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Strength Prediction of Geopolymer Concrete using ANN

A. Siva Krishna, V. Ranga Rao

Abstract: Geopolymer concrete usage is suddenly increasing across the globe due to the inventions in this area. Various types of research works are being conducted by researchers. The molar concentration of the geopolymer solution will have an effect on its strength. Finding the optimum value through experimentation is a tedious task and predicting the strength variations need laborious calculations. Soft computing techniques make this work easy. Artificial Neuron Network (ANN) is an effective soft computing tool to predict the strength variation that may occur due to the variation in concentration of geopolymer solution. In this work, ANN is used to predict strength with molar concentration variation. A good fit was found between experimental and predicted values.

Index Terms: Artificial Neural Network, Strength Prediction, Geo polymer Concrete.

I. INTRODUCTION

Use of cement and ecological effect utilization of concrete as an essential improvement material is a general wonder and the solid industry is the greatest customer of normal resources on the planet (14). Most of the silica sand produced from quartz rock, thus creating a threat to the environment. However, geopolymer concrete is a "new" material that does not require the nearness of Portland cement as a fastener, because of the fly ash. This fly ash can be activated by Sodium Hydroxide Solutions to produce the geopolymer material to act itself as a binder [2],]. Each year thousands of tons of waste materials are disposed on the valuable land which results in the occupation and degradation of valuable land [3].

Sand size of 30 mesh to 80 mesh (500 microns) is used in the glass industries. Sand size 1.18mm to 600 micrometers is used in creating concrete combined as the partial replacement of fine combination. Nearly about two hundred tones of silicon dioxide sand is obtained daily when laundry the raw material. Typically it's used in the glass factories otherwise they dump them back to the mines [4]. Alkali activation of fly ash is a method that differs widely from the Portland cement association and is extremely similar to the

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Chemistry involved in the synthesis of huge groups of zeolites. the most used alkaline activators are a mixture of metal or hydrated oxide (NaOH, KOH) and salt soluble glass |water glass |glass} or metallic element silicate [27,28]. metal or hydrated oxide (NaOH, KOH) and salt soluble glass |water glass |glass} or metallic element silicate [27,28].

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Thus, in the present study, an attempt is done to distinguish and concentrate on the impact of remarkable parameters which influences the properties of class Fly ash based GPC and GPC properties with different activator solution concentrations and how the strength characteristics vary with respect to change in concentration of the solution.

ARTIFICIAL NEURON NETWORK:

ANN became more popular in the field of civil engineering applications as the predictions are more accurate. The models are suitable to examine the complicated relations between variables which saves both money and time for finding the parameters of concrete where the results are obtained in a short period [25].

Many researchers had done research on the prediction of ANN data and they have constructed models on how to find the strength of concrete. Here, we worked on prediction on Compressive strength, Split Tensile strength and Flexural strength of concrete using morality concentration. In the other hand, the researchers were done on varying strength parameters by using different admixtures [23]. Other studies have used ANN for modeling mechanical properties of concrete.ANN is not only used for strength parameters but also on researchers had done modeling for prediction of water-cement ratio and many researchers are going on the usage of these ANN models in an active way which saves more time for other works.

ANN is useful in a place where mathematical calculations are not possible. They are used in a place where results consume more time to achieve. So, ANN is developed to the model of the human brain network [31].

Soft computing techniques are used to develop models that can predict accurate strength parameters of the concrete using morality concentration. This model is built with two parameters they are a percentage of concentration of morality and concrete material which are taken from the experimental data. A neural network technique is carried out to derive an explicit ANN for the Prediction of strength and parameters placed above where concrete consists of cement, fine aggregate and coarse aggregate [32]. This ANN formulation conducted to a model which has physical reality experimental data.

SCOPE OF THE PROJECT

The scope of this project is to utilize the fly-ash and silica sand as a construction material. This projects about replacing the cement in concrete with fly-ash and silica sand as replaced as fine aggregates to reduce the greenhouse gas emission, efforts are needed to develop eco-friendly construction materials. A significant factor in this process occurring is an increase in human population growth, its consumption of energy and the associated carbon dioxide released from this energy consumption; as well as the direct result of changing the land cover for agriculture, mining, industry, and housing[29]. As the human population of the world increases so does the need for housing and infrastructure increase and consequently so does the use of cement. The scope of this project is to utilize the fly ash and silica Sand as a construction material. This project is about replacing the cement in concrete with fly ash and silica sand as replaced as fine aggregates to reduce the greenhouses gas emission, efforts are needed to develop eco-friendly construction materials.

