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# Strength prediction using ANN for concrete with Marble and Quarry dust

S. Anandaraj
*Department of Civil Engineering*
*Hindustan Institute of Technology and Science*
Chennai, India
umailanandkrish@gmail.com

Jessy Rooby
*Department of Civil Engineering*
*Hindustan Institute of Technology and Science*
Chennai, India
civil@hindustanuniv.ac.in

Gobinath Ravindran
*Department of Civil Engineering and Center for construction method and Materials*
*S R Engineering College*
Warangal, India.
gobinathdpi@gmail.com

Arun Kumar Beerala
*Department of Civil Engineering and Center for construction method and Materials*
*S R Engineering College*
Warangal, India.
arun_kumar_b@srecwarangal.ac.in

Vikram Mulukalla
*Department of Civil Engineering*
*S R Engineering College*
Warangal, India.
mulukallavikram@gmail.com

Swathi Koduri
*Department of Civil Engineering*
*S R Engineering College*
Warangal, India.
swathi.koduri1998@gmail.com

***Abstract*—Modern construction material research is picking impetus in the recent two decades; a greater number of admixtures and combinations were tried by bountiful researchers across the globe. In this work an attempt is made to obtain the strength characteristics by using Soft computing techniques in the marble and quarry dust impregnated concrete. Strength characteristics of concrete is studied with reference to the addition of the above-mentioned admixtures and the results were given as input parameters. 28 days compressive strength of concrete with varying marble and quarry dust content is utilized as input data for the neural network and a model is created which is used to predict the strength. To prepare the ANN model the results are taken and the values obtained are mean square propagation and the testing, training, validation and for overall propagation the values are 0.99793, 0.99577, 0.9927 and 0.99073 and the best validation performance is 0.023295 at epoch 7 respectively for MD and for QD the values are 0.9974, 0.94374, 0.94445 and 0.947 and the best validation performance is 0.035578 at epoch 4 respectively. It is found that neural network can be utilized effectively to predict the strength characteristics of concrete.**

***Keywords— ANN, Concrete strength, strength prediction*.**

## I. INTRODUCTION

As per the United Nations report, the world population will be increased to 9800 million and above by the year 2050 and it was 25% more compared with population of present scenario. Due to increase in the population there will be growth in the construction and usage of more and more natural resources for the purpose of the construction will be also increased [1]. Due to these there will be increase of waste in the world rapidly. It was stated that the wastes were using about 28% of land fill in the world as per the report from the Department of Environmental and Food in the year 2016. Among those there is large amount construction and demolition waste is nearly 15 million tons of waste is produced in India every year those waste includes Marble dust (MD), Quarry dust (QD), sand, gravel, bitumen, etc are generated as wastes in the form of byproducts and demolition waste [2].

Filling the land with the waste material increases the pollution directly and it effects the environment..Many researchers had worked on this for reusing the waste in the construction so that it reduces the waste and disposal. Among those waste materials marble dust and quarry dust are two materials which are byproducts of materials producing industry [4].

The requirement of cement concrete for the global population is estimated to be 10 tons per year. Each ton of production takes 1.7 tons of raw materials, 4 GJ of energy and it releases 0.73 to 0.99 tons of Carbon dioxide. Even for manufacturing cement, 8-12 billion tons of raw materials are required per year [3]. This huge demand of raw materials will reduce the natural stone deposits creating a negative impact on environment. The studies made by the researchers concluded that Marble Dust and Quarry Dust can be used as replacing material for the cement and aggregates. The utilization of the byproducts in the concrete leads to tremendous decrease in the waste and the usage of the cement also resulting a very good impact on the built environment [6].

The decrease of cement percentage in the concrete leads to reduction in the use of natural resources and reduce in the emission of carbon dioxide and controls the environment from global warming, decreasing the cement content not only reduces the use of natural resources but also recent studies concluded that usage of 10 percentage of marble dust can increase the strength of the concrete more than 15 percentage when the results compared with the normal concrete [5].

The experimental procedure involves huge man power and time consumption. To overcome this issue, researchers started working to develop models which can predict the engineering properties of concrete [8]. In order to reduce the structural failures and also the overall construction. In recent times, scholars used several methods including analytical, statistical and artificial intelligence to develop models which can predict the strength characteristics. In artificial intelligence, artificial neural network is a popular and widely used method [7]. Some of the applications, where ANN can be effectively used for many civil engineering applications are groundwater monitoring, settlement of foundation and strength prediction.

