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Prediction of mechanical properties of concrete blended with marble stone powder by artificial neural network

T. S. Ramesh Babu[1*], *K.* Thangamani[1], *Mendu* Jugal Kishore[2], *J.* Guru Jawahar[3], *D.* Pavan Kumar[4], *Satish* Garigipati[5] and *Khristina* Maksudovna[6]

[1]Department of Civil Engineering, K. G. Reddy College of Engineering and Technology, Moinabad, Hyderabad, T.S. 501504.
[2]Department of Civil Engineering, Kallam Haranadha Reddy Institute of Technology, Guntur, A.P – 522006.
[3]Department of Civil Engineering, Annamacharya Institute of Technology and Sciences, Tirupati, A.P
[4] Department of Civil Engineering, Jawahar Lal Nehru Technological University College of Engineering Anantapur, Anantapur, A.P.
[5]Department of CSE, GRIET, Hyderabad, Telangana, India
[6]Lovely Professional University, Phagwara, Punjab, India.

Abstract. The current research work is mainly concentrated on the mechanical properties concrete blended with marble stone power resulted from waste sludge marble processing it has a high specific area. M25 grade concrete mix design was considered for this research work. The mechanical properties of concrete i.e. compressive strength, unit weight, splitting tensile strength, modulus of elasticity and flexural strength were considered for the study. The compressive strength of these mixes was measured on 150mm ×150mm × 150mm cubes and tension test split tensile test 150 mm dia × 300 mm height cylinders. The concrete unit weight was considered for calculating the elastic modulus of concrete. The investigational values were matched with ACI, CEB-FIP, BIS and AASHTO LRFD empirical equation and regression analysis was done. The empirical equation result was compared with regression analysis of Artificial Neural Network, and conclusion was brough down that regression analysis of artificial neural network had better prediction than that of above-mentioned empirical equations. The study concluded that 15% replacement of marble power attained highest strength and optimum replacement, 25% replacement was concluded as economical replacement to attain designed strength.

1 Introduction

Marble is most common material used since olden times. Marble is also used for construction and elevation purposes, and it’s had mineral property. Marble is process for different application it will generating a huge number of wastes at quarries or at marble plants. During this process marble becomes waste because of being irregular shape and smaller size. Waste

* Corresponding author: drtsrameshbabu@gmail.com

materials recycling is the very important tool to protect the environment and to achieve sustainable development. 7 million tons of wastes are discharging from marble industry by cutting of marble, polishing of marble, and grinding of marble. Pollution problem is a very significant cause of anxiety in Rajasthan, there are around more than four thousand marble mines and more than thousand marble cutters in Rajasthan districts. In India, total waste generation from Rajasthan is more than six million tons over a year. The dust of marble stone generally possesses a main environmental anxiety. The marble dust powder freely hangs in the air during the summer season and it travels in air and deposits on the crops and green vegetations. During rainy season the dust particles of marble disposed on the river-bed and that causes reduction in permeability and porosity of the top of the soil and it will result in water logging.

Artificial Neural Network (ANN) is the methodical approach that involves complex network. It is used to develop the relationship between empirical results and predicting the output from ANN models with the given inputs. ANN exclusively discoveries the non- linear analysis. There are amply of ANN software packages like MATLAB, SPSS and SCILAB. MATLAB has been working owing to its highest precision in civil engineering for compressive strength concrete prediction. The Fig. 1 show the schematic diagram of ANN model. ANN are gauging techniques, that imitate the human brain's biological neural systems for processing the data [1-4]. ANN had some significant properties in information handling and managing that can assist to work out the challenges that are very complex [3-5].

2 Material Properties

2. 1 Cement

53 Grade Ordinary Portland Cement [6] was referred for moulding of cubes and cylinders for all designed concrete mixes. The unique grey colour cement with a greenish and it was lumps free. Table 1 shows the cement properties.

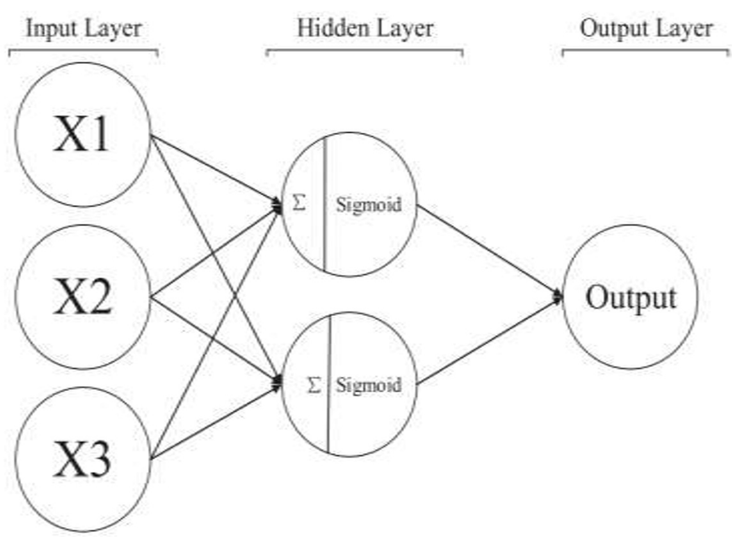

Fig. 1. Schematic diagram ANN Structure

Table 1. Cement Properties

S. No.	Property	Value	Standard Values
1	Standard Consistency	32%	-
2	Initial Setting time	50 minutes	Should Not less than 30 minutes
3	Final Setting time	400 minutes	Should Not greater than 600 minutes
4	Fineness	5.2%	<10
5	Specific gravity	3.15	-

2. 2 Fine Aggregate and Coarse Aggregate

The locally available Fine Aggregate (FA) was used for the investigational work [7]. The FA was sieved and those properties were shown in Table 2.

Table 2 Fine Aggregate Properties

S. No.	Characteristics	Value
1	Aggregate type	Uncrushed (Natural)
2	Specific Gravity	2.53
3	Fineness Modulus (FM)	2.99
4	Grading zone	1

FM of fine aggregate was 2.99, the gradation was shown in Fig. 2 and the FM of coarse aggregate was 2.68. The water absorption of coarse aggregate was calculated as 1.14%.

3 Experimental Investigation

3.1 Introduction

The conventional concrete M25 mix was designed as per IS 456 -2000 and 10262 – 2009 [8-9]. In the present investigation marble power was replaced to cement as like 0%, 5%, 10%, 15%, 20% and 25%. The concrete cubes of size 150mm and 150mm diameter with 300mm deep of cylindrical specimens was cast and concrete compressive strength was tested [10], splitting tensile strength [11], unit weight, modulus of elasticity [10] and flexural strength [10] tested at 7, 14 & 28 days. The water cement ratio was fixed as 0.5 for entire research.