II. OBJECTIVE

- To develop a mixture proportioning process to manufacture silica sand and fly ash based concrete.
- To identify and study the impact of salient parameters that affects the properties of silica sand and fly-ash basedconcrete.
- To study the short engineering properties of fresh and hardened silica sand and fly ash based concrete.
- To study the chemistry of geo polymermechanism.
- To study the design of geo polymer concretemix.
- To develop a prediction model

DESCRIPTION OF MATERIALS

The class F fly ash is used in this geopolymer concrete as it is collected from thermal power generating station of matter. The silica sand utilized as of river sand conforming zone II and sieved with 4.75mm sieve. The locally available coarse aggregate are utilized these are having the maximum size of 12mm are used in this experiment. The sodium silicate is utilized in the gel formation and NaOH was used in the form of flakes or pallets, which are used for preparing the solution. Following are the materials used for the study, finely graded (silica sand), Coarse aggregate, Fine aggregate –Natural sand (IS383-1970) [15,16].

Flyash

Fly ash is a by-product of combustion of pulverized coal in power generation plants. The sizes of ash particles square measure slightly larger than cement sort one. Silica has high chemical content in ash and alternative chemical materials square measure iron, alumina and calcium [8]. The colour of the fly ash is dark grey. The class f fly ash has more pozzolanic properties compare to class „c" fly ash. Class F fly ash imparts significant sulphate resistance and alkali combination reaction (ASR) resistance to the different Concrete mixes fly ash additional economical compare to ordinary cement.[12]. Worldwide, the calculable annual production of coal ash in 1998 was more than 390 million tons. The main contributors for this quantity were China and India. Only concerning 14% of this flyash was utilized, whereas there was disposed in landfills. By the year 2010, the number of fly-ash made worldwide is calculable to be concerning 780 million tons annually. The fly ash used in this study was a low-calcium (ASTM class F) of approximate particle size of 16 mm and specific surface of 420 m2 kg-1. It was sourced from Matter thermal power station. The environmental consideration on the use of fly ash can be a major concern during its reuse; however, when fly ash is to be used in concrete, its effect on the environment can be monitored through a process is known as beneficiation, which entails the reduction of the amount of heavy metals content in fly ash. Low calcium fly ash was preferable due to its slow setting time compared to the class C fly ash (having high calcium) [5].

The chemical composition of class F are given in the table 1 (ASTM C618)

S.No	Name of the chemical	% by weight
1	Alumina(Al2O3)	20.08
2	Calcium oxide(Cao)	6.32
3	Ferric oxide(Fe2O3+Fe3o4)	4.13
4	Titanium Dioxide(TiO2)	0.44
5	Silica(SiO2)	63.98
6	Magnesium Oxide(MgO)	0.89
7	Sulphate	1.22
8	Loss on Ignition	1.24

The properties class f flyash are given in the table2

Sl.no.	Properties	Values
1	Specific gravity	2.2
2	Fineness	98%

Silica Sand

Silica sand is finely powdered crystalline silicon oxide which can be used as a replacement of cement and fine combination. Its micro-filling effect reduces pores in concretes and provides better wetness resistivity and so the chemical composition of class F are given in table 3 (ASTM C618) sturdiness. The silicon oxide sand has various advantages such as energy efficiency, fire resistance, durable lightweight, low maintenance and low construction cost. Using silicon oxide sand in concrete can reduce the cost of concrete and ay increase the strength to some extent.[15] silicon oxide sand is obtained from the raw materials. After laundry, the raw materials the silicon oxide sand is separated from the sieve size1.18 of raw materials. Raw materials are washed for removing the clay material that is useful in making the tiles. In the raw materials, about 10 is clay that is supplied to the ceramic chemical industries.[3]Business Silica Sand is generally utilized as a proppant by organizations engaged with oil and petroleum gas recuperation in traditional and unpredictable asset plays. The asset is additionally utilized as a part of mechanical preparing to make ordinary things, for example, glass, development materials, individual care items, gadgets, and even inexhaustible materials.

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Composition of Class F Are Given in the Table 3 (ASTM) C618

Sl .No.	Descriptions	Values
1	Specific gravity	2.8
2	Crushing Strength	6.54%
3	Impact Strength	27.3%
4	Water Absorption	2%

Coarse aggregate

Fundamentally coarse combination assumes an essential half in blend configuration of solid. Most of the body is covered with coarse aggregates. in this experimental work, the coarse aggregates which area unit retained in 10mm I.S Sieve and passed through 12mm I.S Sieve are thought of as per I.S 383-1970[12].

