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PREDICTION OF COMPRESSIVE STRENGTHOF METAKAOLIN BLENDED WITH CONCRETE USING ANN

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ABSTRACT: Compressive strength mainly depends on the ingredients of concrete mix design. Concrete is generally used as construction material. Due to the vast construction in urban areas, there is high demand of concrete. The work is experimentally carried out by partial replacement of Ordinary Portland Cement (OPC) with Metakaolin (MK) additive and total replacement of fine aggregate that is river sand with steel slag sand. The cement content will be replaced by 0%,5%,10%,15% and 20% of Metakaolin in the grade of concrete M60 at 3 days,7 days and 28 days. Due to the replacement of the Pozzolanic material and fine aggregate the strength properties will be achieved. Artificial Neural Networks (ANN) is used to predict the strength properties. ANN has three layers which include output, input and hidden layer. The input layer consists of the quantity of cement, coarse aggregate, water content, percentage of Metakaolin and steel slag sand. The output consists of compressive strength of concrete. While developing ANN model 45 samples will be used as training testing data sets. Two assessments will be carried out one is to determine the effective number of neurons in the hidden layer for predicting the network system and second is to evaluate the accuracy of predicted network will be done under different load conditions. Generally Artificial neural network learns from training and gives extremely good results. ANN can be used to escalate the experimental data to determine the compressive strength of concrete. High accuracy outcomes might be observed when compared with the experimental results and results obtained after training of neural network.

KEYWORDS: Compressive strength, Metakaolin (MK), Steel slag sand, Artificial Neural Networks (ANN).

INTRODUCTION

Concrete is composition of cement, fine aggregate, coarse aggregate and water. It is the second most used material in the world after water. When aggregate is mixed with dry Portland cement and water, the mixture forms a fluid slurry that is easily poured and moulded into shape. The cement reacts with the water through a process called concrete hydration that hardens over several hours to form a hard matrix that binds the materials together into a durable stone-like material that has many uses. This time allows concrete to not only be cast in forms but also to have a variety of tooled processes preformed. The hydration process is exothermic, which means ambient temperature plays a significant role in how long it takes concrete to set. Binding

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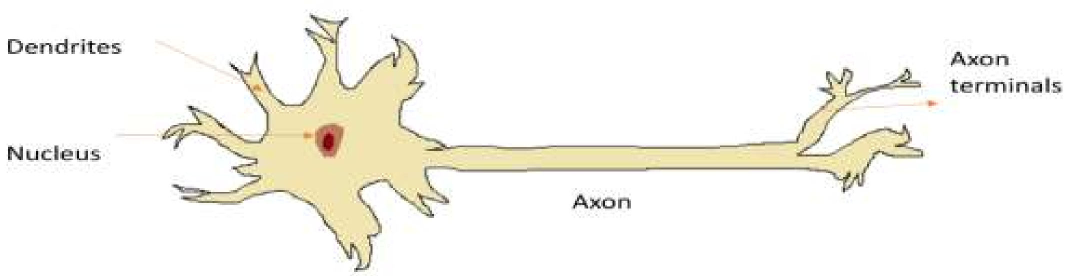
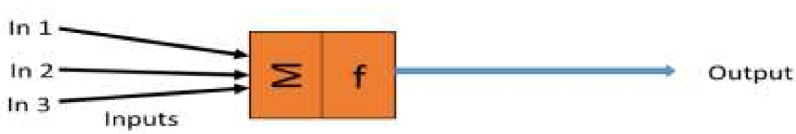
of cement represents the strength of concrete and Based on the importance of construction cement with different grades are 33 grade, 43 grade, 53grade cement are used. By changing the grade of cement one can achieve variation in strength of concrete. The advancement in construction industry helps making concrete more advance by admixtures, pozzolans, polymers etc. Metakaolin is the anhydrous calcined form of the clay mineral kaolinite. Minerals that are rich in kaolinite are known as China clay or kaolin, traditionally used in the manufacture of porcelain. The particle size of metakaolin is smaller than the cement particles. High -reactive metakaolin (HRM) is highly processed reactive aluminosilicate pozzolana, a finely-divided material that reacts with slaked lime at ordinary temperature and in the presence of moisture to form a strong slow-hardening cement. It is formed by calcining purified kaolinite, generally between 650–700 °C in an externally fired rotary kiln. It is also reported that HRM is responsible for acceleration in the hydration of ordinary Portland cement (OPC), and its major impact is seen within 24 hours. It also reduces the deterioration of concrete by Alkali Silica Reaction (ASR), particularly useful when using recycled crushed glass or glass fines as aggregate. Considered to have twice the reactivity of most other pozzolans, metakaolin is a valuable admixture for concrete/cement applications. Replacing Portland cement with 8–20% (by weight) metakaolin produces a concrete mix that exhibits favourable engineering properties. Including: the filler effect, the acceleration of OPC hydration, and the pozzolanic reaction. The filler effect is immediate, while the effect of pozzolanic reaction occurs between 3 and 14 days. Increased compressive and flexural strengths, Reduced permeability, Reduced potential for efflorescence, which occurs when calcium is transported by water to the surface where it combines with carbon dioxide from the atmosphere to make calcium carbonate, which precipitates on the surface as a white residue. Increased resistance to chemical attack, Increased durability, Reduced effects of alkali-silica reactivity (ASR), Enhanced workability and finishing of concrete, Reduced shrinkage, due to "particle packing" making concrete denser, Improved colour by lightening the colour of concrete making it possible to tint lighter integral colour. The development of eco-friendly and sustainable construction materials has gained major attention by the construction industry. One of the most significant activities stressed by the engineers and scientists related to the concrete industry were aims to use raw materials with the possibility of improvement of cement characteristics of concrete that will support the thought of green concept in concrete. The three major objective behind green concept in concrete is to reduce greenhouse gas emission (carbon dioxide emission from cement industry, as one ton of cement manufacturing process, emits one ton of carbon dioxide), secondly to reduce the use of natural resources such as limestone, shale, clay, natural river sand, natural rocks that are being consume for the development of human mankind that are not given back to the earth, thirdly use of waste materials in concrete that also prevents the large area of land that is used for the storage of waste materials that results in the air, land and water pollution. This objective behind green concrete will result in the sustainable development without destruction natural resources. Alternative materials that can be used to substitute natural aggregates to support green concrete are industrial by-products that are easily available. One of the wastes generated from industries were looked upon as possible alternatives to be used in concrete production is steel slag, which is a waste product generated from the steel industry. Steel slag is the inevitable by-product which is 15 - 20% of the production of crude steel in steel making process. Steel slag can be seen as a potential alternative to natural aggregates. The uses of steel slag as an alternative material help save a large share of natural resources and protect the environment. In This study steel slag is used as a substitute material for fine aggregate.

Artificial neural networks: Artificial neural networks are developed from the inspiration and study of human nerve system. The human nerve system generally learns to perform tasks by consideration of previous examples. Same as such neural networks also by consider inputs example data and after sum function the output layer gives the result. A typical neural network consists of 5 parts input, weights, sum function, activation function, and output. Input layer consists of number of neurons, which corresponds to number of inputs to neural network. In inputs layer the neurons are passive nodes, which transmit signal to the following layer. Weights are to adjust learning procedure and are at edges of neurons. Hidden layer receives signal from input layer, the neurons in this layer are active nodes. Output neuron indirectly represent input given neuron; output layer gives the result for different sampling conditions.