3.2 Artificial neural networks (ANN)

ANN is used as a effective tool in predicting the values from trained data. ANN artificially copying the neurons in biological neurons system. An artificial system of neuron contains of five primary parts those are parameter of inputs and weights, the summation function (Σ), the function for activation F(Σ) and with output (y). Inputs cover the date that arrives into the cell from other cells in the same network (Serin, 2011). Weights or values that display the impact of the previous layer in the operation system of input set [12]. The summation function computes the outcomes of all weights and inputs. This function also computes the cell profit [13]. The function of sigmoid is considered as an triggering function in the prediction of multilayer. ANN deal with data managing system created in input layer with one or more layers in hidden form, and a layer of harvesting or outcome. The author stated that every layer comprises many plain or dense parallel connected internally for managing units, termed as neurons that was illustrated in Fig. 1. [13-17]. The interlinked neurons, and address is allotted to each connection said as weight, that accepts neurons communication [18]. Every neuron had inputs of several links, those are reproduced by the weights of analogous data, added all together, combined additional bias and employed to a function for activation and to create a single specific output that is explained by following Eq. 1.

$$Z=f(\sum_i^n w_i x_i + d) \quad (1)$$

where 'Z' = neuron output, x_i = input value, w_i = linking weight, d = bias value, and f = Function of activation [19].

The Multi – Layer Perception (MLP) is termed in ANN, since it is consisting of an input layer with one or huge intermediary layers, and an exist layer called output layer [20]. The existing research explained that the Neural Networks with Feedforward system is a fragment of a MLP, it was guided by means of the backpropagation (BP) algorithm [21]. The Feed forward Neural Network system, the stream of data begins from the nodes of input, moves through the nodes in the form of hidden mode, and ends at the exit or output nodes without repetition [22]. The research illustrated that Back-propagation is a controlled studying technique applied for algorithms training that minimize the errors by altering the biases and weights [23-24]. The existing research stated that Back-propagation is most widespread and popularly used technique due to its well-defined and agreed studied laws [25].

4 Results and Discussion

4.1 Compressive Strength:

The Compressive Strength (CS) of concrete cube and cylinder test was conducted at 7, 14 and 28 days curing. CS of conventional concrete increase with increase in age shown in Fig. 3 and Table 3. Compressive strengths concrete increases with increase in marble power replacement from 0 to 15%, thereby increase in replacement level decrease in strength was observed. The strength increments from 0 to 15% replacement at 7, 14 and 28 days was 20.19 to 27.56, 24.31 to 31.09 and 32.79 to 36.79. It was observed that the strength was enhanced considerably with replacement of marble power. The strength enhancement was due to presence of lime in marble power enhances the C-S-H(gel) formation, that causes the strength increment. CS enhancement from conventional concrete with 15% marble power replacement was 26.80%, 20.59% and 10.86% at 7, 14, and 28 days curing of one-to-one. It was evident there was a considerable strength increment with 15% replacement of marble power to cement. 15% replacement of marble power is concluded that it attained highest strength among the all the replacement level. Hajmeer and Basheer [25] examined on the add-on of marble dust. The result of several proportions of marble dust such as swelling, physical parameters and mechanical were stated. The output shown as enhancement of the tensile strength and addition of MP result in quick hardening. Thereby again increasing the marble power replacement falling in strength was noted. It is due to existence of excess lime may lead to interruption to hydration and root to soundness of cement. In this present study, 25% replacement of MP attained M25 aimed strength of concrete at 28 days maturity period. The replacement level higher than 25% was failed to achieve the designed strength. So that it can be concluded that 25% replacement of marble power is optimum replacement level.

The research examined the blending of fly ash and MP for mixtures of polyester composites and studied the impact of the MP with fly ash blending percentage and effect on the hardened and mechanical properties were described [26]. The 1/3 ratio achieved optimum effect with flexural strength value of 30.4 MPa. The authors stated that industrial by-products those are fly ash, MP and silica fume can be employed as a void filler [27].

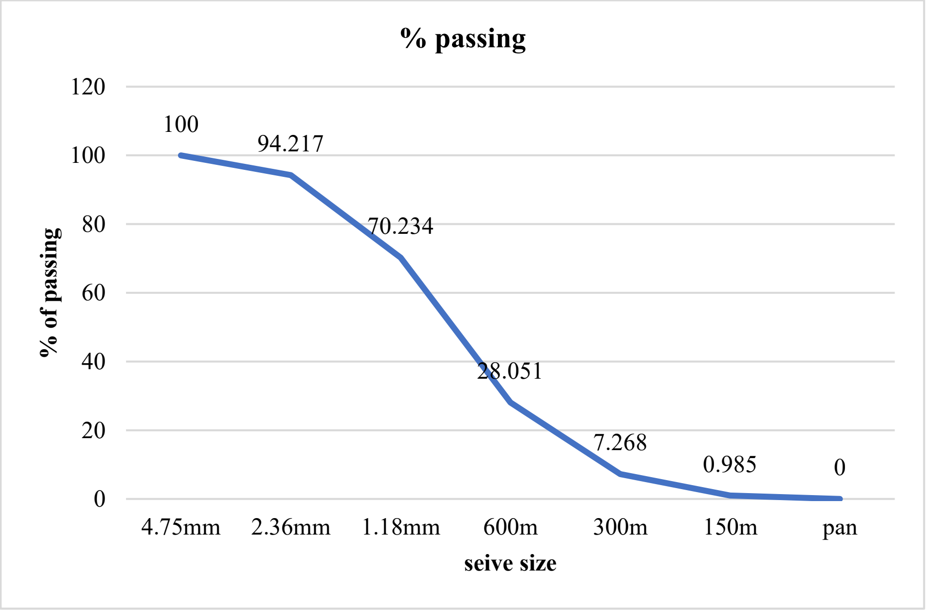

Fig. 2. Sieve Analysis Graph

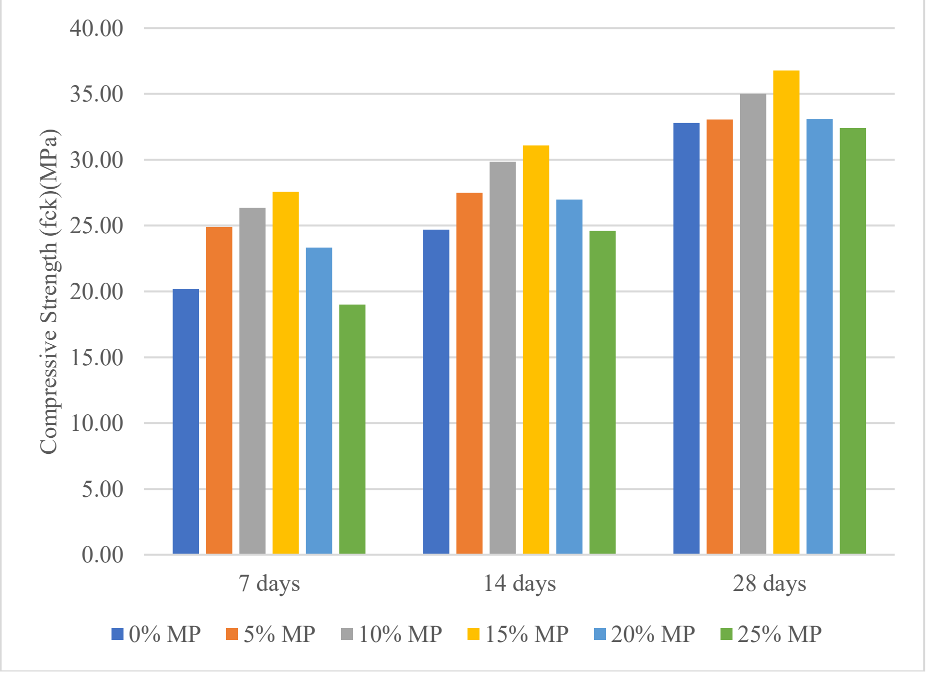

Fig. 3. Compressive Strength of Marble Blended Concrete

Table 3. Compressive Strength of Marble Power Blended Concrete (MPa)