Sodium silicate

Palomo et al concluded that the type of activator plays an important role in the method. [30] Chemical change |chemical action} process. Reactions occur at a high rate once the alkaline activator contains soluble salt, either metallic element or metal salt, compared to the use of only alkaline hydroxides. A study conducted by Xu and Van Deventer(2000) showed that the addition of glass answer to the hydroxide answer because the basic substance increased the reaction between the supply material and also the solution [8].

Sodium hydroxide

The most common alkaline substance used in polymerization is a combination of sodium hydroxide (NaOH) or hydroxide (KOH) and salt |soluble glass water glass |glass} or atomic number19silicate.The type and concentration of alkali solution result the dissolution of ash [8].

Preparation of solution

Separate solutions of NaOH and Na2SiO3 of needed concentrations were ready intermixture along before 24hours before casting. NaOH solutions ought to be ready in varied concentration by exploitation following equation. Molar solution concentration equation:

$$C = (m/V) \times (1/MW)$$

Where,

C = concentration in mol/L

m = mass of substance in grams (g) that has to be dissolved in volume v of the solution to form the required concentration(c)

V = Volume of solution in liters (L) within which the indicate mass (m) of substance should be dissolved to form the required concentration (c). Note that V is that the final or total volume of the solution when the substance has been superimposed to the solvent.

MW = relative molecular mass in g/mol. relative molecular mass is additionally mentioned as formula weight and, in fact, several scientists value more highly to use the latter. The relative molecular mass may be obtained from the chemical formula, information tables, or the label on the bottle containing the chemical of interest.

Fig. 1 Alkaline solution

MIXING

Weighed amount of fly ash, silica sand, fine aggregate and coarse aggregate were dry mixed for 1 minute. After drymixing,

III. METHODOLOGY

ANN simulates the function of the biological neuron by imitating the working principles of the human brain. ANN is based on a set of connected units called Artificial Neurons; each neuron transmits a signal to another neuron by a connection. Each connection is assigned a weight, which can modify the strength of the signal sent to downstream [29].

The construction of ANN model can be divided into three main steps:

- Defining inputs and outputs of theproblem.
- Training the network by the weights and bias of the input, hidden and output layersand
- Testing the network performance by comparing predicted values and actualvalues.

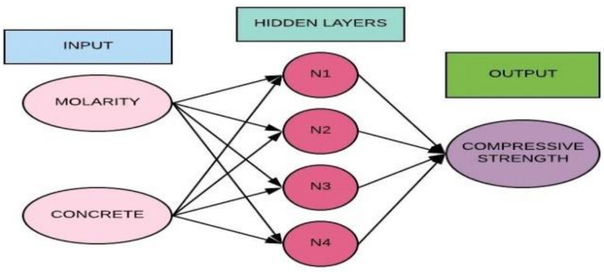

Fig.2 working of artificial neuron network

The signals from the inputs are sent to the hidden nodes and calculated by a linear function which depends on the input weights and bias before they are passed through a transfer function to produce the output of this hidden node[29].

The output from the hidden node is sent to the output layer and calculated by a linear function to output values. Mean square error (MSE) is used to evaluate the training process.

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The error E is calculated by:

$$\frac{\sum_{i=1}^{n}(R_{mi} - R_{ci})^2}{n}$$

where Rmi the training error at output o when applying instance n; n is the index of the training instance; N is a number of instances; o is the index of the output, Nout is the number of outputs; is the predicted output by ANN and Y is the actual output[27].

Next process is the weights and bias parameter are modified to minimize the error E by the learning algorithm. The Levenberg– Marquardt algorithm, which was independently developed by Kenneth Levenberg and Donald Marquardt is used as the learning algorithm in this study.

This algorithm provides a numerical solution to a nonlinear function and is suitable for small and medium-size training problems [28].

Hyperbolic tangent sigmoid is one of the well-known activation functions, which is expressed as:

$$\mathrm{f}\,(net_j) = \frac{2}{1+\exp(-2net_j)} - 1$$

In ANN, a training process is required to find the linking weights such that the distance between the predicted values of the model and the actual values is minimized. In this study,

The levenberg-marquardt algorithm was used for training of the ANN model because of its superior performance compared to other algorithms in the prediction of the mechanical properties of concrete mixtures (Golafshani and Behnood, 2018a). Levenberg-Marquardt training algorithm, as an extension of Quasi-Newton training method, is an iterative method which is used to solve non- linear least squares problems without calculating the Hessian matrix. The sum of squared error (SSE) can be considered as the performance function for the training of an ANN.