LITERATURE REVIEW

(R. Padma Priya *et al.*, 2019) In the present research work, metakaolin is used to replace a portion of the cement and induction furnace steel slag as partial replacement of fine aggregate in concrete. Metakaolin is a dehydroxylated aluminium silicate pozzolanic material obtained from kaolinite clay mineral. Induction Furnace steel slag is obtained as an industrial by-product during steel production. Hexagonal shaped paver block specimens of side 120 mm and height 80 mm are casted. Compressive strength, flexural Strength, split tensile strength, abrasion, water absorption, acid and alkali attack tests were performed. The increased strength is obtained by replacing cement by metakaolin up to 10% and steel slag as 20% constant for all mixes. Due to shape size and surface texture of steel slag aggregate and also by the nature of the metakaolin which provides better adhesion between the particles and cement mix. The optimum level of replacement for metakaolin is found as 10% and increase in strength initially and decreases in strength beyond 10%. The results show that optimum level replacement of metakaolin (cement) and IF steel slag (fine aggregate) in concrete is 10% and 20% respectively.

(Shaik Fazlur Rahman *et al*., 2019) In This research work experimental investigation carried out to evaluate effects of replacing coarse aggregate with blast furnace slag and cement with metakaolin. Slag is a by-product generated during manufacturing of pig iron and steel. Primarily the slag consists of calcium, magnesium, manganese and aluminium silicates in various combinations. The cooling process of slag is responsible mainly for generating different types of slags required for various end use consumers. The raw material in the manufacturing of metakaolin is Kaolin clay. The properties of metakaolin are very similar to the cement properties. Metakaolin is also a mineral admixture which converts calcium hydroxide into advantageous cementitious material. In this investigation we are going to replace 10% of cement with metakaolin and coarse aggregate with blast furnace slag with increasing percentages of 0%, 10%, 20%, 30%, 40%. cubes and cylinders were casted at various percentages of replacements and compressive strength and tensile strength tests were carried out. The physical and chemical properties of GBFS are suitable for the production of concrete mix. The compressive strength and split tensile strength are higher for replacement of 30% of GBFS and replacement of cement with 10% Metakaolin. The compressive strength and split tensile strength are lower for 0% replacement. The results showed that using Metakaolin and increasing % of flash with GIBFS an improvement in the impermeability of concrete. The replacement of cement by Metakaolin leads to decrease in pore space.

(P. Jaishankar *et al*., 2016) In this project, experimental study was carried out on M-30 grade of concrete. In these concrete mixes sand was replaced by M-sand by a constant percentage and cement was replaced by metakaolin in various percentages such as 5%, 10%, 15% and 20%. Concrete specimens containing metakaolin were studied for their compressive, split tensile and flexural strengths according to Bureau of Indian standards. The results thus obtained were compared and examined with respect to the control specimen. From the test results, the compressive strength values were increased with metakaolin content if cement was replaced with metakaolin up to 15%. After this replacement percentage the strength was reduced even after increase in replacement of metakaolin content. From the comparison of the compressive strength test results at 7, 14 and 28 days, it was observed that MK15 (15%MK & 50% M-Sand) showed maximum strength compare to other replacement percentage. MK15 showed there was 32.55% increase in compressive strength at 28 days compared to normal concrete. From the results it is concluded that the M-Sand can be used as a replacement for fine aggregate. It was found that 50% replacement of fine aggregate by M-Sand give maximum result in strength.

(A Rahmawati et al., 2017) This study was motivated by the need for the development of eco-friendly concrete, and the use of large quantities of steel slag as an industrial waste which is generated from the steel manufacturers. This eco-friendly concrete was developed with steel slag as a substitute for natural sand. Properties of concrete which used waste slag as the fine aggregate with the 1 cement: 2 sands: 3 coarse aggregate ratio mixing method were examined. That ratio was in volume. Then a part of natural sand replaced with steel slag sand in six variations percentages that were 0 %, 20 %, 40 %, 60 %, 80 % and 100 %. The compressive strength, tensile strength, and flexural strength of concrete specimens were determined after curing for 28 days. The research results demonstrate that waste steel slag can increase the performance of concrete. The optimal percentage substitution natural sand by steel slag sand reached of slag on the percentage of 20 % which reached strength ratios of steel slag concrete to the strength of conventional concrete with natural sandstone were 1.37 for compressive strength and 1.13 for flexural strength. While the tensile strength reached a higher ratio of concrete with steel slag sand to the concrete with natural sand on the 80% substitution of natural sand with steel slag sand.

(ROOPA BALIGA *et al*., 2018) Concrete is the largely utilized construction material. The fine aggregates used in the production of concrete is twice the consumption of cement. But restriction on sand mining has created a need to replace the same by industrial by-products which are threat to environment if disposed unscientifically. Slag sand is one such by-product obtained from smelting process in blast furnace of steel plants. Unscientific dumping and non-utilization of these creates serious environmental issues for dwellers living in the vicinity of steel plants. Hence, in this experimental investigation an attempt is made to find a secondary application to slag sand as fine aggregate by replacing river sand in the production of M25 grade concrete. River sand was replaced by 0%, 50%, 75% and 100% by slag sand designated as S0, S1, S2 and S3 in the preparation of concrete cubes of standard size 150 mm x 150 mm x 150 mm and prisms of standard size 100 mm x 100 mm x 500 mm were cast. Their mechanical properties such as compressive strength and flexural strength were tested. Fresh concrete was also tested for its workability. This study has revealed that slag sand is a promising alternative to river sand up to 75% replacement to river sand.

(Chia-Ju Lin *et al*., 2021) An artificial neural network (ANN) model for predicting the compressive strength of concrete is established in this study. The Back Propagation (BP) network with one hidden layer is chosen as the structure of the ANN. The database of real concrete mix proportioning listed in earlier research by another author is used for training and testing the ANN. The proper number of neurons in the hidden layer is determined by checking the features of over-fitting while the synaptic weights and the thresholds are finalized by checking the features of over-training. After that, we use experimental data from other papers to verify and validate our ANN model. The final result of the synaptic weights and the thresholds in the ANN are all listed. Therefore, with them, and using the formulae expressed in this article, anyone can predict the compressive strength of concrete according to the mix proportioning on his/her own.

Prediction of mechanical properties such as compressive and flexural strengths of concrete improves the quality and it reduces the testing specimens (Emamian *et al*., 2019). ANN gives good results with an acceptable error (Behnood *et al*., 2018). Instead of using regression, MFNN (Multi-layer – feed forward – Neural – Network) model is useful to solve complex non – linear problems accurately (Aa – Salloum *et al*., 2012). In predicting the strength ANN require large number of inputs and gives an output after training of network (Eskandari

– Naddaf *et al*., 2017). In ANN model using the Levenberg – Marquardt as training function for predicting compressive and flexural strengths is the best prediction tool (Chopra *et al*., 2016).

(Ni Hong-Guang *et al*., 2000) In this paper, a method to predict 28 - day compressive strength of concrete by using multi -layer feed - forward neural networks (MFNNs) was proposed based on the inadequacy of present methods dealing with multiple variable and nonlinear problems. A MFNN model was built to implement the complex nonlinear relationship between the inputs (many factors that influence concrete strength) and the output (concrete strength). The neural network (NN) models give high prediction accuracy, and the research results conform to some rules of mix proportion of concrete.

MATERIALS AND TESTING

In the present research work, 53grade cement was used. For this 53grade cement laboratory tests were conducted to find the mechanical properties of cement.

Standard consistency test: Consistency of the cement paste is measured by using Vi-cat's apparatus using 10mm diameter plunger fitted to needle-holder, vicat mould, glass plates, stop watch, sample of cement. 300 gm of cement taken and 100ml water added to it. Vicat mould is filled with cement paste. The mould is placed on non-porous resting plate under the rod attached with the plunger. The point of the plunger is lowered until it gently touches surface of the mould, after arraigning the plunger set the stop watch on. The plunger is released quickly to allow the needle sink into paste. The height of the plunger is noted which is not penetrated into cement paste. The trail pastes were prepared with varying percentages of water within the interval of 0.25 to 1%. Test is conducted until plunger penetrates to a point 5 to 7mm from the bottom of the vicat mould, which is read on the scale. The depth of penetration is noted 7mm with the moisture content of 32.96%.