Age	0% MP	5% MP	10% MP	15% MP	20% MP	25% MP
7 days	20.18	24.90	26.34	27.57	23.33	19.00
14 days	24.69	27.49	29.85	31.09	26.99	24.60
28 days	32.80	33.06	35.01	36.79	33.09	32.39

The particles with reinforcement property tend to enhance the performance of material and reduces the production cost and may leads to reduce the pollution. The addition of MP dust to matrix leads to has a considerable effect on the hardened property of composites [28]. The compressive strength, bond strength and workability of concrete decreased due to presence of excess walnut shell in mix [29].

The Table 4 shows the prediction result of ANN model, and it was compared with experimental values. It was observed that at early age 20 layers model predicted values were close to investigational values. Whereas at advanced ages the predicted values of 20 layers the error percentage increases. Then, 10 layers ANN model predicted values were much close to investigational values and the R^2 values was about 0.99 for one and remaining equation are 0.92. But the 30 layers model most of the graphs R^2 values are close to 0.99. So, it was evident that the predicted values of 30 layers model can be considered for future prediction, but due to huge number of layers the prediction time increases. Gregor et al. [32] were also created a Gene Expression Programming model with 36 experimental data to forecast the CS of concrete integrating with corrugated steel fibres and PET chips by recycled subjected to elevated temperature. From Fig. 4, 5 and 6 illustrates the variation of R values for 10-, 20- and 30-layers ANN models. Fig. 7 illustrates the variations of experimental values and ANN model predicted values of 10-, 20- and 30-layers models.

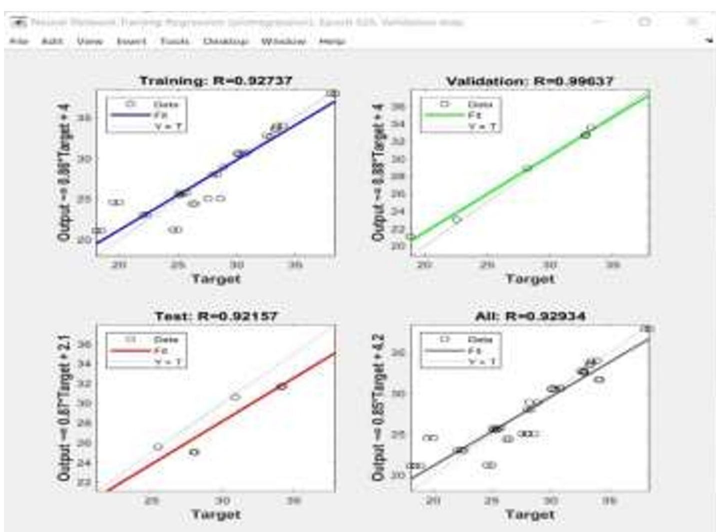

Fig. 4. R values of Target and Output for 10 Layers of ANN Model

Shahmansouri et al. [33], Asteris et al. [34] and Duan et al. [35] revealed that both the predicted and experimental results was be studied, they are close to each other. They studies revealed that R^2 is greater than 0.7. The accuracy is improved when it approaches to 1.

Artificial Neural Network (ANN) is one of the best learning techniques with deep learning that is extensively recommended in analytical investigative studies of material having nature of cementing properties. The prediction simulations or models for supervising the actions or properties of hardened structures with cementitious nature [36-37]. A number of investigation works have been performed for the estimate of several concrete properties, in particular the compressive strength, from its ingredients. Baykasoglu et al. [39] offered optimization technic with a multiple objectives and prediction of concrete properties having strength more than 80MPa through regression analysis, ANN, and GEP. Saridemir [40] and Topcu and Saridemir [41] studied the difference between ANN and fuzzy logic estimation or prediction of result of concrete CS containing fly ash and methacholine mortars, respectively.