The SSE can be expressed as:

$$\mathrm{SSE}(w_k) = E^{T}(w_k)E(w_k)$$

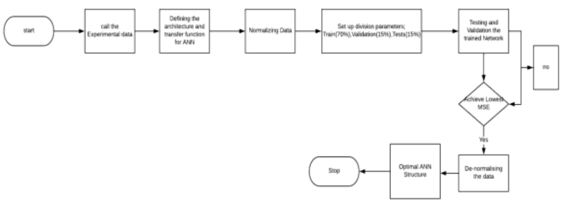
$$E(w_k) = [e_1(w_k)\ e_2(w_k) \ldots\ldots\ e_p(w_k)]^{T}$$

Where (w_k) is the vector o f linking weights and biases in k_{th} iteration and P is the number of training patterns[26].

The hessian and gradient matrixes can be calculated as:

$$H(w_k) = JT(w_k)J(w_k)$$

$$g(w_k) = JT(w_k)E(w_k)$$



Algorithm showing the methodology ofANN

where J is the Jacobian matrix which contains the first derivatives of network errors with respect to the linking weights and biases[26]. In Levenberg-Marquardt training algorithm, the value of weights in (k+1)th iteration can be computed as (Hagan and Menhaj, 1994)where I is the identity matrix and μk is a non-negative real number damping factor in kth iteration.

Three random data partitions, namely training, validating and testing datasets, are necessary to build an ANN model. The best-linking weights and biases are found using training dataset.

Validating dataset is employed to monitor the training process of ANN model and refrain from the over-fitting phenomena, while testing dataset is used to verify the model for unknown data and generalization capability of the developed model [26].

IV. RESULT

Compressive strength:

Wet mixing was done for 2 minutes. Cubes of size 150x150x150 mm and Cylinders of size 150 x300 mm Prisms of size 100x100x700 mm were casted. Compaction was done by needle vibrator.

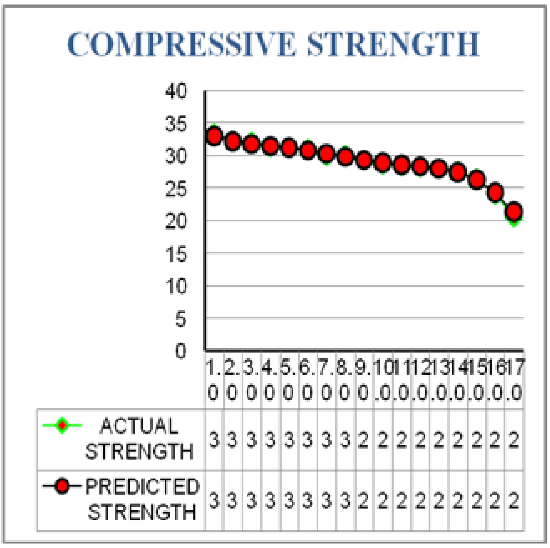


Fig. 3 Performance of compressive strength by model against the actual and predicted values.

The compressive strength test values indicate that the 12 and 14 molarity mix compressive strength is slightly less

Than that of the conventional mix. At the same period, the 16 molarity compressive strength value is more than the conventional mix. The 14 days compressive strength test value indicates that the 12molarity mix compressive strength is more that of the conventional mix. The 28 days compressive strength test values indicate that 12 molarity mix compressive strength is slightly less than that of the conventional mix. At the same time, 28 days compressive strength of 14 molarity is the same as a conventional mix but 16 molarity compressive strength value is more than the conventional mix.

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 and for overall propagation, the values are 0.99768, 0.97299, 1, 0.99792 and the best validation performance is 0.21672at epoch 4.

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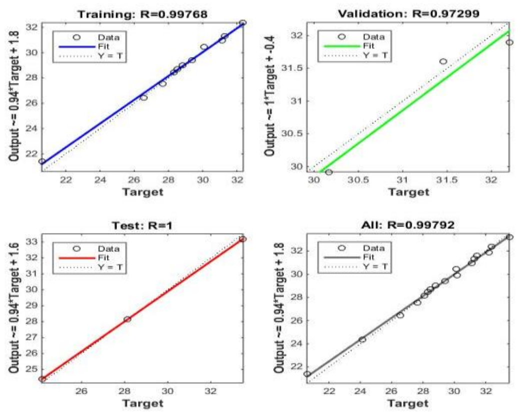

Fig.4 Regression for compressive strength of concrete.