The main objective of this study is to develop models using the strength parameters obtained from experimental investigations conducted by the proper utilization of marble dust and quarry dust to get the maximum strength [8].

## II. MATERIALS AND METHODS

### A. *Materials*

In this mix design is evolved by using the grade of cement is 53 and the fine aggregate used is of zone III and the coarse aggregate used is of size 20mm, the specific gravities of cement, coarse aggregate and fine aggregate are 3.12, 2.6 and 2.5 and the water used for mixing and curing of the concrete is potable water throughout the investigation [9]. By this the mix design obtained is M25.

The replacing materials used are Marble dust (MD) and Quarry dust (QD) in the production of concrete.

The present study is investigated in two fields one is the study of properties of concrete using the replacing material as MD and the other is similar but using the QD by this the Mechanical properties of Concrete such as Compressive, split tensile and the flexural strengths are known [10]. Marble dust will be added to concrete in percentages of 0%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% by replacing cement and in the same manner the sample is made by using QD also for this W/C ratio adopted is 0.44 and the cement content is taken as 423.7 kg/m3. The cement quantity will be varied for modified cement concrete based on the choosing of percentage of replacing material. These ratios of replacing materials will be same for MD and QD.

#### *1.Marble dust:*

Marble dust is the byproduct produced at the time of preparation of marble stone marble is a metamorphic rock composed of recrystalized materials [11]. It can be used as the best filler material in the concrete replacing of concrete with marble dust can increase about 15% strength of the concrete than normal concrete so now a days it is widely used in the construction industry for the better results [12]. The marble dust is shown in fig 1.

Fig. 1. Marble dust

#### *2. Quarry dust:*

Quarry dust is a byproduct of granite and coarse aggregates produced at the time of crushing of aggregates and blasting of rocks during this process powder material is generated in the form of waste that is known as quarry dust [14]. That can be used in the construction activity in the replacement of cement, sand, coarse aggregate and in the preparation of bricks also it can be used by using this material in the concrete it makes the concrete stronger than regular concrete. The quarry dust is shown in fig 2.

Fig. 2. Quarry dust

### B. *Tests done:*

#### ***1***.*Compressive strength:*

Compressive strength is one of the important engineering properties of the concrete, and it is found by considering the load applied for crushing the concrete specimens. In general concrete is classified based on grades, which are the compressive strength results obtained from the tests conducted on concrete cube or cylinder [13]. Some portion of cement is replaced with marble dust and quarry dust alone for calculating the engineering properties of the concrete. The samples were cured for standard ages 7, 28 days and tested for the compressive strength. The addition of MD and QD up to some extent resulted in increase in the strength properties [14].

#### *2.Split -tensile strength of concrete:*

Split tensile strength is to measure the tensile strength of material like metal concrete etc. Tensile strength is an important property of concrete as its strength is different for different densities of materials. Split tensile strength is calculated by replacing of concrete with Quarry dust and Marble dust alone at 7,14- and 28-days age of curing. By replacement of these materials the strength increases and in the same way as it is waste materials polluting affecting the environment so it can be used for concreting purpose [16]. The basic and important property that effect the extent and size of cracking in structure is tensile strength of concrete. Moreover, concrete is very weak in tension due to its brittle nature. Hence, it is not expected to resist direct tension, so concrete develops cracks when tensile forces exceeds its tensile strength. So therefore it is necessary to determine the tensile strength of concrete to determine the load at which the concrete members may crack.

#### *3. Flexural Strength of concrete:*

Flexural strength represents the highest stress experienced among the material at its moment of yield. Flexural Strength is measure of tensile strength of concrete and unreinforced concrete beam or slab to resist failure in bending. It is determined by standard test strategies like ASTMC 78(third point loading) or ASTM C298 (centre-point loading) [15]. The idea of flexural strength is to design the pavements thus, laboratory mix design supported flexural strength tests is additionally needed, or building material content is additionally chosen from past expertise to induce the required design [28]. For structural concreting solely some use flexural testing. The flexural strength increase when the compression strength and age of concrete will increase. the rise in compressive strength at same age of concrete is lower increase in flexural strength. Flexural strength represents the highest stress experienced among the fabric at its moment of yield. This test is sensitive to specimen preparation; handling and curing procedures [16]. Beam specimens are significant and may be broken during handling or transportation.