Initial and final setting time test: Vicat apparatus is used to determine setting time of cement, the test conducted with the same mould that is used for the consistency test.

300 gm of cement is taken, 0.85 times of water added to it. As same as standard consistency test cement paste is prepared and filled in mould, top level of paste is cleaned by trowel. The mould is placed under vicat needle apparatus with 1mm square needle in position. Needle is lowered gently in contact with surface of the test block, quickly released into test box and set the stop watch on to determine penetration of needle. For determining the final setting time, replace the needle of the Vicat's apparatus by the needle with an annular attachment. The cement is considered finally set when upon applying the final setting needle gently to the surface of the test block; the needle makes an impression thereon, while the attachment fails to do so. Record this time. Initial and final setting time is noted down as 47 min and 234 min with the moisture content of 32.96%.

Fineness test: Fineness of the cement is determined by using 90**µm IS sieve as per** IS: 4031 (Part 1) – 1996. The sample of cement is collected and rubbed with hands. The Fineness test sample should be free of lumps. Take 100 gm of cement sample and note its weight. 100 gm of cement is dropped in 90 µm sieve and close it with the lid. Shake the sieve whit hands by agitating the sieve in planetary and linear movements for 15 min. After that take weight the retained cement on the 90 µm sieve is weighed. The ratio of initial and final weights is the fineness of the cement. The fineness of cement is noted down as 3.8.

Sieve analysis of artificial fine aggregate: The fine aggregate is replaced with the artificial fine aggregate i.e., Steel slag sand sieve analysis is test is conducted on the artificial fine aggregate to determine the particle size distribution. A series of IS sieves 10 mm,4.75 mm,2.36 mm,1.18 mm,600 µm,300 µm,150 µm are used in this test. 1000g of sample is exactly weighed. All the sieves are cleaned using a wire brush to be clear of aggregates stuck in some gaps. Then the sieves are arranged onto the shaking machine from top to bottom, by the size from biggest (10 mm) to smallest (150 µm). The sample is sieved by using the set of IS Sieves for 10 minutes. After the sieving is done, the aggregates on each sieve are weighed individually. Cumulative weight passing through each sieve is calculated as a percentage of the total sample weight.

Sieve analysis

SieveSize	**Cumulative% Passing**
10mm	100
4.75mm	99.8
2.36mm	99.6
1.18mm	85.45
600µm	34.5
300µm	17
150µm	4.6

EXPERIMENTAL INVESTIGATION

Experimentation is done to check the properties of concrete when cement is partially replaced by metakaolin. In this present research to check the workability of concrete slump cone test is conducted on fresh concrete and for hardened concrete compressive strength test is conducted. Compression strength test is conducted after curing of 3, 7 and 28 days. The test conducted is based on I.S 516: 1959

Slump cone test: Slump cone test is to determine the workability or consistency of concrete mix prepared. The mould for the test is in the form of the frustum of a cone having height 30 cm, bottom diameter 20 cm and top diameter 10 cm. The tamping rod is of steel 16 mm diameter and 60cm long and rounded at one end. A concrete mix (M60) by weight with suitable water/ cement ratio is prepared. The internal surface of the mould is cleaned and oil is applied. The mould is placed on a smooth horizontal non- porous base plate. Fill the mould with the prepared concrete mix in 4 approximately equal layers. Each layer is tamped with 25 strokes of the rounded end of the tamping rod in a uniform manner over the cross section of the mould. For the subsequent layers, the tamping should penetrate into the underlying layer. Excess concrete is removed and the surface is levelled with a trowel. Clean away the mortar or water leaked out between the mould and the base plate. Raise the mould from the concrete immediately and slowly in vertical direction. The slump is measured as the difference between the height of the mould and that of height point of the specimen being tested. The Slump value or the workability if the concrete mix is measured as 100 mm.

Compressive strength test: To determine the compressive strength of concrete by crushing test on cubes the apparatus used for this test are compression testing machine, specimen and scale Required quantities of materials for M60 mix design are taken. Cement and sand are thoroughly mixed until the mixture is of uniform colour. The aggregate is taken added and mixed dry. Water added and the whole mass is mixed for 2 min to get uniform colour. The moulds of dimensions for cubes 150x150x150 mm and cylinders of 150 mm diameter and 300 mm height are initially oiled inside to prevent the concrete from sticking. The concrete was filled in mould in 3 equal layers, each layer is compacted with 16mm rod after completion of 3 layers the surface is neatly strike off with a trowel. The specimens were kept in moist of air and at room temperature for 24 hrs, next day specimens are taken out from moulds and kept for curing under clean, fresh water. Specimens were tested under compression testing machine after 3,7 and 28 days of curing, load applied on transverse sides and the rate of loading is 14 kg/sq.cm/minute. The mode of failure and angle of plane on which specimen fails is observed and the ultimate load is recorded during the test. The results obtained when specimen tested under compression testing machine was listed below.

Experimental results of compressive strength

S.No	Quantity of Cement (Kg/m3)	Fine aggregate (Kg/m3)	Coarse aggregate (Kg/m3)	Water content (Kg/m3)	Super plasticizer (Kg/m3)	Percentage of Metakaolin	Curing period	Compressive strength (Kg/m3)
1	352	814.74	1092.1	140	7.7	0	3	20.54
2	352	814.74	1092.1	140	7.7	0	3	20.34
3	352	814.74	1092.1	140	7.7	0	3	20.5
4	352	814.74	1092.1	140	7.7	5	3	21.36
5	352	814.74	1092.1	140	7.7	5	3	21.12
6	352	814.74	1092.1	140	7.7	5	3	21.9
7	352	814.74	1092.1	140	7.7	10	3	22.69
8	352	814.74	1092.1	140	7.7	10	3	22.53
9	352	814.74	1092.1	140	7.7	10	3	22.47
10	352	814.74	1092.1	140	7.7	15	3	22.55
11	352	814.74	1092.1	140	7.7	15	3	23.35
12	352	814.74	1092.1	140	7.7	15	3	23.4
13	352	814.74	1092.1	140	7.7	20	3	19.25

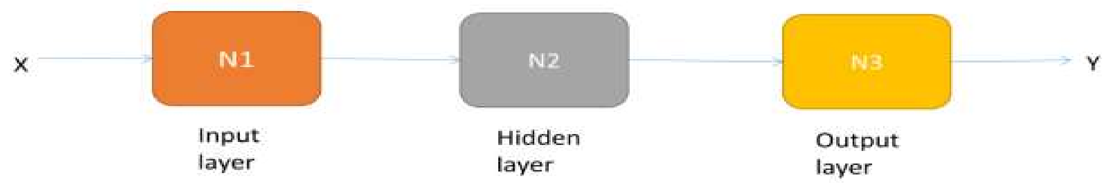
14	352	814.74	1092.1	140	7.7	20	3	19.13
15	352	814.74	1092.1	140	7.7	20	3	19.58
16	352	814.74	1092.1	140	7.7	0	7	40.73
17	352	814.74	1092.1	140	7.7	0	7	39.59
18	352	814.74	1092.1	140	7.7	0	7	39.93
19	352	814.74	1092.1	140	7.7	5	7	39.02
20	352	814.74	1092.1	140	7.7	5	7	39.56
21	352	814.74	1092.1	140	7.7	5	7	39.65
22	352	814.74	1092.1	140	7.7	10	7	41.06
23	352	814.74	1092.1	140	7.7	10	7	40.25
24	352	814.74	1092.1	140	7.7	10	7	40.57
25	352	814.74	1092.1	140	7.7	15	7	40.61
26	352	814.74	1092.1	140	7.7	15	7	41.16
27	352	814.74	1092.1	140	7.7	15	7	41.29
28	352	814.74	1092.1	140	7.7	20	7	38.24
29	352	814.74	1092.1	140	7.7	20	7	38.45
30	352	814.74	1092.1	140	7.7	20	7	38.57
31	352	814.74	1092.1	140	7.7	0	28	57.55
32	352	814.74	1092.1	140	7.7	0	28	57.89
33	352	814.74	1092.1	140	7.7	0	28	57.51