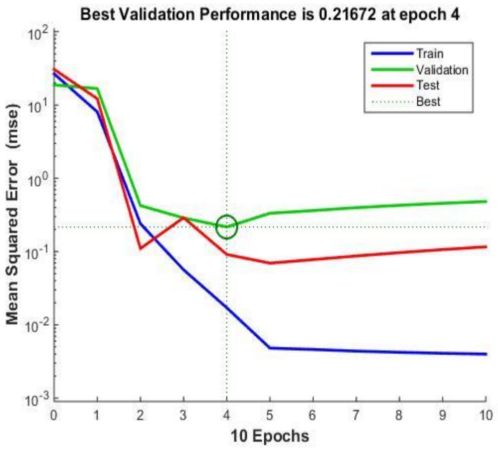

Fig. 5. validation performance for compressive strength

Split tensile strength test results

The test result shows that 12, 14, and 16 molarity mix less compressive strength than the conventional mix. The 14 days test result indicates that the 12 molarity less then than the conventional mix but the same time 14 and 16 molarity is more than the conventional mix. The 28 days test indicates that the 12, 14 and 16 molarity is less than the conventional mix.

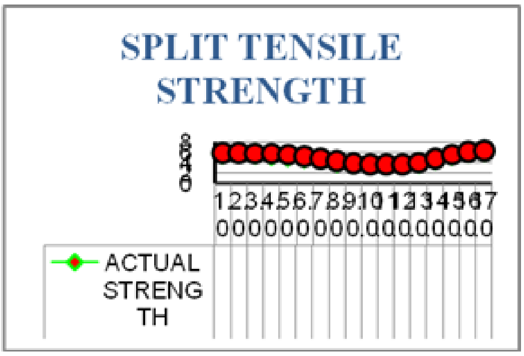

Fig. 6 Performance of Split tensile strength by model against the actual and predicted values.

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 0.99763,99745,99861 and 0.99599 and the best validation performance is 0.011951 at epoch 7.

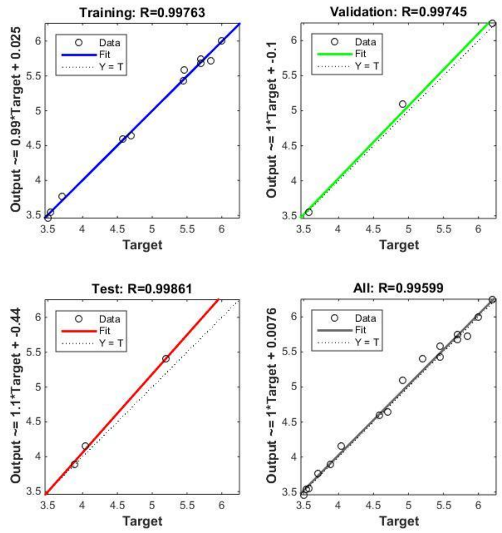

Fig.7.Regression for split tensile strength of concrete

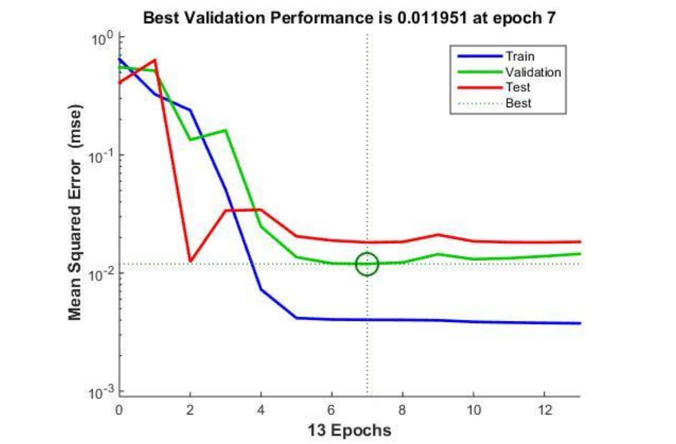

Fig. 8 validation performance for split tensile strength of concrete

Flexural strength test results

The flexural test result shows that 10 molarity mix is slightly less than that of the conventional mix. The difference between the 10 molarity mix and the conventional mix is 2.5 N/mm^2. The 10 molarity mix lags by 1.5 N/mm^2 than the conventional mix**.**