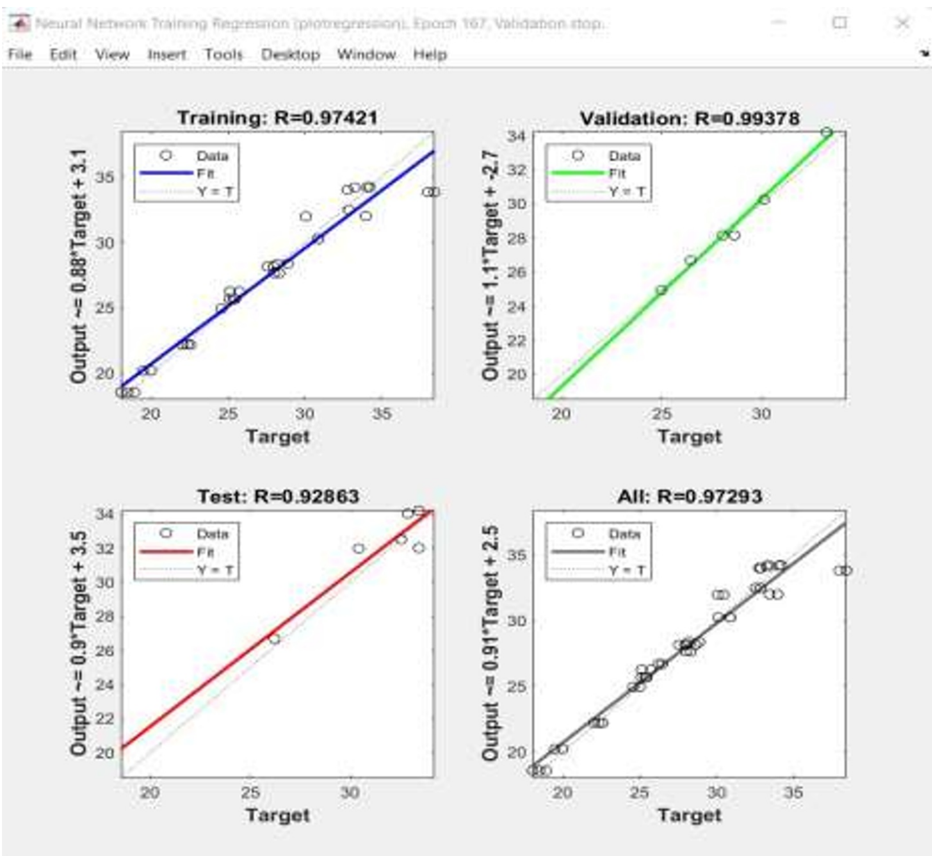

Fig. 5. R values of Target and Output for 20 Layers of ANN Model

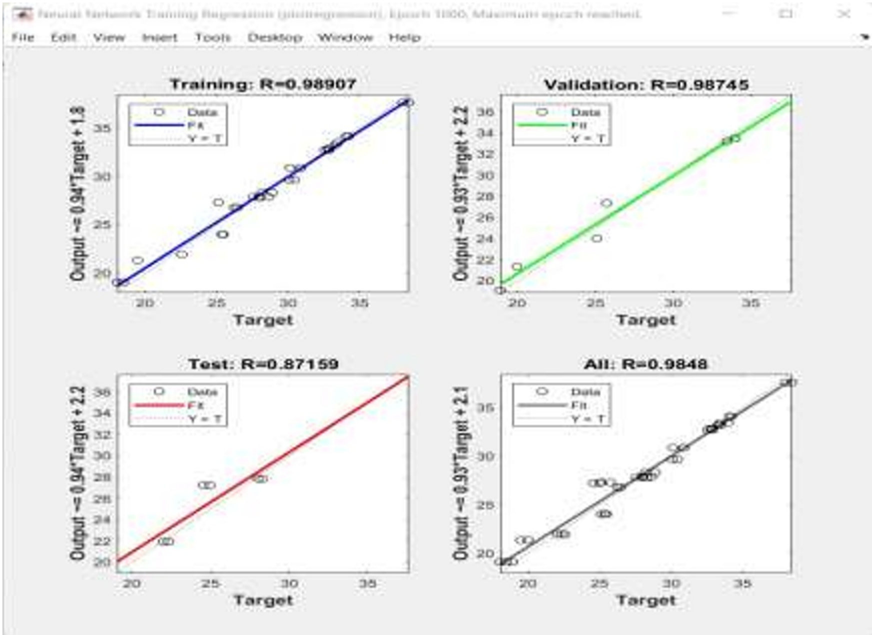

Fig. 6. R values of Target and Output for 30 Layers of ANN Model

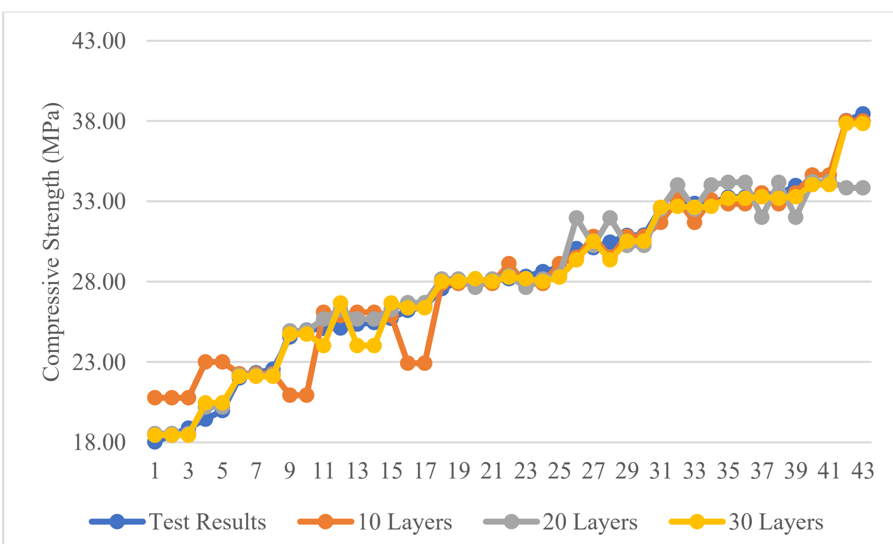

Fig. 7. Compressive Strength Result of Experimental Values, 10, 20 and 30 layers Predicted Values.

Safarzadegan Gilan et al. [42] performed a study and compared between the regression of ANFIS and ANN, for the assessment CS of non-slump concrete and decided that the models of ANFIS and ANN were more consistent for estimating or prediction of strengths [43]. Lampinen and Vehtari [44] developed a layered neural network with standard feed-forward system model for estimating or prediction of concrete CS, slump and density properties presented as 27 variables as input. They successfully employed, learning neural network model with Bayesian approach for final prediction and concluded that neural network model predicted results and test result are close to each other.

Table 4 Investigation Results and ANN Model Values of Compressive Strength of Concrete (MPa)

S. No.	Test Results	10 Layers	20 Layers	30 Layers	S. No.	Test Results	10 Layers	20 Layers	30 Layers
1	18.02	20.77	18.55	18.45	23	28.32	27.84	27.65	28.20
2	18.45	20.77	18.55	18.45	24	28.63	27.90	28.16	28.01
3	18.89	20.77	18.55	18.45	25	28.89	29.13	28.37	28.29
4	19.45	23.00	20.20	20.45	26	30.07	29.52	31.98	29.37
5	19.97	23.00	20.20	20.45	27	30.12	30.82	30.26	30.52
6	22.02	22.27	22.20	22.12	28	30.45	29.52	31.98	29.37
7	22.33	22.27	22.20	22.12	29	30.87	30.82	30.26	30.52
8	22.56	22.27	22.20	22.12	30	30.89	30.82	30.26	30.52
9	24.56	20.93	24.94	24.74	31	32.56	31.69	32.50	32.63
10	24.98	20.93	24.94	24.74	32	32.78	33.08	34.02	32.68
11	25.09	26.09	25.67	24.03	33	32.87	31.69	32.50	32.63
12	25.12	25.89	26.26	26.67	34	32.89	33.08	34.02	32.68
13	25.36	26.09	25.67	24.03	35	33.26	32.85	34.19	33.19
14	25.45	26.09	25.67	24.03	36	33.26	32.85	34.19	33.19
15	25.72	25.89	26.26	26.67	37	33.45	33.53	32.01	33.29
16	26.22	22.93	26.69	26.38	38	33.45	32.85	34.19	33.19
17	26.45	22.93	26.69	26.38	39	33.98	33.53	32.01	33.29
18	27.56	27.90	28.16	28.01	40	34.06	34.64	34.23	34.04
19	27.96	27.90	28.16	28.01	41	34.23	34.64	34.23	34.04
20	28.01	27.84	27.65	28.20	42	38.02	38.02	33.84	37.84
21	28.05	27.90	28.16	28.01	43	38.45	38.02	33.84	37.84
22	28.19	29.13	28.37	28.29	44	38.12	38.47	38.15	37.93

