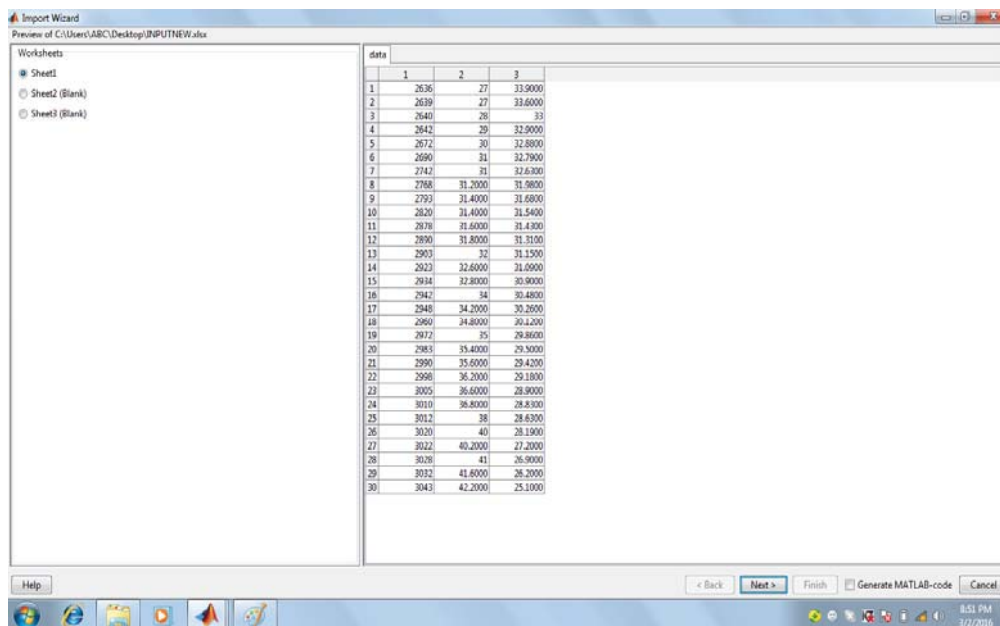
Table 5.2 input data and output data for ANN analysis

BULK DENSITY (kg/m <sup>3</sup> )	UPV ( $\mu$ s)	REBOUND NUMBER	COMPRESSIVE STRENGTH (Mpa)
2636	33.9	27	29.85
2639	33.6	28	29.90
2640	33	28	29.95
2642	32.9	30	30.20
2672	32.88	31	30.35
2690	32.79	31	30.92
2742	32.63	31.2	31.06
2768	31.98	31.4	31.25
2793	31.68	31.4	31.43
2820	31.54	31.6	31.52
2878	31.43	31.6	31.58
2890	31.31	31.8	31.65
2903	31.15	32	32.03
2923	31.09	32.6	32.42
2934	30.45	33	32.85
2942	30.13	34	33.36
2948	29.82	34.2	33.60
2960	29.65	34.8	33.90
2972	29.34	35	34
2983	29.23	35.4	34.3
2990	29.20	35.6	34.85
2999	29.18	36.2	33.36
3005	29.09	36.6	33.60
3010	28.83	36.8	33.90
3012	28.63	38	34
3020	28.19	40	34.30
3022	27.2	40.2	34.85
3028	26.9	41	35.25
3032	26.2	41.6	36.96
3043	25.1	42.2	37.92

### STEPS INVOLVED IN ARTIFICIAL NEURAL NETWORK

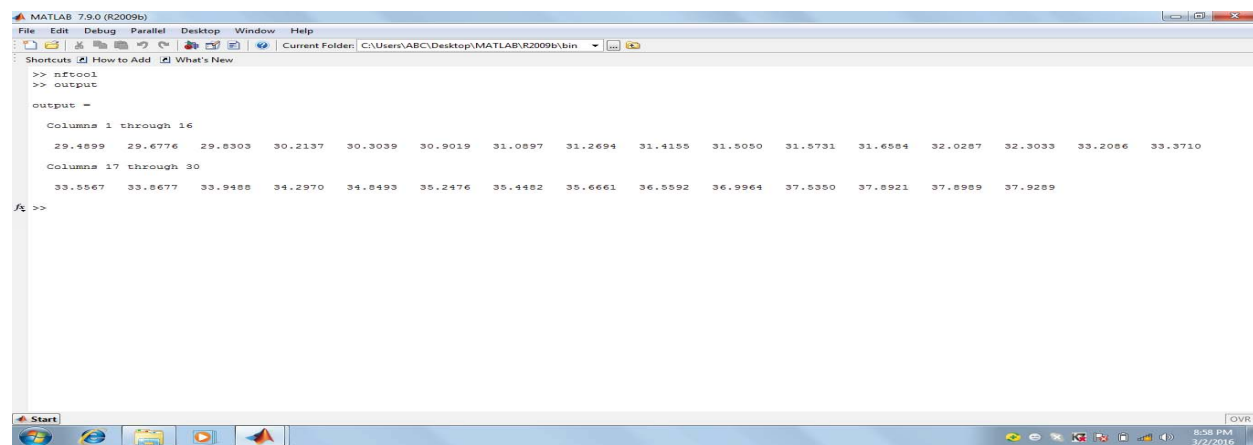
- Opening the MATLAB window.
- Enter input values of bulk density, pulse velocity and rebound number.
- After entering the input values click the start then go to tool boxes and choose the (NEURAL FITTING TOOL) NF tool.
- After the above step NF tools will appear in window, show the instruction click the next button to continue.
- Now the training and testing values are entered and to fit the input and output target data.
- Train the network will be stop after the target value obtain.
- After the train and testing the network the trained and tested network weights are taken as a permanent value for predicting the next network also.
- And then the regression analysis of the output and targets are takes place. The best fit is in red line.
- Final step is to save the output.