## III. Artificial Neural Network

In 1943, the studies on ANN were started. Artificial neural networks were developed to model the human brains consisting the neurons [29]. Earlier it was a single layered function for solving the problem, then learning algorithms called back propagation was introduced and now also it was being used widely for various engineering applications [18].

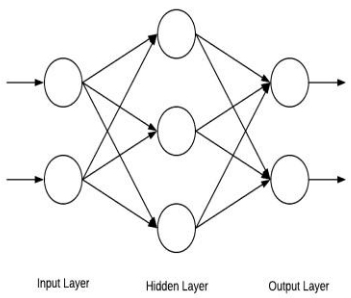


Fig. 3. Artificial Neural Network Architecture

An artificial neuron consists five parts: input, output, weights, sum function and activation function [30]. Weights are the essential part which shows adverse effects on the output. Sum function will build the relationship between inputs and weights, which will have serious impact on the element process [17]. The weighted sum is calculated by using the following equation:

$$(net)_j = \sum_{i=1}^{n} \mathrm{W_{ij}} \mathrm{X_i} + \mathrm{b} \quad ....(1)$$

The network learns from the output data obtained from the model and then comparing it with the actual experimental data. Then the calculated error is propagated through backward function [29]. While doing this, the weights are modified accordingly, to fit the information provided for the training purpose [19]. After identifying the model, the performance must be tested. By giving input parameters to the developed model, network calculates the output by using the existing weights and thresholds developed in the learning process. Coefficient of regression values are calculated to test the accuracy of the developed model. The higher the regression value indicates the best prediction from the network [21].

As a part of this study, the prediction of engineering properties was done by taking the experimental data obtained by taking marble dust and quarry dust as partial replacement of cement. Models were trained with Levenberg-Marquardt algorithm was used for training the feed forward networks [20]. The available data was divided into three parts: training, testing and validation. Identifying the proper architecture for the network is the typical issue which need to be studied thoroughly to avoid complexity in the network [22]. Multilayer feed forward network models can be solved easily and more approximately by using one hidden layer. To predict any parameter using ANNs, selection of hidden neurons plays a vital role, but unfortunately no theory is available for selecting neurons for a particular problem [28]. To overcome this issue, starting from lesser neurons increase in number of neurons was applied till the satisfactory minimum error is obtained [24]. Once the learning phase done, the model was tested for the validation by using the validation data set to check with the reliability of the model.

## IV. Results and Discussions

### *A. Compressive strength*

The compressive strength of the cubes when the Marble dust and Quarry dust used alone in the concrete mixture in different percentages the strengths are shown in the fig. It is observed that there is increase in the strength of cube at replacing of 20% of marble dust in the concrete and the strength is increased in the other sample that is using the quarry dust as replacing material in concrete at same percentage of replacing material [23]. And it is observed that when the marble dust is increased above 20% then the strength parameters are falling down but it is observed that is gaining more that the characteristic strength and for 28 days the test results [31] are shown in fig. It is observed that replacing material can be used to 60% of concrete the strengths gained using the percentage are equal as when compared with the traditional mixture of concrete [24].

When overall strengths are compared by using this QD and MD both gave approximate nearly strengths for all curing ages [26]. The strengths at different curing ages are shown in fig 4.

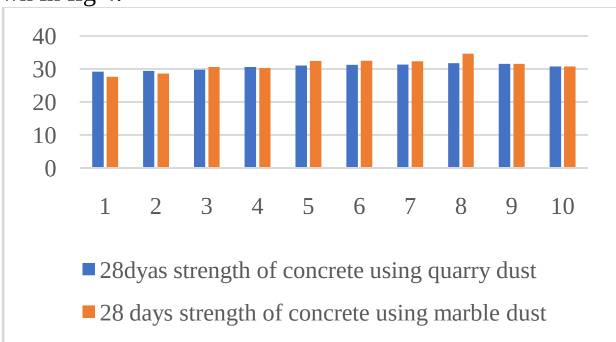


Fig. 4. Compressive Strength For Quarry Dust And Marble Dust

Among the data 70% of data is for training the model. Performance of compressive strength through model prediction (L.M Algorithm) against the Experimental values for the training are mean square propagation and the testing, training, validation [31] and for overall propagation the values are 0.9799, 0.9920, 0.9977and 0.98901 and the best validation performance is 0.1197 at epoch 3 respectively for marble dust and the results are shown in graph and for the quarry dust are 0.9972, 0.9952, 0.99 and 0.9957 and the best validation performance is 0.11048 at epoch 3 respectively. The regression plots for MD and QD were shown in fig 5 & fig 6. The mean squared error plot was shown in fig 7 & fig 8 for MD and QD respectively.