34	352	814.74	1092.1	140	7.7	5	28	59.32
35	352	814.74	1092.1	140	7.7	5	28	59.77
36	352	814.74	1092.1	140	7.7	5	28	59.77
37	352	814.74	1092.1	140	7.7	10	28	62.07
38	352	814.74	1092.1	140	7.7	10	28	61.71
39	352	814.74	1092.1	140	7.7	10	28	61.98
40	352	814.74	1092.1	140	7.7	15	28	61.87
41	352	814.74	1092.1	140	7.7	15	28	62.46
42	352	814.74	1092.1	140	7.7	15	28	62.09
43	352	814.74	1092.1	140	7.7	20	28	58.37
44	352	814.74	1092.1	140	7.7	20	28	58.52
45	352	814.74	1092.1	140	7.7	20	28	58.07

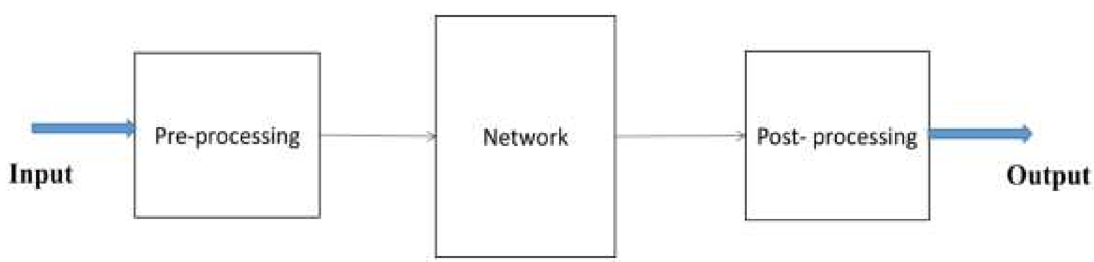
I.S. 456:1978 classified concrete mixes according to its strength. The concrete is classified into seven grades, and the grades are based on the basis of compressive strength of 15 cm cubes at 28 days mixed and cured under required conditions. In this present study total numbers of samples tested were 45 with proportions of variation in percentage of Metakaolin.

ARTIFICIAL NEURAL NETWORK

ANN is introduced to solve non-linear problems using small interconnected units called neurons. ANN is an information – processing structure, neurons process all the information. Signals are transferred by connection links. The links are possessed with related weight, which extend along with input signal for a neural network. The output signal acquired by applying activation function to the input. The neural network usually be single layer or multiple layered network. Multi-layered neural network (MNN) consists of input, hidden and output layers. In MNN input unit is connected to hidden layer, which is connected to output unit. The raw information from input unit is fed to the network and the hidden layer activity is determined by activity of input neurons and weights between input and hidden layers. Similarly, the behaviour of output neuron is depends on activity of hidden layer and weights between hidden and output layers. MNN have capabilities such as, nonlinear function approximation, learning and generalization.



In this present work a multi layered feed forward neural network (MFNN) is used. In MFNN generally sigmoidal function is used in hidden layer. Pre processing and post processing technique improves the efficiency of network training and assessing network performance. The most common pre-processing and post processing functions are map minmax, mapstd, process pca, fix unknowns, remove constant rows etc. Simulink blocks are used for building and evaluating neural networks and control system applications. Using Simulink or train the network, both pre-processing and post processing will be done automatically.



In this present network a MFNN with backpropagation and using trainlm as a function for training. Trainlm is used because it is a fastest training function and it is a default training function for feed forward networks. Trainlm save the memory usage by splitting the larger data into n parts, which represents memory reduction.

Levenberg-Marquardt algorithm, training automatically stops when the generalization of network has no improvement which indicates increase in mean square error (MSE) of validating samples. The default generalization feature for MFNN is early stopping. Data is automatically divided into testing, training and validation sets. MSE is monitored during training and it stops when the validation reaches maximum.

Procedure followed in backpropagation is as follows, Eq{ 5.1 to 5.6}

$$net_i^n = \sum_{k=1}^{7} w_{ik} x_k^n \ldots\ldots\ldots\ldots\ldots\ldots\ldots(5.1)$$

Here net_i is the input received by hidden neuron, i is the neuron in hidden layer, w_{ik} weight of link between i and k, neuron in input layer is n.

$$Y_i^n = f(net_i^n) = f(\sum_{k=1}^{7} w_{ik} x_k^n) \ldots\ldots\ldots\ldots\ldots\ldots(5.2)$$

Y is the output received from the hidden layer {Eq 5.2}.

$$(net_j^n = \sum_{i=1}^{h} w_{ji} y_i^n = \sum_{i=1}^{h} (W_{ji}.\ f(\sum_{k=1}^{7} w_{ik} x_k^n)) \ldots\ldots\ldots\ldots(5.3)$$

net_j is the input received by the output layer where j is the output neuron. W_{ji} is the weight of the link between hidden neuron i and output neuron j.

$$O_j^n = f(net_j^n) = f(\sum_{i=1}^{h} w_{ji} V_i^n) = f(\sum_{i=1}^{h} (W_{ji}.\ f(\sum_{k=1}^{7} w_{ik} x_k^n)) \ldots\ldots\ldots\ldots(5.4)$$

O_j is the final output {Eq 5.4} where h is the number of neurons in hidden layer.

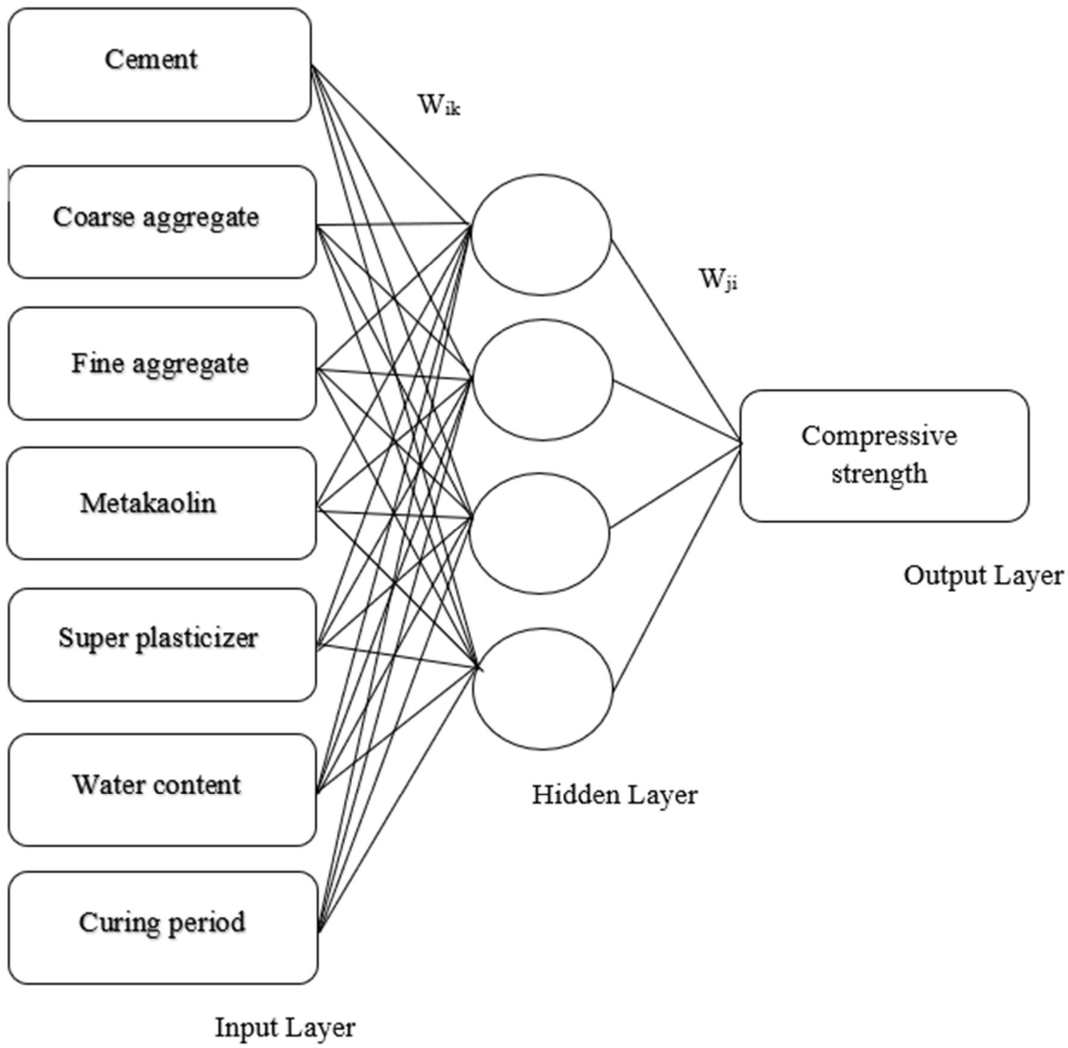
$$E[\vec{w}] = \frac{1}{2} \sum_n (t_n - o_n)^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots(5.5)$$