Input Data for ANN Analysis :



	1	2	3
1	2636	27	33.9000
2	2639	27	33.6000
3	2640	28	33
4	2642	29	32.9000
5	2672	30	32.8800
6	2690	31	32.7800
7	2742	31	32.6300
8	2788	31.2000	31.8600
9	2793	31.4000	31.6800
10	2820	31.4000	31.5400
11	2878	31.6000	31.4300
12	2890	31.8000	31.3100
13	2903	32	31.1500
14	2922	32.6000	31.0900
15	2934	32.8000	30.9000
16	2942	34	30.4800
17	2948	34.2000	30.2600
18	2960	34.8000	30.1200
19	2972	35	29.8600
20	2983	35.8000	29.3000
21	2990	35.6000	29.4200
22	2998	36.2000	29.1800
23	3005	36.6000	28.9000
24	3010	36.8000	28.8300
25	3012	38	28.6300
26	3020	40	28.1900
27	3022	40.2000	27.2000
28	3026	41	26.9000
29	3032	41.6000	26.2000
30	3043	42.2000	25.1000

Output Data from Analysis



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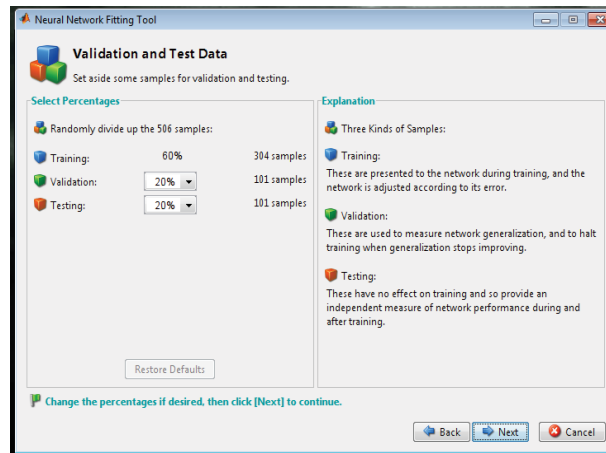
MATLAB 7.9.0 (R2009b)
File Edit Debug Parallel Desktop Window Help
Current Folder: C:\Users\ABC\Desktop\MATLAB\R2009b\bin
Shortcuts How to Add What's New
>> nftool
>> output

output =

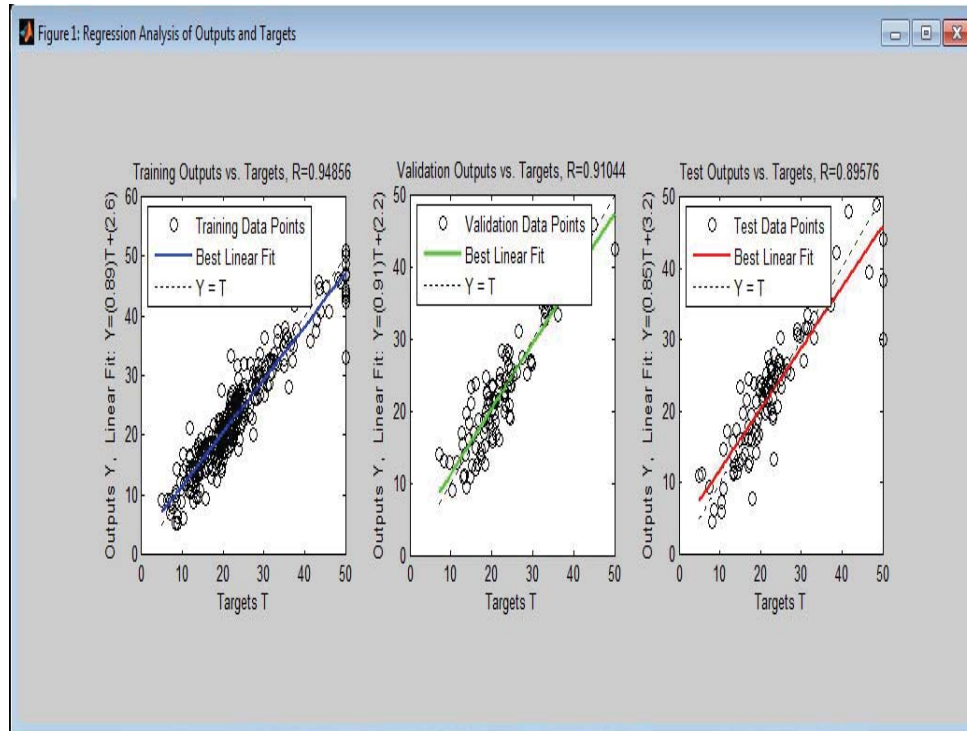
Columns 1 through 16
29.4899 29.6776 29.8303 30.2137 30.3039 30.9019 31.0897 31.2694 31.4155 31.5050 31.5731 31.6584 32.0287 32.3033 33.2086 33.3710

Columns 17 through 30
33.5567 33.8677 33.9488 34.2970 34.8493 35.2476 35.4482 35.6661 36.5592 36.9964 37.5350 37.8921 37.8989 37.9289
  
```

Training Phase



Results :



The relationship between destructively determined compressive strength and Artificially trained compressive strength are pictured above.

#### IV. CONCLUSION

The results presented here demonstrate that the assessment of the compressive strength of artificial replaced aggregate concrete by artificial neural networks by several non destructive techniques is a viable method. It is highly significant for determination of compressive strength of concrete. Artificial Neural Network gives accurate results than any other training software.

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