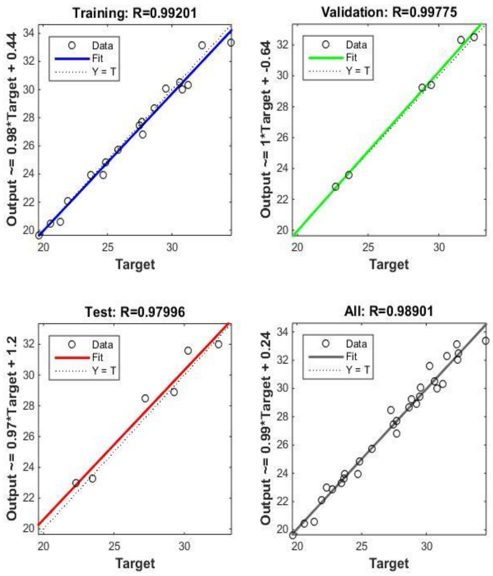


Fig. 5. Scatter Plots Showing The Performance Of Compressive Strength Through Model Prediction Against The Experimental Values For Training, Testing, Validation Of Marble Dust.

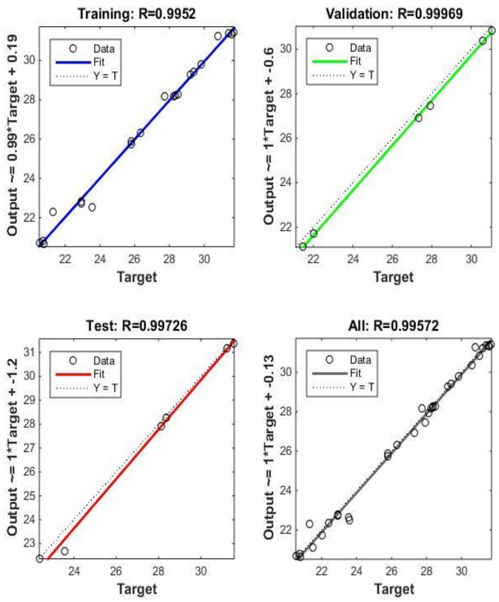


Fig. 6. Scatter Plots Showing The Performance Of Compressive Strength Through Model Prediction Against The Experimental Values For Training, Testing, Validation Of Quarry Dust.

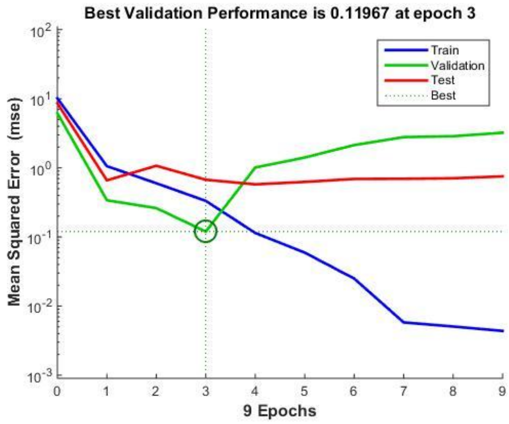


Fig. 7. Mse Against Different Epochs For The Validation Of The Performance Of The Compressive Strength Of The Concrete Using Replacing Material Md

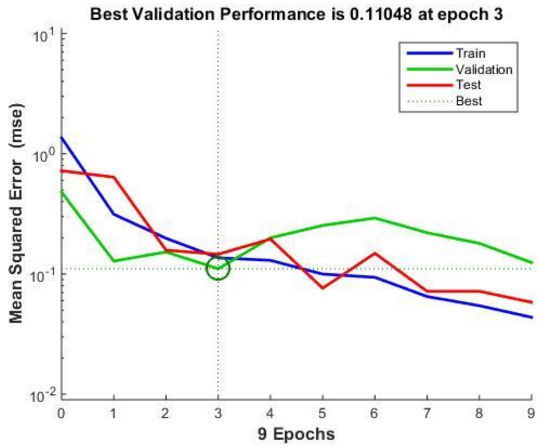


Fig. 8. Mse Against Different Epochs For The Validation Of The Performance Of The Compressive Strength Of The Concrete Using Replacing Material Qd