4.2 Splitting Tensile Strength

The Splitting Tensile Strength (STS) of MP blended concrete was graphically presented Fig. 8 and tabulated in Table 5. It was noticed that the STS improved with increase in age in conventional concrete. It was observed that STS is directly proportional to compressive strength, it indicates STS also maintained same pattern of strength enhancement like compressive strength. STS was increased with increase in marble power up to 15% replacement. The improvement of strengths due to lime present in the marble power enhances the compressive strength and STS and also enhancement of interfacial transition zone Thereby increasing in replacement level decreasing STS was observed. The experimental result was compared with CEB-FIP [45] and ACI 363R [46] and the corresponding expressions were shown in Table 6. From the Table 7, it was observed that determined values of CEB-FIP [45] equation gives underestimated values than that of experimental values. ACI 363R [46] estimates the reasonable values and approximately lower than experimental values, for safety in designing lower values will have higher safety. So that for future determinations ACI 363R [46]can be consider. Fig. 9 shows the regression analysis for experimental results. It was observed that regression equation R^2 values is 0.946 and it shows that the error percentage will lead to more. That means the determination values using these empirical equations may give either lower or higher values than that of experimental values. Table 7, show the ANN model results. From the Fig. 10 'R' value for target and output is equal to unity. That shows the predicted result from ANN model give very close values of experimental values. So that for future determination of STS, ANN model is very much helpful and gives more accurate values than that of CEB-FIP, ACI 363R and linear regression equation values. Wei Jiang et al. [47] concluded that prediction of the STS of the bonding interface by ANN were compared with experimental values of STS. The percentage error between ANN and experimental values were less than 5% and those are within acceptable limit.

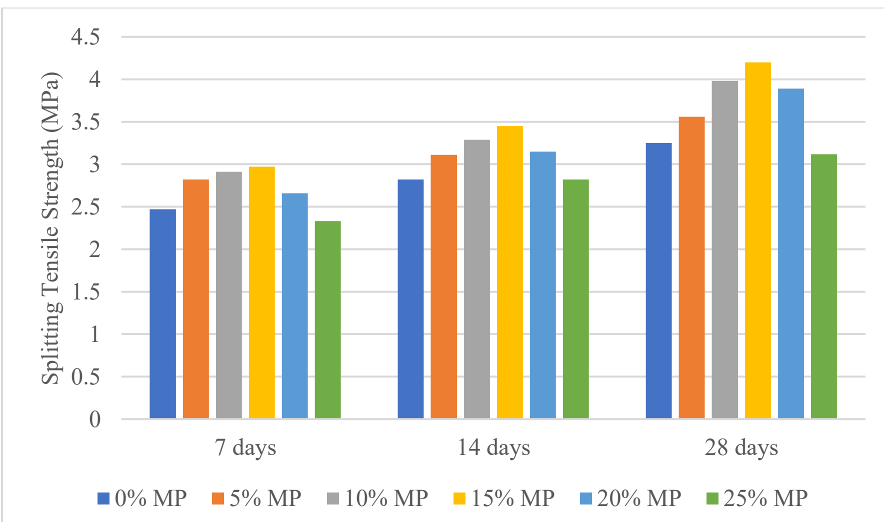

Figure 8. STS of MP Blended Concrete

Table. 5 STS of MP Blended Concrete (MPa)

Age	0% MP	5% MP	10% MP	15% MP	20% MP	25% MP
7 days	2.47	2.82	2.91	2.97	2.66	2.33
14 days	2.82	3.11	3.29	3.45	3.15	2.82
28 days	3.25	3.56	3.98	4.2	3.89	3.12

Table 6. Expressions for STS.

Code of Practice	Expression for STS	Range of C S
ACI 363 R (ACI 1992) [46]	$=0.59\times\sqrt{f_{ck}}$	21 MPa < f_{ck} < 83MPa
CEB-FIP (1990) [45]	$= 1.56 \times \left[\frac{f_{ck}-8}{10}\right]^{\frac{2}{3}}$	f_{ck} < 80MPa
IS 456: 2000 [8]	$= =0.7\times\sqrt{f_{ck}}$	--

f_{ck} is compressive strength of cylinder

Table 7. Splitting Tensile Strength of Experimental, ACI 363, CEB -FIP, IS 456 and ANN Model Predicted Values (MPa)

Comp. Strength	STS (Experimental)	IS 456:2000	ACI 363 R	CEB-FIP (1990)	ANN Model
19.00	2.65	2.92	2.57	2.60	2.65
20.18	2.82	3.01	2.65	2.63	2.82
23.33	3.06	3.24	2.85	2.72	3.04
24.60	3.20	3.32	2.93	2.75	3.19
24.69	3.15	3.33	2.93	2.75	3.26
24.90	3.21	3.34	2.94	2.76	3.22
26.34	3.26	3.44	3.03	2.79	3.26
26.99	3.33	3.48	3.07	2.81	3.32
27.49	3.29	3.51	3.09	2.82	3.34
27.57	3.31	3.52	3.10	2.83	3.35
29.85	3.41	3.66	3.22	2.88	3.41
31.09	3.49	3.74	3.29	2.91	3.49
32.39	3.59	3.81	3.36	2.94	3.59
32.80	3.67	3.84	3.38	2.95	3.67
33.06	3.71	3.85	3.39	2.95	3.71
33.09	3.73	3.85	3.39	2.95	3.75
35.01	3.79	3.96	3.49	3.00	3.79
36.79	3.86	4.06	3.58	3.04	3.80

4.3 Modulus of Elasticity

The Modulus of Elasticity (MOE) of conventional and marble power blended concrete were shown in Table 8. Unit weight of concrete cylindrical and compressive strength of cylinder was calculated to predict the strength parameters. It is observed that MOE of CC and marble power blended concrete also maintained the same trend as CS. Growth in MOE was observed with rise in age of curing for all the mixes, it was due to improvement of particles bonding and development of C-S-H(gel). Ali Alsalman et al. [48] reported that modulus of elastic plays a key role in design of structures elements and it also concluded that MOE is directly depending on ingredients of concrete and compressive strength. Medine Ispir et al. [49] investigated and illustrated about the curve pattern of stress-strain of lean concrete. Low strength concrete material characteristics concrete has substantial importance for seismic performance evaluations of existing poor-quality structures. Semih Gonen and Serdar Soyoz [50] evaluated the MOE of masonry is the main parameters applied in both the evaluation of the existing structures and proposed design of new structures. With their study, compressive has significant effect on MOE. Guru Jawahar et al. [51] reported that MOE is a function of compressive strength, it depends on density and strength of concrete. Ramesh Babu and Neeraja [52] stated that CS plays a major role to enrich the mechanical properties of concrete. They proposed the empirical equation by employing the unit weight and CS are the major parameter that effects the MOE.