Eq 5.5 represents the mean square error function, where t is target and o is the output.

$$E[\vec{w}\ ] = \frac{1}{2} \sum_{n=1}^{m} \sum_{j=1}^{l} (t_j^n - O_j^n)^2 \ldots\ldots\ldots\ldots\ldots\ldots(5.6)$$

Total sum of squared error is represented in Eq 5.6, where m is the number of weighted links between input and output and l is the number of output units.

MFNN backpropagation network is used to train four number of layers, that are input, hidden and output layers. In the present research work the network is generated for prediction of compressive strength. Input layer consists of sever number of neurons for the network. The properties of mix design are taken as inputs that are cement content, coarse aggregate, fine aggregate, and % of Metakaolin, super plasticizer, water content and curing period. Target for the network is compressive strength test results. Hidden layer consists of four numbers of neurons based on trial and error to get better accuracy and performance. After designing ANN, number of training of network is done until the performance is good with minimum error. The training of network is stopped when there is no change in the performance.



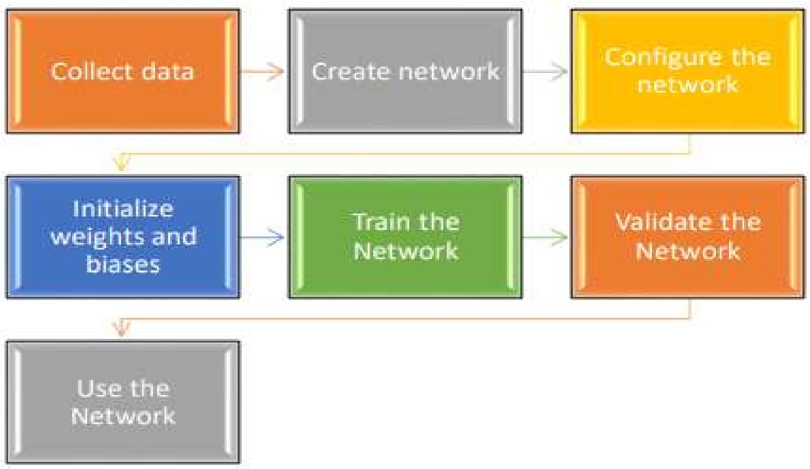
Using MATLAB network is generated in Neural Network (NN)tool, which supports four ways of usage that are listed below,

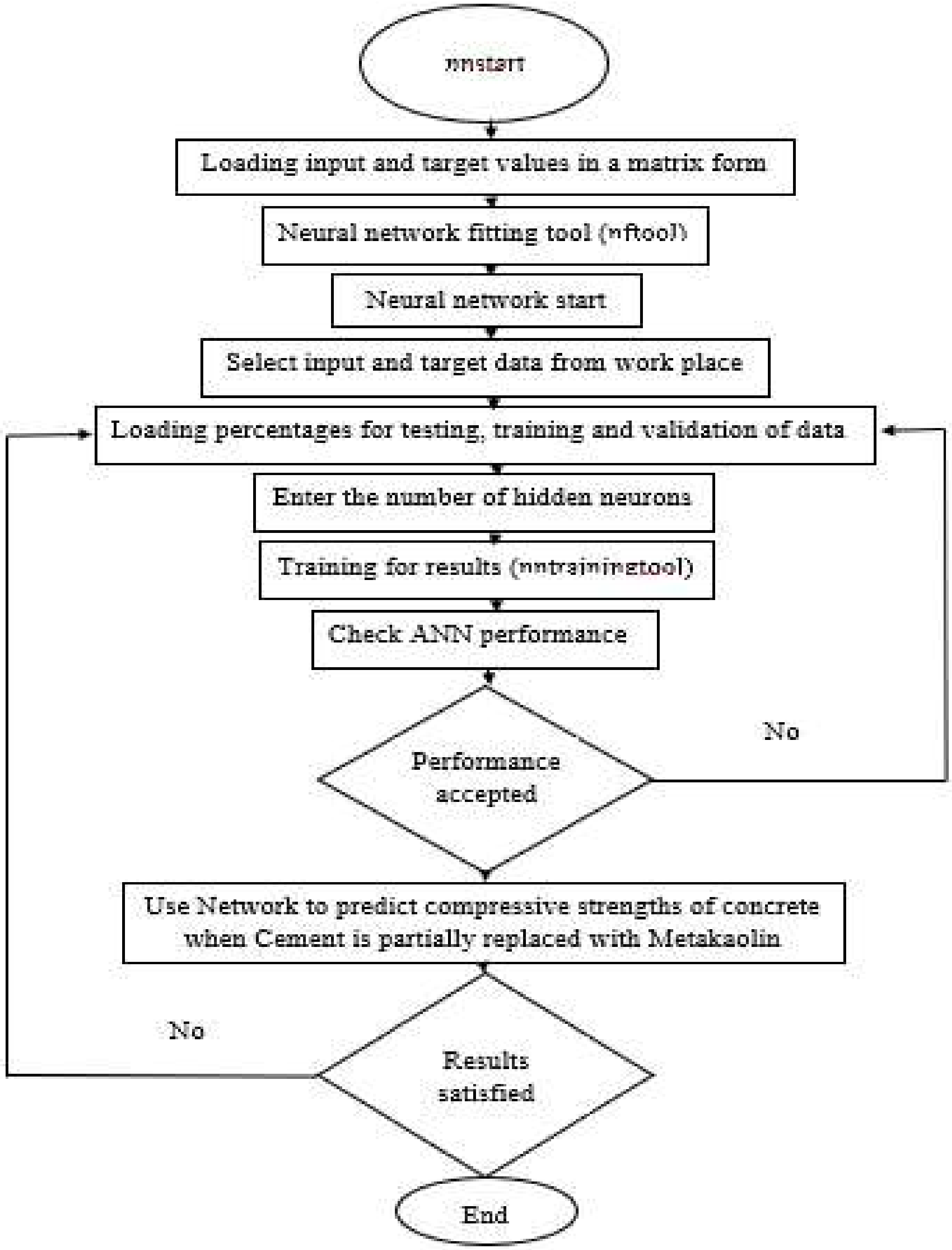
- GUI method
- Command Script
- Training custom networks
- Modifying functions in a network.