### *B. Tensile strength:*

The tensile strength of concrete containing M.D and Q.D alone as replacing material in the percentages as 0, 10, 20, 30, 40, 50, 0, 70, 80 and 90 results are shown in the figure the samples were tested at 3 different curing ages i.e., 7, 14and 28 days respectively [25]. The use of MD and QD in the concrete has tremendous impact in the tensile strength of concrete. It is seen that tensile strength increases with increase in the MD and similarly for QD also the increased strengths are shown in fig. Max tensile strength is achieved at 20% usage of MD and also it attained nearly equal value in the QD also [27].

This increase in the strength is due to increase in the finer material in the mixture of concrete due to this the voids will be closed and there will be decrease in the porosity so that the tensile strength increases [32]. The strengths at different curing ages are shown in fig 9.

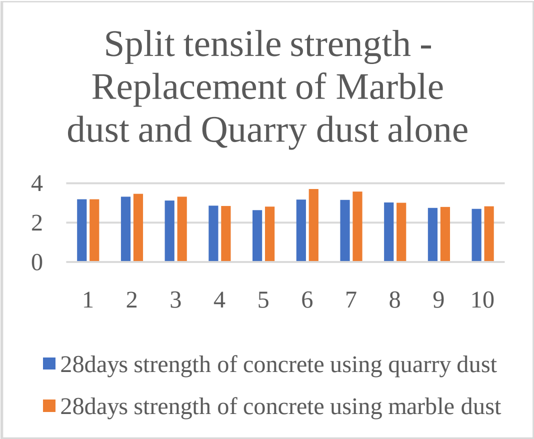


Fig . 9. Tensile Strength For Quarry Dust And Marble Dust

To prepare the ANN model the results are taken and the values obtained are mean square propagation and the testing, training, validation and for overall propagation the values are 0.99793, 0.99577, 0.9927 and 0.99073 and the best validation performance is 0.023295 at epoch 7 respectively for MD and for QD the values are 0.9974, 0.94374, 0.94445 and 0.947 and the best validation performance is 0.035578 at epoch 4 respectively. The regression plots for MD and QD were shown in fig 10 & fig 11. The mean squared error plot was shown in fig 12 & fig 13 for MD and QD respectively.

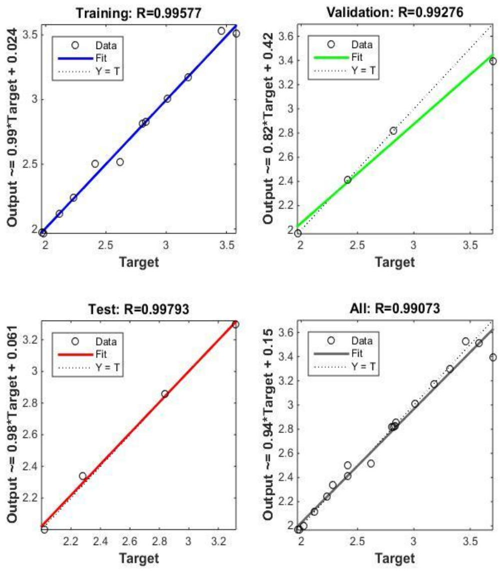


Fig. 10. Scatter Plots Showing The Performance Of Compressive Strength Through Model Prediction Against The Experimental Values For Training, Testing, Validation Of Marble Dust.

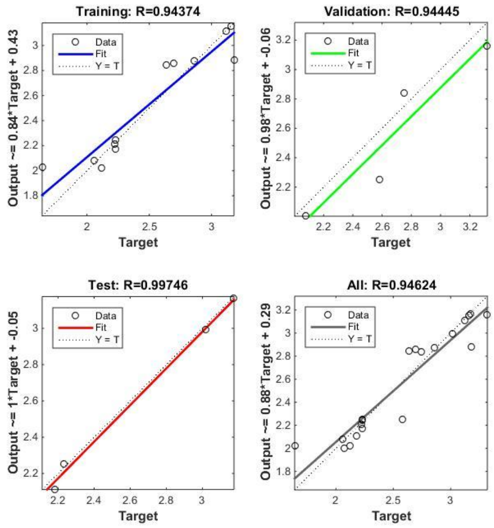


Fig. 11. Scatter Plots Showing The Performance Of Tensile Strength Through Model Prediction Against The Experimental Values For Training, Testing, Validation Of Quarry Dust.