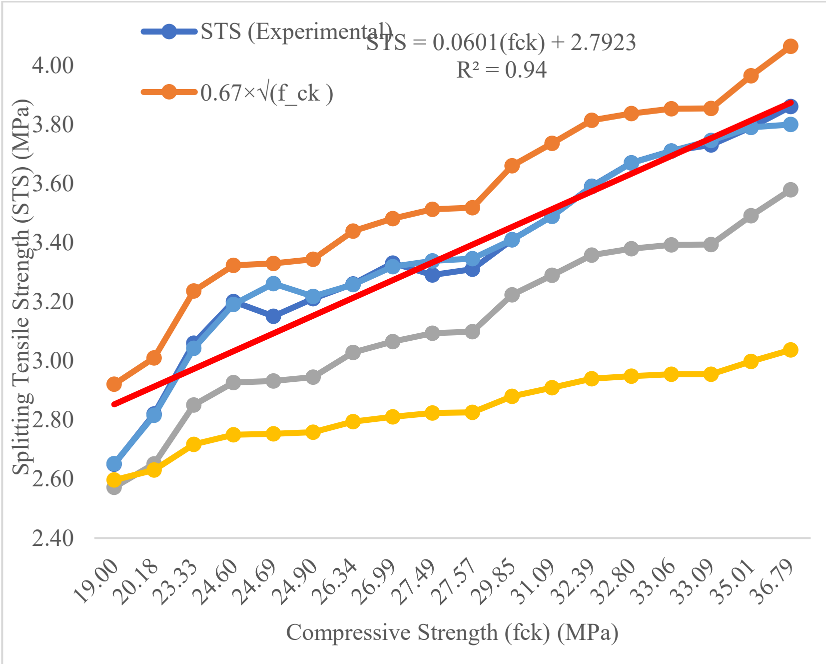

Fig. 9. Graph showing Splitting Tensile Strength of Experimental, CEB-FIP, ACI 363R and ANN model predicted values

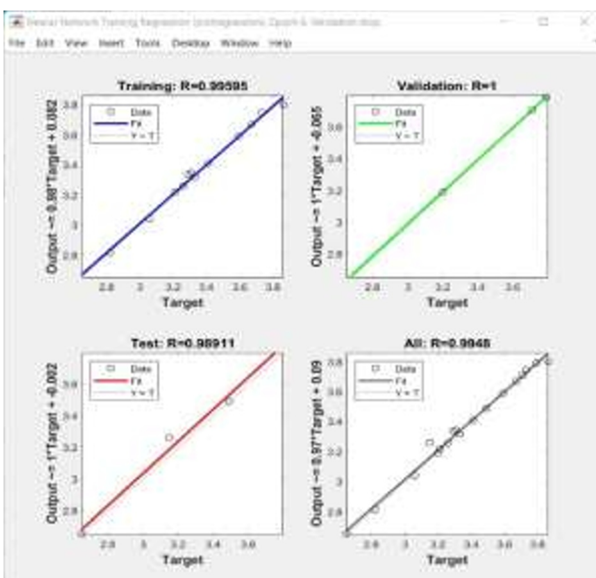

Fig. 10. R values of Target and Output for Splitting Tensile Strength of ANN Model

The ACI 318, IS 456-2000, ACI 318 and ACI 363R suggested empirical models were stated in Table 8. MOE of empirical equation and experimental values were presented in Table 8 and illustrated in Fig. 11. It was noticed that ACI 363R empirical model predicts very little values of MOE as matched with the investigational values. It was evident that equation considering only CS as a function to calculate the MOE without considering its unit weight. Whereas IS 456:2000 equation estimates more advanced values at early age and lower values at later ages than that of investigational values, it is also considering only the CS as a parameter.

AASHTO LRFD or ACI 318 [53] predicts the much higher values at all the ages of curing and also it can be considered for designing purposes. So that empirical equation was developed by regression analysis and shown in Fig. 11. It has R^2 values 0.98 that indicates the predicted values may near to experimental values. To reduce the error percentage ANN model was developed and trained with experimental values and the stimulation values were presented in Table 8 and graphically shown in Fig. 12. ANN model values were near equal to unity and stimulation values were very near to investigational values. It was evident that ANN model empirical equations may use for future determination of MOE to reduce the experimental works.

Table 8. Modulus of Elasticity of Marble Power Blended Concrete

Comp. Strength of Cube (MPa)	Comp. Strength of Cylinder (MPa)	Unit weight (kN/m³)	ACI 318 equation : Ec =4730 $\sqrt{f_{ck}}$ (MPa)	IS 456:2000 $5000\sqrt{f_{ck}}$ (MPa)	ACI 363 equation: Ec =3320 $\sqrt{f_{ck}}$ +6900 (MPa)	AASHTO LRFD/ACI 318 = 0.043 × $\gamma_c^{1.5}$ + $\sqrt{f_{ck}}$	Experimental (MPa)	ANN Model (MPa)
19.00	14.63	23.44	18.09	19.13	19.60	18.67	18.98	19.07
20.18	15.94	23.58	18.89	19.96	20.16	19.66	19.36	19.31
23.33	18.43	23.62	20.31	21.47	21.15	21.19	20.56	20.76
24.60	19.68	23.71	20.98	22.18	21.63	22.02	21.45	21.50
24.69	19.80	24.12	21.05	22.25	21.67	22.67	21.32	21.86
24.90	20.07	24.07	21.19	22.40	21.77	22.75	21.89	21.89
26.34	21.33	24.10	21.85	23.09	22.23	23.50	22.86	22.60
26.99	21.78	24.16	22.07	23.33	22.39	23.83	23.29	23.23
27.49	22.40	24.18	22.39	23.66	22.61	24.20	23.74	23.66
27.57	21.23	24.20	21.79	23.04	22.20	23.59	24.12	23.93
29.85	23.58	24.26	22.97	24.28	23.02	24.95	24.75	24.85
31.09	24.56	24.29	23.44	24.78	23.35	25.51	24.99	24.87
32.39	25.91	24.36	24.08	25.45	23.80	26.32	25.09	25.45
32.80	26.30	24.39	24.26	25.64	23.93	26.56	26.23	26.09
33.06	26.65	24.41	24.42	25.81	24.04	26.77	26.89	26.31

33.09	26.80	24.45	24.49	25.88	24.09	26.91	26.77	26.40
35.01	28.25	24.63	25.14	26.58	24.55	27.94	27.89	27.80
36.79	29.99	24.69	25.90	27.38	25.08	28.89	28.99	28.95

4.4 Flexural strength:

The Flexural Strength (Fx.S) of Marble Power blended concrete samples was showed in Tabel 9 and graphically showed in Fig. 13. As it can be observed that, flexural strength increases with curing period for all the MP blended mixes. The increase in MP replacement increase in flexural strength up to 15% replacement, thereby increase in MP replacement decreases in strength was observed. It shows the same pattern of compressive strength. It is the evident that all mechanical properties are directly related to compressive strength. Similarly, without MP and 25% MP blended attained same strength. So, 25% blended mix can be recommended to attained designed M25 grade concrete. Jianyu et.al [54] reported that the flexural strength enhancement can be accredited to the sealing effect of the low metal melting into the matrix voids, connecting the metal particles effect of metal and the elevated flexural strength. Xianyue et al. [55] reported that compressive and flexural strength of WGMt-PC mortars were measured at 1 to 28 days with related mechanism was examined by hydration heat. The strength was improved, and both are inter dependents.