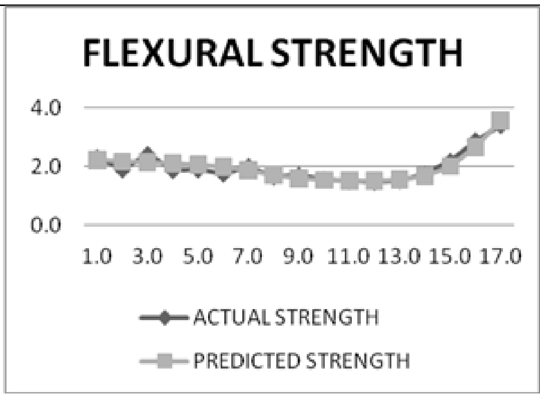

Fig. 9 Performance of flexural strength by model against the actual and predicted values.

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 0.96697, 0.99806, 0.99998 and 0.95095 and the best validation performance is 0.055826 at epoch 3.

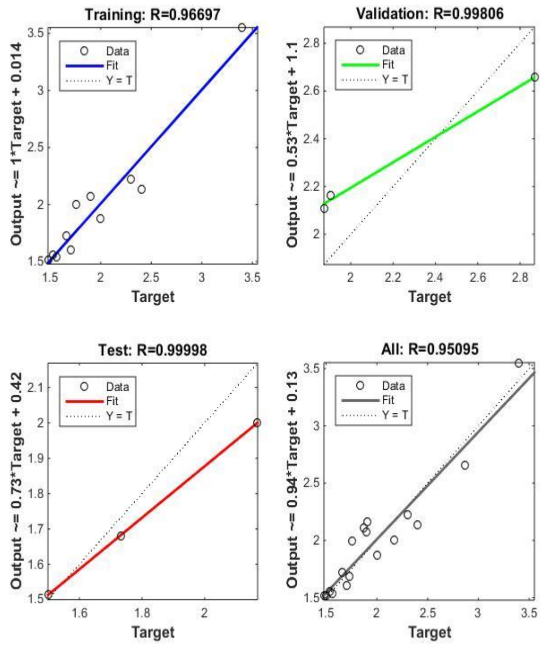

Fig. 11 Regression performance for flexural strength of concrete

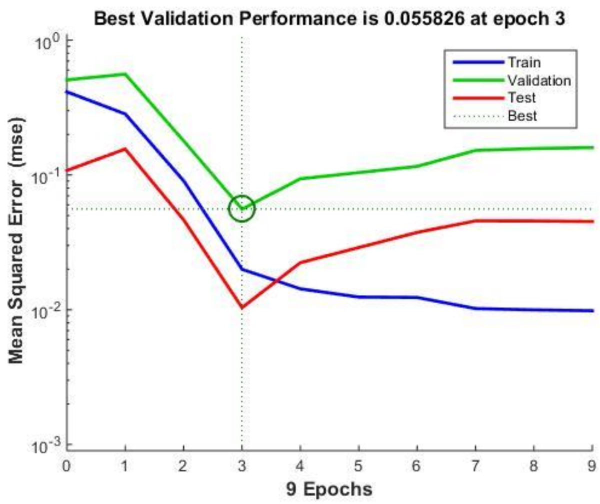

Fig.12 Validation performance for flexural strength of concrete

V. CONCLUSION

In order to predict the mechanical properties such as compressive, split tensile and flexural strength values of concrete without conducting any experiments, models were developed in an artificial neural network using levenberg-Marquardt and Bayesian regularization algorithms. These models were trained using the input and output data obtained from the experimental investigations. Among the two algorithms, the Levenberg-Marquardt algorithm gave more accurate results. The predicted values from the models were very nearer to the experimental data. The results with small errors show that the strength properties of concrete can be predicted by using artificial neural networks without conducting any experiments.

Geopolymer concrete is extra environmental pleasant and has the capacity to update regular cement concrete in lots of programs which include precast gadgets. As the share of alternative in molarity increases the stoop cost also increases regularly. By the increase of the molarity inside the solution the compressive strength additionally will increase gradually. within the 12m and 14m of the solutions aren't gain the minimum compressive electricity of M30 grade of concrete.with the aid of growing within the molarity of the answer as 10m, the compressive electricity reaches 30N/mm2with the aid of the increasing the molarity of the answer the split tensile fee increases gradually. By the substitute of the molarity of the answer the flexural electricity additionally increases gradually. From the results, we prefer 16M concentration gives the best results when compared to the other concentration of the solution.

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