GUI means Graphical User Interface; this method is quick and easy to access the nntool. To get started with GUI method, enter nnstart in command box. To access the power of tool box there are four tasks,

- Function fitting
- Pattern recognition
- Data clustering
- Time series analysis

Command Script is the method using command line operations, this method is more flexible than GUI method. In addition to GUI method, command line operation also generated.
In Neural Network (NN)tool using customization method a network can be trained, this is an advanced method. Here the network is object oriented and flexible which allows many types of networks to be created with functions like init, train and sim. This representation gives various architectures and various algorithms can be assigned to those architecture. By these novel architectures created with minimum effort.
In Neural Network (NN)tool there is an ability to modify any function in the toolbox. The computational component is written in toolbox and it is fully accessible in MATLAB. Based on specific applications in this present study GUI and Command line operations are used.





Command line operations: Using command script, the command line operations also generated in the workspace. It is the easiest way to understand the design of ANN. This code can be customized based on requirement of network and future use. After generating the code by just clicking on RUN the program runs and the result of performance is shown in the command window.

The Code for predicting Compression strength

```
% Solve an Input-Output Fitting problem with a Neural Network
% Script generated by Neural Fitting app
% Created Fri Jul 29 17:03:55 IST 2022
%
% This script assumes these variables are defined:
%
%   i - input data.
%   t - target data.
x = i';
t = t';
% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. NFTOOL falls back to this in low memory situations.
trainFcn = 'trainlm';  % Levenberg-Marquardt

% Create a Fitting Network
hiddenLayerSize = 4;
net = fitnet(hiddenLayerSize,trainFcn);

% Setup Division of Data for Training, Validation, Testing
net.divideParam.trainRatio = 80/100;
net.divideParam.valRatio = 10/100;
net.divideParam.testRatio = 10/100;

% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
```

```
%figure, plottrainstate(tr)
%figure, plotfit(net,x,t)
%figure, plotregression(t,y)
%figure, ploterrhist(e)
```

Mean absolute error (MAE) is a measure of errors between paired observations expressing the same phenomenon. Examples of *Y* versus *X* include comparisons of predicted versus observed, subsequent time versus initial time, and one technique of measurement versus an alternative technique of measurement. It is an arithmetic average of the absolute errors $e_i=y_i-x_i$, where y_i is the prediction and x_i the true value. Note that alternative formulations may include relative frequencies as weight factors. The mean absolute error uses the same scale as the data being measured. This is known as a scale-dependent accuracy measure and therefore cannot be used to make comparisons between series using different scales. The mean absolute error is a common measure of forecast error in time series analysis sometimes used in confusion with the more standard definition of mean absolute deviation.

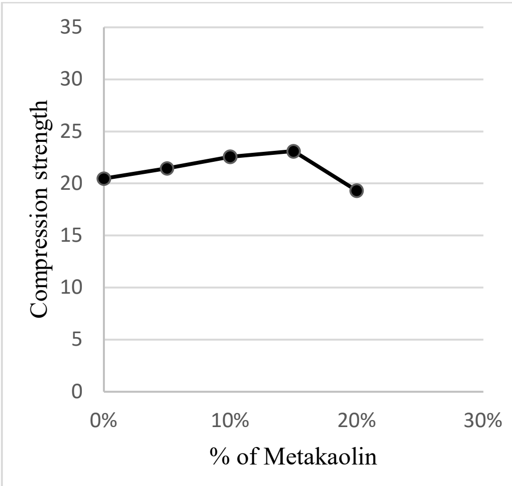
Mean square error(ESA) measures the average of the squares of the errors—that is, the average squared difference between the estimated values and the actual value. MSE is a risk function, corresponding to the expected value of the squared error loss.

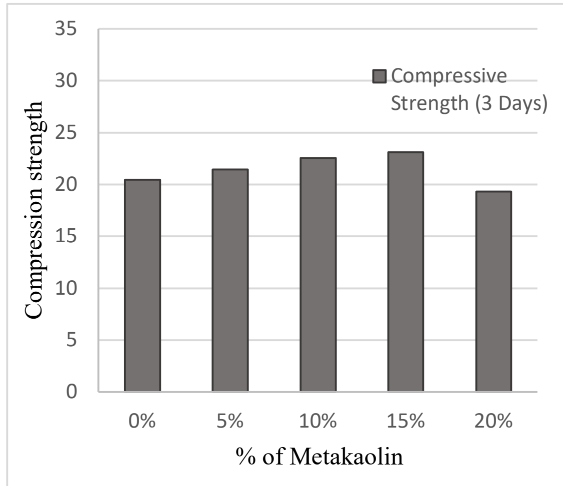
The root-mean-square error (RMSE) is a frequently used measure of the differences between values (sample or population values) predicted by a model or an estimator and the values observed. The RMSE represents the square root of the second sample moment of the differences between predicted values and observed values or the quadratic mean of these differences. These deviations are called residuals when the calculations are performed over the data sample that was used for estimation and are called errors (or prediction errors) when computed out-of-sample. The RMSE serves to aggregate the magnitudes of the errors in predictions for various data points into a single measure of predictive power. RMSE is a measure of accuracy, to compare forecasting errors of different models for a particular dataset and not between datasets, as it is scale-dependent.

RESULTS

In this present research work, determination of compressive strength of concrete when Cement is partially replaced with the metakaolin is carried out with 45 number of samples were tested with 3,7 and 28 days of curing. The percentage of Metakaolin varied from 0 to 20% by weight of cement. Along with the experimental work the prediction of future strengths of concrete is also done to reduce the number of mixes, using ANN. In this study M60 mix design is prepared with partial replacement of cement with different percentages of Metakaolin and total replacement of fine aggregate with steel slag sand, and no other changes in properties of the mix design. The percentages of Metakaolin are from 0 to 20%. The percentages of Metakaolin from 0 to 20%. The Graph represented shows the compressive strength on Y-axis and % of Metakaolin on X-axis. The graph shows the experimental results of compressive strength with the variation of Metakaolin. By increasing % of Metakaolin up to 15%, gives increase in compressive strength of concrete.

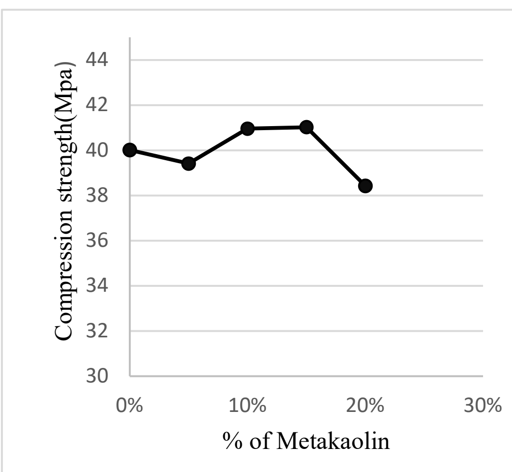
The compressive strength determined at the age of 3day strength of concrete is, at 0% replacement of cement is 20.46 Mpa, at 5% is 21.46 Mpa, at 10% is 22.56 Mpa, at 15% is 23.10 Mpa and at 20% replacement of cement is 19.32 Mpa.