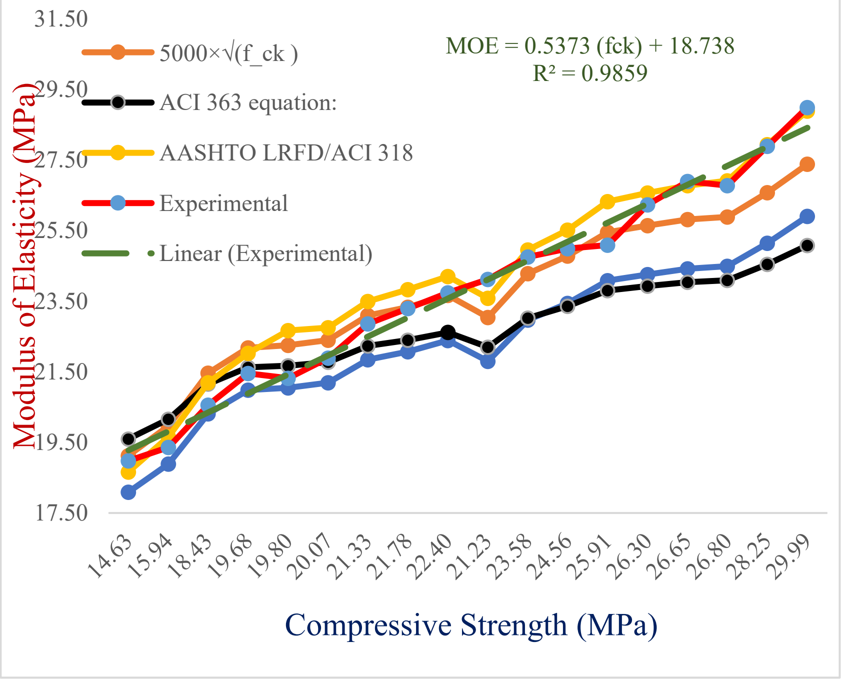

Fig. 11. Modulus of Elasticity of Concrete

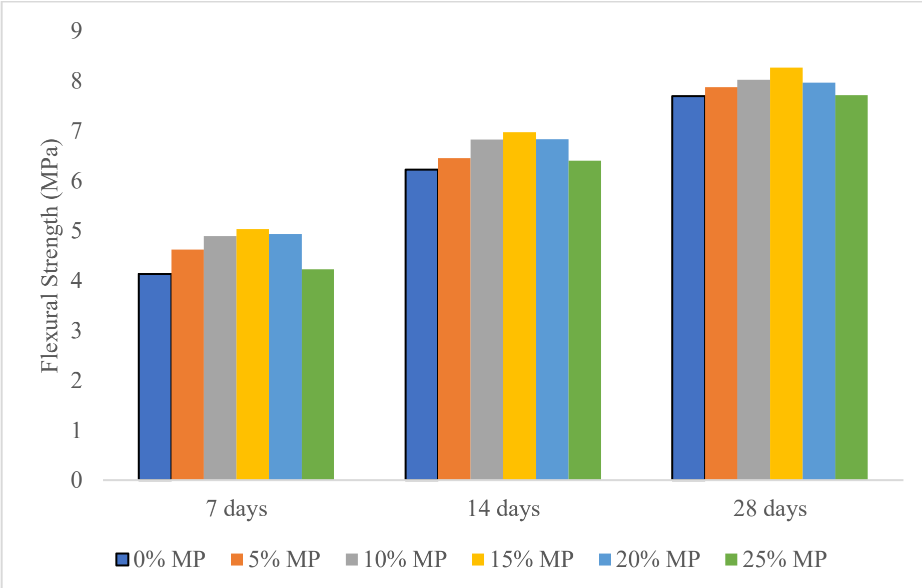

Fig. 13. Flexural Strength of Marble Power Blended Concrete

Table 9. Flexural Strength for Conventional Concrete

Age	0% MP	5% MP	10% MP	15% MP	20% MP	25% MP
7 days	4.13	4.62	4.89	5.03	4.93	4.22
14 days	6.22	6.45	6.82	6.97	6.83	6.4
28 days	7.69	7.87	8.02	8.26	7.96	7.71

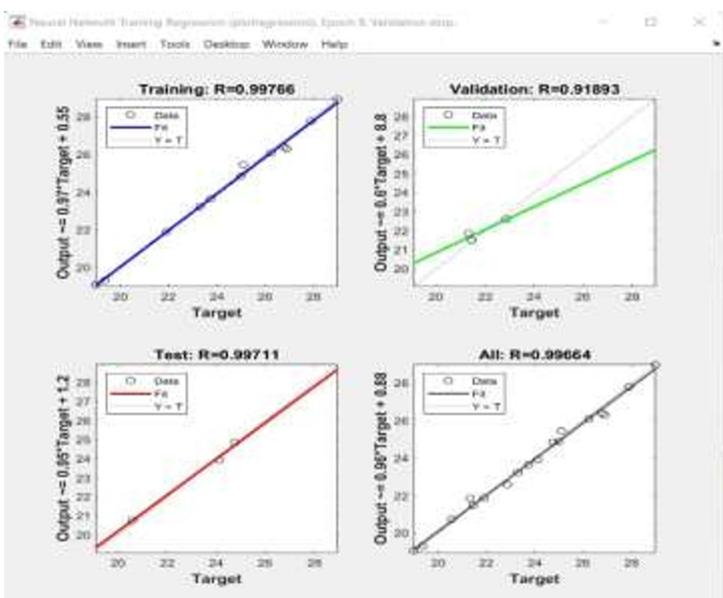

Fig. 12. R values of Target and Output for Modulus of Elasticity of ANN Model

The relationship between CS (vs) Fx. S and STS was presented in Fig. 14. The slope of flexural strength increments was high than that of STS slope. It was evident that the flexural strength enhancement was so effective than that of STS. Majority of structural elements are subjected to flexural effect so it was evident that flexural strength calculation will be helpful in designing part. Fig. 15 shows that the regression analysis and R^2 values developed between compressive strength and flexural strength. R^2 values is 0.96, it may be used to predict the strength values for future mixes. To minimise the error percentage ANN model was developed and the predicted result were presented in Table 10. Fig 15 shows the R value of output and target. The R values of ANN model is unity, that was the evident that the predicted and experimental values are very near to each other, and they are within acceptable limits. This increase in bending strength is due to incorporation of polymers of thermoplastic composites and that was due to the loading of particle and good interface distribution of the dust particles [56-57].