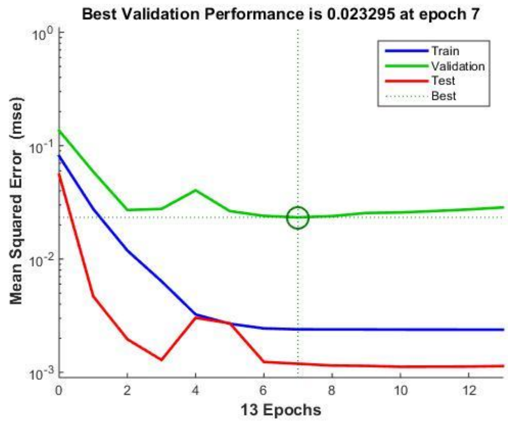


Fig. 12. Mse Against Different Epochs For The Validation Of The Performance Of The Tensile Strength Of The Concrete Using Replacing Material Md

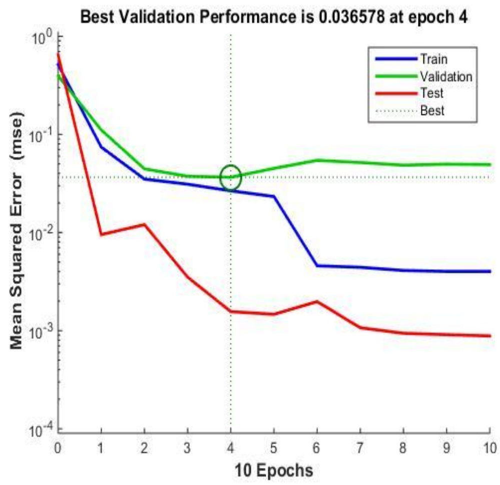

Fig. 13. Mse Against Different Epochs For The Validation Of The Performance Of The Tensile Strength Of The Concrete Using Replacing Material Qd

### *A. Flexural strength:*

Flexural strength properties are also same impact of using these materials as replacing materials and this also achieved max strength at replacing of 20 percentage of MD in concrete and achieved same using quarry dust (QD) also [29]. The results are for different proportions of MD and QD alone are shown in the fig 14.

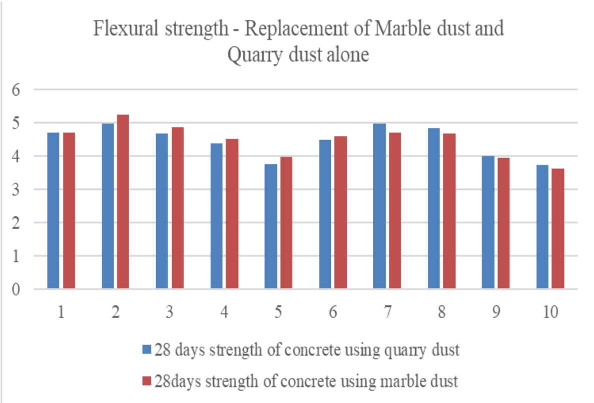


Fig 14. Flexural Strength For Quarry Dust And Marble Dust

The ANN models also were generated for flexural strength also the obtained values are mean square propagation and the testing, training, validation and for overall propagation the values are 1, 0.999, 1and 0.9909 and the best validation performance is 0.0040679 at epoch 4 respectively for MD and for QD the values are 1, 0.91019, 1 and 0.93108 best validation performance is 0.099793 at epoch 0 respectively. The regression plots for MD and QD were shown in fig 15 & fig 16. The mean squared error plot was shown in fig 17 & fig 18 for MD and QD respectively.