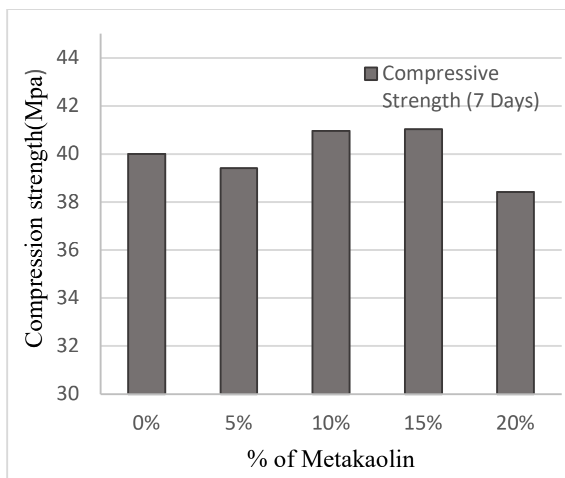




Experimental results of Compressive strength (3 days)

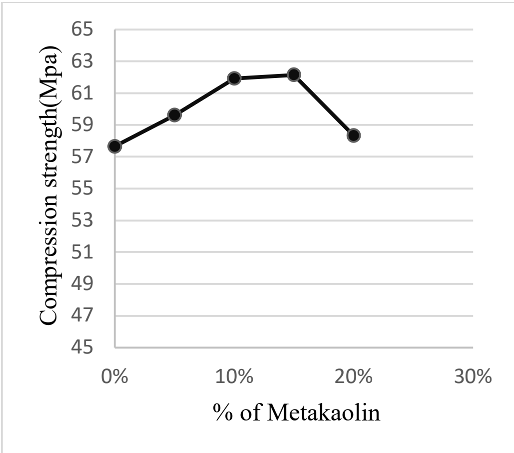
Compressive strength results of concrete at the age of 7 days are, for 0% replacement of cement the compressive strength is 40.01 Mpa, at 5% is 39.41 Mpa, at 10% is 40.96 Mpa, at 15% is 41.02 Mpa and at 20% is 38.42 Mpa.

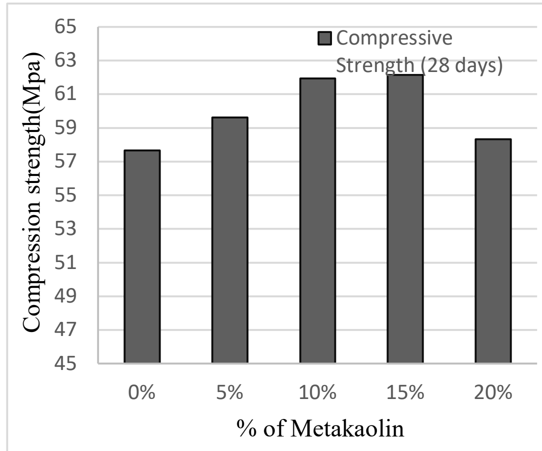




Experimental results of Compressive strength (7 days)

Concrete at the age of 28days test results are at 0% replacement 57.65 Mpa, at 5% is 59.62 Mpa, at 10% is 61.92 Mpa, at 15% is 62.14 Mpa and at 20% is 58.32 Mpa. The test result shows that with increase in percentage of Metakaolin from 0 to 20% the compressive strength of concrete improves, at the age of 28days concrete shows good results for 15% replacement of cement.

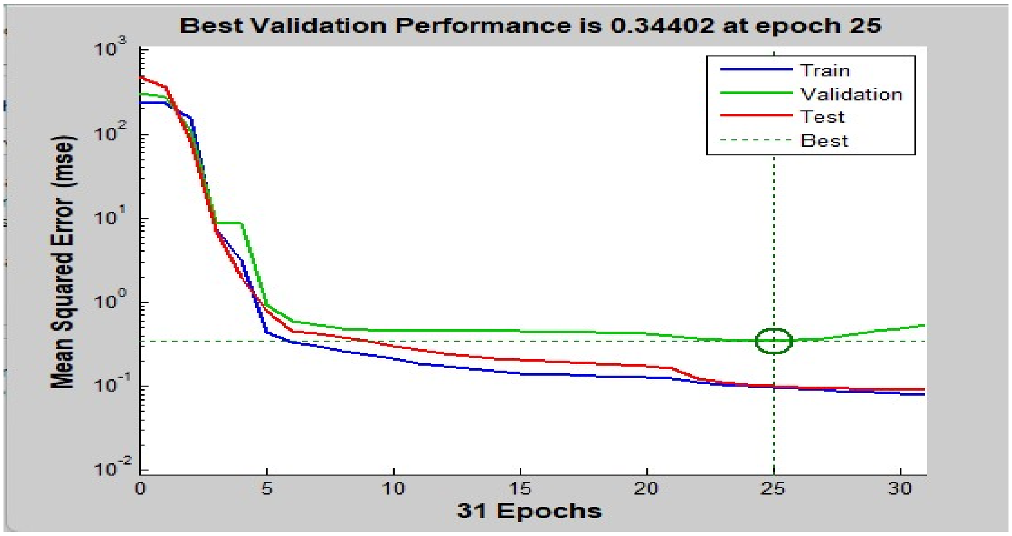




Experimental results of Compressive strength (28 days)

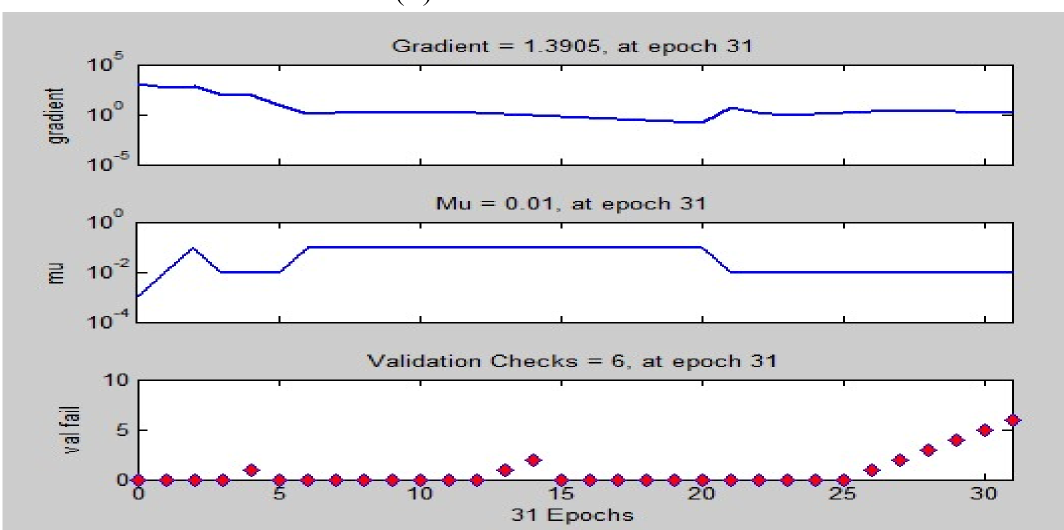
ANN results: Prediction of strengths for concrete with partial replacement of metakaolin done by using ANN method. The inputs are cement content, coarse aggregate, fine aggregate, water content, age of concrete, super plasticizer and % of Metakaolin. The target is compressive strength. So, by using nntool the prediction is done using GUI and Command Script methods. Before the prediction, initially a network is created and it is trained, tested with all the experimental results. The training and testing of experimental data is done by number of iterations to get appropriate output with minimum error. The network diagram which consists of four layers one is input, second layer is a hidden layer with the connected weights, the third layer is output with weights and the fourth layer is total output. The performance plot is the network shows three different coloured lines. Blue represents the training data, red represents the test data and green represents validation data of the total data. The graph shows linear and parallel lines of test, training and validation checks. Epochs represents the number of times the data is changed with the mean square error. The performance plot of compression strength respectively. After learning, testing and training the data the error histogram for compression strength test is as follows. Histogram plot is the error plot that is observed in the final network. The error is divided into 20 bins that is 20 divisions in an order of totals errors shown. The plots also include the colour coding for test, training and validation.