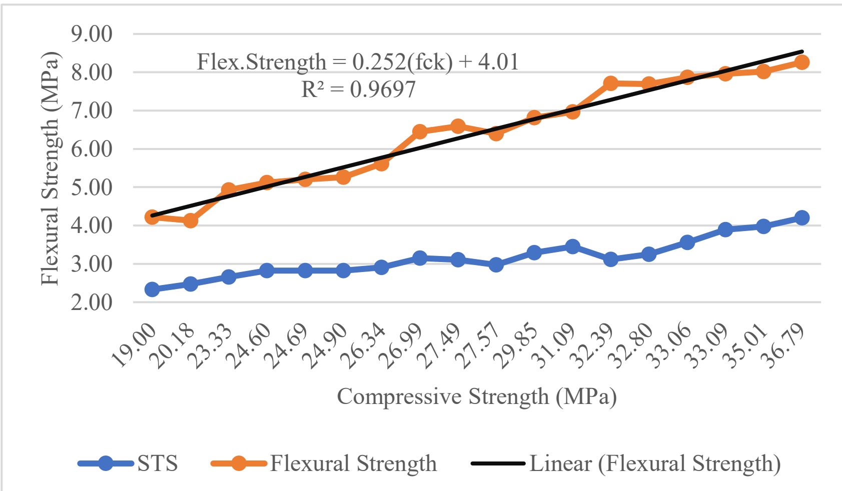

Fig. 14. Relationship between Compressive Strength, Splitting Tensile Strength and Flexural Strength.

Table 10. Flexural Strength of Experimental and ANN Model Results

Compressive Strength	Splitting Tensile Strength	Flexural Strength (Experimental Values)	ANN Model
19.00	2.33	4.22	4.22
20.18	2.47	4.13	4.27
23.33	2.66	4.93	4.78
24.60	2.82	5.12	5.12
24.69	2.82	5.20	5.13
24.90	2.82	5.26	5.18
26.34	2.91	5.61	5.61
26.99	3.15	6.45	6.38
27.49	3.11	6.59	6.51
27.57	2.97	6.40	6.52

29.85	3.29	6.82	6.79
31.09	3.45	6.97	6.69
32.39	3.12	7.71	7.72
32.80	3.25	7.69	7.71
33.06	3.56	7.87	7.89
33.09	3.89	7.96	7.96
35.01	3.98	8.02	8.03
36.79	4.20	8.26	8.20

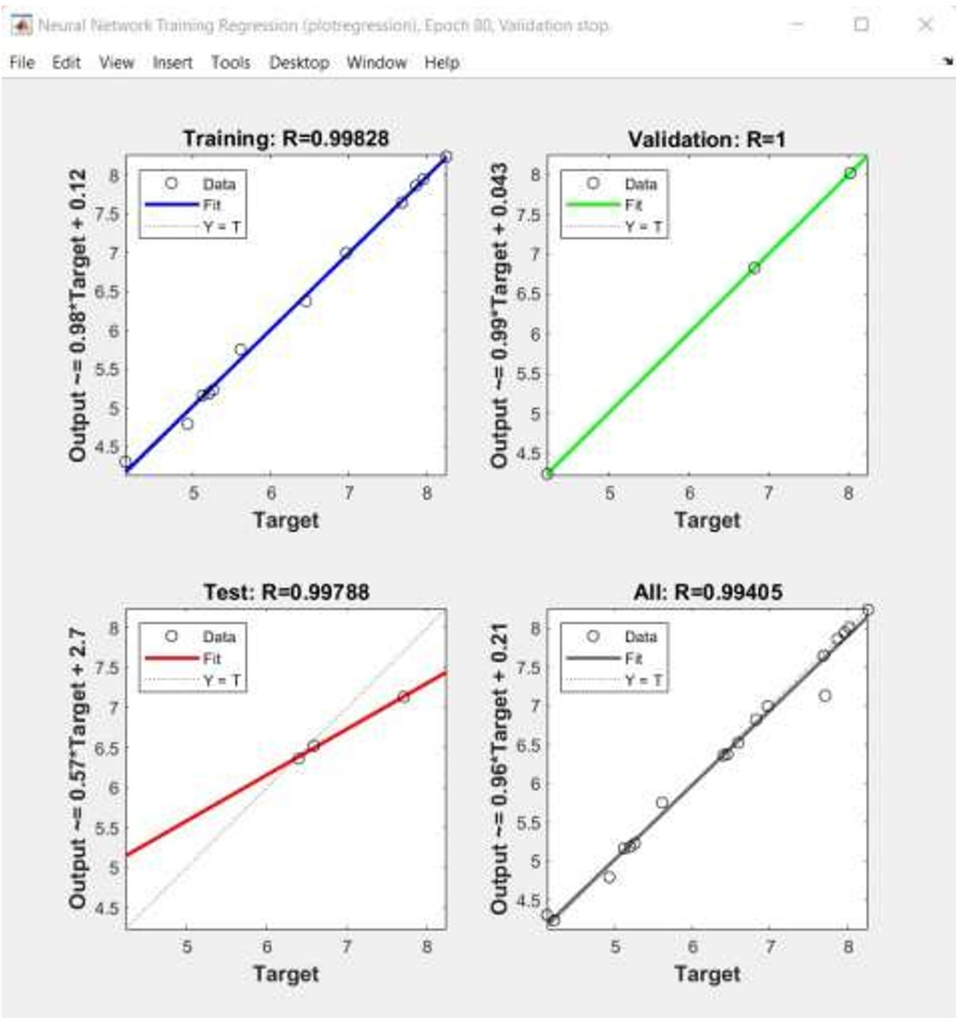

Fig. 15. R values of Target and Output for Flexural Strength of ANN Model

5 CONCLUSION

1. The effect of blending of marble power (MP) was studied with various replacement levels from 0 to 25% with constant increments of 5%.
2. The compressive strength of MP blended mix was d at higher compressive strength at 15% replacement. It was concluded as optimum replacement.
3. 25% replacement of MP was achieved designed compressive strength of M25 grade concrete. It can be considered as economical replacement.
4. Artificial Neural Network model with 30 layers predicted the compressive strength, and it was very closed to the experimental values. It can be used for future prediction.
5. The STS and MOE of MP was maintained same patten of compressive strength enhancement.
6. ACI 363R empirical equation predicts lower values of STS experimental values, but the lower values lead to uneconomical design. ANN model predicted values are very closed to experimental values and R value is equal to unity.
7. The Indian code IS 456:2000 empirical equation values are very reasonable, and that are close to investigational values of MOE. But ANN estimated or predicted values are very closed to investigational values.
8. ANN model predicted flexural strength values of MP blended concrete are very much close to investigational values and R values is equal to unity, that indicates ANN model is suitable to predict the flexural strength.
9. The study concluding that ANN model predicts the most suitable values than that of empirical equation mentioned in the study.
10. ANN is most powerful tool to predict the strength and can be used to avoid the experimental works, time and money can be saved.

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