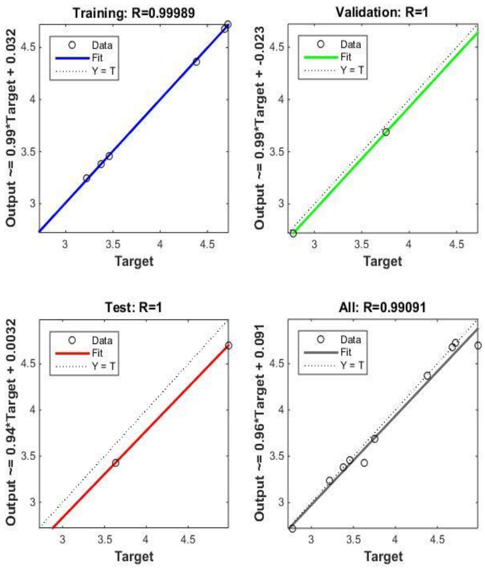


Fig. 15. Scatter Plots Showing The Performance Of Flexural Strength Through Model Prediction Against The Experimental Values For Training, Testing, Validation Of Marble Dust.

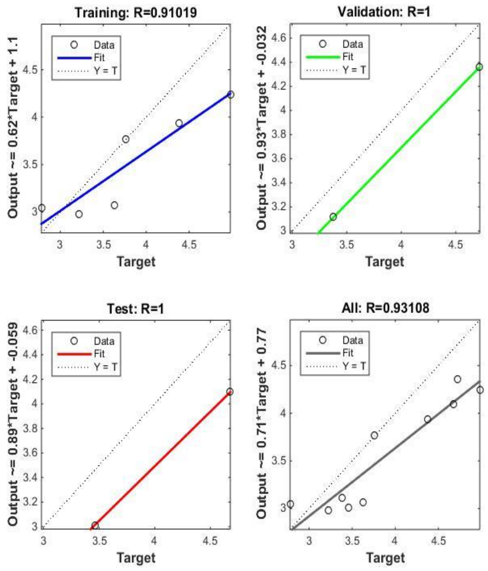


Fig. 16. Scatter Plots Showing The Performance Of Flexural Strength Through Model Prediction Against The Experimental Values For Training, Testing, Validation Of Quarry Dust.

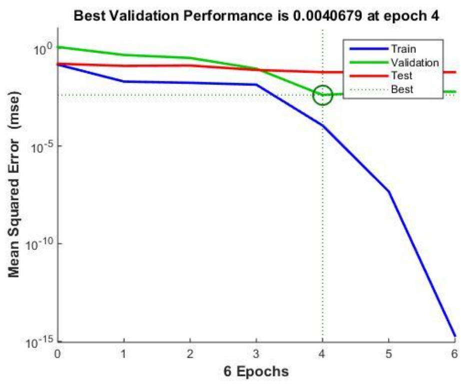


Fig. 17. Mse Against Different Epochs For The Validation Of The Performance Of The Flexural Strength Of The Concrete Using Replacing Material Md

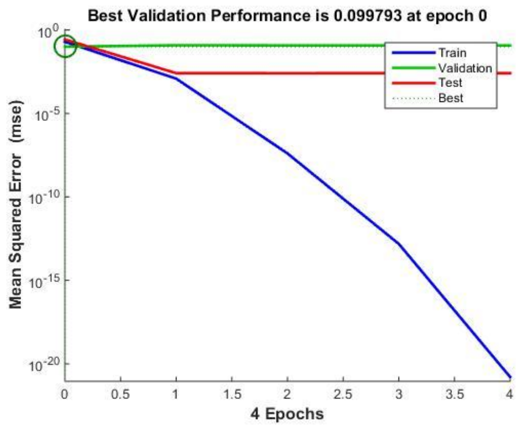


Fig. 18. Mse Against Different Epochs For The Validation Of The Performance Of The Flexural Strength Of The Concrete Using Replacing Material Qd

## V. Conclusion

As the necessity of developing prediction models to find the mechanical properties of concrete, an artificial neural network model was developed using the 7 and 28 days strength characteristics obtained by the experiments conducted on concrete by partial replacement of cement with marble dust and quarry dust. From the experimental data, 70% was used for training, 15% for validation and 15% for testing purpose. When marble dust is replaced, the regression values for compressive, split tensile and flexural strengths were observed as 0.98901, 0.99073 and 0.9901. For quarry dust, the regression values were found to be 0.99572, 0.94624 and 0.93108 for compressive, tensile and flexural strengths respectively. The higher coefficient of regression indicates the higher accuracy of the model for prediction. Interestingly the predicted values from model were very close to the experimental values of respective strengths.

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