- Plot perform (TR) plots the training, validation, and test performances given the training record TR returned by the function train.
- Syntax: [x, t] = house dataset;
  net = feedforward net (10);
  [net, tr] = train (net, x, t);
  Plot perform(tr)



Performance plot for compressive strength

- Plottrainstate (tr) plots the training state from a training record tr returned by train.
- Syntax: [x, t] = house dataset;
  net = feedforward net (10);
  [net, tr] = train (net, x, t);
  Plottrainstate (tr)

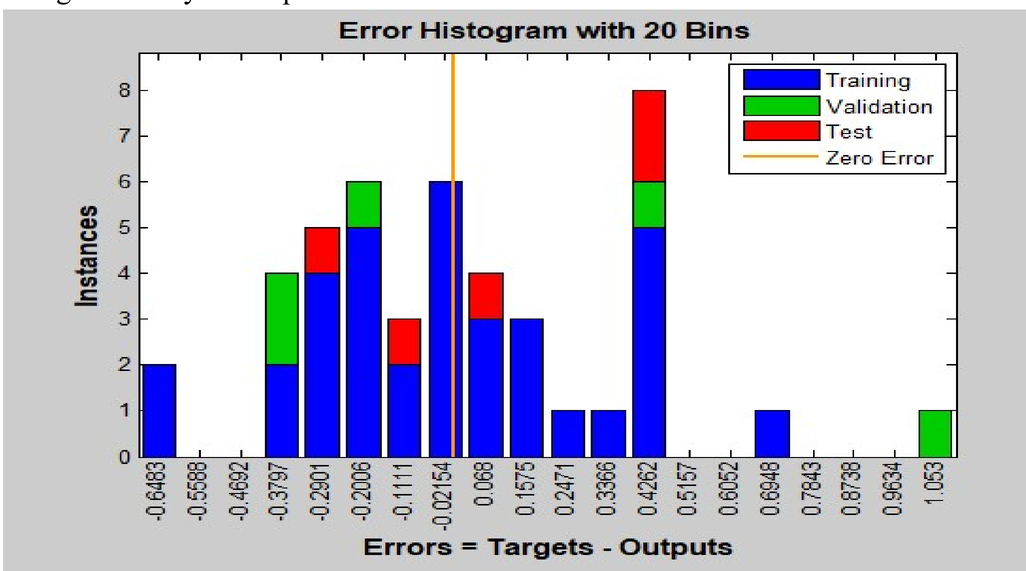


Training state for compressive strength

- Ploterrhist(e) plots a histogram of error values e.
- Ploterrhist (e1,'name1',e2,'name2',...) takes any number of errors and names and plots each pair.
- Ploterrhist(...,'bins',bins) takes an optional property name/value pair which defines the number of bins to use in the histogram plot. The default is 20.
- Suntax: [x,t] = simplefit_dataset;
  net = feedforwardnet (20);

net = train (net, x, t);
y = net (x);
e = t - y;
ploterrhist (e, 'bins', 30)

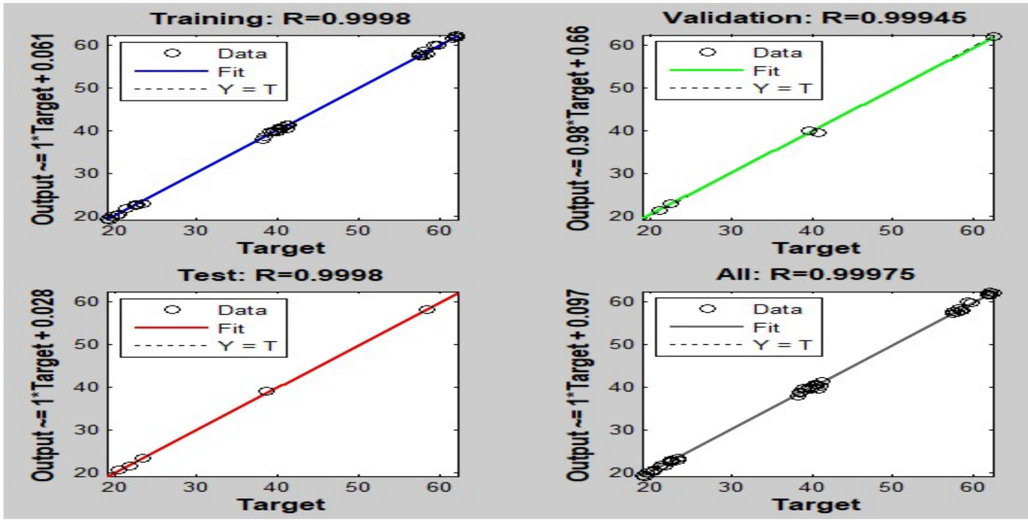
During the prediction of strengths using experimental results, a very reducible error obtained. After learning, testing and training the data the error histogram for compression strength test is as follows. Histogram plot is the error plot that is observed in the final network. The error is divided into 20 bins that is 20 divisions in an order of totals errors shown. The plots also include the colour coding for test, training and validation. The Mean absolute error occurred is 0.1703, Mean square error occurred is 0.0423,root mean square error occurred is 0.2056 and the percentage accuracy of the prediction is 99.98%.



Error Histogram for Compressive strength test.

- Plot regression (targets, outputs) plots the linear regression of targets relative to outputs.
- Plot regression (targs1, outs1,'name1', targs2, outs2,'name2', ...) generates multiple plots.
- Syntax: [x, t] = simplefit_dataset;

net = feedforward net (10);
net = train (net, x, t);
y = net (x);
Plot regression (t, y, 'Regression')



Conclusions:

Based on the experimental and numerical investigations following conclusions are drawn:

- After the addition of Metakaolin, a significant improvement of mechanical properties were observed in M60 grade concrete with different ages.
- The optimum dosage of Metakaolin is 15% for 100% replacement of steel slag aggregate, if exceeds the limit of workability of concrete is not achieved.
- Prediction of mechanical properties of concrete by ANN model provides more exact result with minimum error.
- The Artificial Neural Network model (ANN) has been developed using MATLAB which is used to predict the compressive strength of concrete by considering the factors influencing the properties of concrete and the obtained R value is 0.99 which is nearly equal to 1 that shows that there is well-built correlation between predicted and measured values
- ANN methodology allows a rapid and accurate prediction of compressive strength at site which helps to predict the formwork requirement
- This model helps to control quality and economics (i.e., saving time and expense) in construction and hence necessary changes in mix proportion can be adopted to avoid situation where, required design strength is not reached by concrete or avoiding concrete which is unnecessarily strong
- Multi-layered-feed-forward network model provide a quick prediction based on influencing parameters. This type of computing problems is helpful to civil engineers to avoid number of mixes, which is a cost effective.
- ANN method can be preferably adopted in the ready-mix concrete plants for mix designing and batching
- ANN also minimizes the experimental works to be carried out for other mix designs with similar properties are considered for the training of the network.

Future scope:A detailed investigation involving the properties of concrete such as cement content, coarse aggregate, steel slag aggregate, water content, percentage of Metakaolin, super plasticizer are considered to train ANN. Random selection of data set can be adjusted by selecting the appropriate set of training, validation and test data sets. The default parameters of percentage of test, validation and training can be changed. Different learning functions and also training functions can be adopted and compared. To estimate the strengths of concrete the learning phase of artificial neural networks is influenced by a variety of parameters, such as maximum number of iterations, learning step size, geometry of the network and most importantly data. Considering the geometry of artificial neural networks, it can be precisely defined which one corresponds to the specific data. More number of variations and change in the above parameters will lead to better result.

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