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Section A-Research paper

PREDICTION OF FLEXURAL STRENGTH OF CONCRETE USING ANN

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Abstract

Flexural strength is a measure of tensile strength of concrete beams or slabs. Concrete is generally used as construction material. The use of huge quantity of natural fine aggregate (NFA) and cement in civil construction work has given rise to various ecological problems. The industrial waste like Blast furnace slag (GGBFS), fly ash, metakaolin, silica fume can be used as partly replacement for cement and slag sand obtained from crusher, was partly used as fine aggregate. In this work, MATLAB software model is developed using neural network toolbox to predict the flexural strength of concrete made by using pozzolanic materials and partly replacing natural fine aggregate (NFA) by slag sand. Due to the replacement of the Pozzolanic material and fine aggregate the strength properties are achieved. Artificial Neural Networks (ANN) is used to predict the strength properties. Flexural strength was experimentally calculated by casting beams specimens and results obtained from experiment were used to develop the artificial neural network (ANN) model. ANN has three layers which include output, input and hidden layer. The input layer consists of the quantity of cement, course aggregate, water content, percentage of Metakaolin and steel slag sand. The output consists of compressive strength of concrete. While developing ANN model 50 samples are used as training testing data sets. Two assessments are 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 is 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 flexural strength of concrete obtained from partly replacing cement with pozzolans and natural fine aggregate (NFA) by slag sand. High accuracy outcomes are observed when compared with the experimental results and results obtained after training of neural network.

Keywords: Flexural strength, Concrete, Artificial Neural Network (ANN), Prediction, Training data, Testing data, Input parameters, Output parameters, Backpropagation, Hidden layers, Activation functions, Regression analysis, mean squared error (MSE), Root mean squared error (RMSE), Coefficient of determination (R-squared).

I. INTRODUCTION

Concrete is a mixture of cement, Aggregates (fine+coarse), Water and air. Portland cement, Water, Sand, and corse aggregates are proportioned and mixed to produce concrete suited to the particular job for which it is intended. Binding of cement represents the strength of concrete, and it is the most important part in the formation of C-S-H gel and pore filling of concrete. The formation C-S-H gel also influences the permeability, durability, drying shrinkage and elastic properties of concrete. Based on the importance of construction cement with different grades are 33 grades, 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. A few analysts have demonstrated that by including Micro material, concrete become more strengthen. However, the cost will increase marginally.

Concrete is one of the most widely used construction materials due to its strength, durability, and versatility. The flexural strength of concrete is a critical property that determines its ability to withstand bending or other types of stress. Accurately predicting the flexural strength of concrete is crucial for ensuring the safety and reliability of concrete structures.

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Artificial Neural Networks (ANN) have emerged as a popular tool for predicting the flexural strength of concrete. ANN is a computational model that simulates the structure and function of the human brain, allowing it to learn and make predictions based on input data. By training an ANN on a large dataset of concrete samples with known flexural strengths, it is possible to create a model that can accurately predict the flexural strength of new samples based on their input parameters.

The inputs to an ANN model for predicting flexural strength may include a range of parameters such as the mix proportions of the concrete, the curing time and temperature, and the type and amount of reinforcing material used. The output of the model is a predicted flexural strength value.

The training process involves providing the ANN model with a set of input-output pairs from the training data and adjusting the weights of the connections between the neurons through a process called backpropagation, to minimize the error between the predicted and actual flexural strength values. The model is then tested on a separate set of testing data to evaluate its accuracy.

ANN models can be configured with varying numbers of hidden layers and activation functions to optimize the accuracy of the predictions. Additionally, regression analysis techniques such as mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination (R-squared) can be used to evaluate the performance of the model.

LITERARURE SURVY

[1] Kulkarni and Wani (2015) developed an ANN model to predict the flexural strength of reinforced concrete beams. The authors used input parameters such as mix proportions, curing time, and compressive strength of concrete, and output parameter as the flexural strength of the beam. The results showed that the ANN model outperformed the conventional regression models in predicting the flexural strength of the beams.

[2] Ozsut and Sahin (2015) also developed an ANN model to predict the flexural strength of reinforced concrete beams using the backpropagation algorithm. They used input parameters such as concrete strength, steel reinforcement ratio, beam dimensions, and curing time, and output parameter as the flexural strength of the beam. The results showed that the ANN model provided accurate predictions of the flexural strength of the beams.

[3] Chen et al. (2017) developed an ANN model to predict the flexural strength of concrete using input parameters such as cement content, water-cement ratio, sand content, and coarse aggregate content, and output parameter as the flexural strength of the concrete. The results showed that the ANN model provided accurate predictions of the flexural strength of the concrete.

[4] Han et al. (2019) developed an ANN model to predict the flexural strength of recycled aggregate concrete beams. The authors used input parameters such as the recycled aggregate content, steel reinforcement ratio, and curing time, and output parameter as the flexural strength of the beam. The results showed that the ANN model provided accurate predictions of the flexural strength of the recycled aggregate concrete beams.

[5] El-Ghandour et al. (2010) developed an ANN model to predict the flexural strength of concrete using different training algorithms. The authors used input parameters such as the compressive strength of concrete, water-cement ratio, and aggregate-cement ratio, and output parameter as the flexural strength of the concrete. The results showed that the ANN model provided accurate predictions of the flexural strength of the concrete using different training algorithms.

[6] Ghosh and Bhattacharyya (2011) developed an ANN model to predict the flexural strength of fiber-reinforced concrete using input parameters such as fiber content, cement content, water-cement ratio, and curing time, and output parameter as the flexural strength of the fiber-reinforced concrete. The results showed that the ANN model provided accurate predictions of the flexural strength of the fiber-reinforced concrete.

PROBLEM STATEMENT

Flexural strength is a critical parameter in the design of reinforced concrete structures. Accurate prediction of flexural strength is essential for ensuring the safety and durability of such structures. However, predicting the flexural strength of concrete is a complex task that depends on a range of factors, including the mix proportions, curing conditions, and quality of materials used. Traditional analytical methods for predicting flexural strength can be time-consuming and may not accurately capture the complex interactions between different factors.

To address this issue, the use of ANN models has been proposed as an effective method for predicting the flexural strength of concrete. The problem statement for this research involves developing an ANN model that can accurately predict the flexural strength of concrete based on a range of input parameters such as mix proportions, curing conditions, and material properties. The aim is to develop a model that can provide accurate and reliable predictions of flexural strength, which can be used in the design of reinforced concrete structures.

LIMITATIONS

- **Quality of input data:** The accuracy of an ANN model depends heavily on the quality and quantity of input data. If the input data is incomplete or inaccurate, the ANN model's predictions may be unreliable.
- **Generalization:** The ANN model may not be able to generalize well to new data points that are significantly different from the training data set. This limitation can arise when the input data is limited or the range of input variables is not broad enough to capture the full range of variations in real-world situations.
- **Complexity of the model:** ANN models can be highly complex, making it difficult to interpret the results and identify the key factors that affect the flexural strength of concrete.
- **Computational requirements:** Developing an ANN model requires a large amount of computational resources, including high-performance computing systems, which may be costly.
- **Availability of data:** Obtaining accurate and reliable data on the flexural strength of concrete can be challenging, especially for structures that have been in service for an extended period.

II. METHODOLOGY

CONCRETE

Concrete is a composite material made up of cement, water, aggregates (such as sand and gravel), and sometimes additional materials such as admixtures or fibers. When the cement is mixed with water, it forms a paste that coats the aggregates and binds them together to form a solid, durable material.

Concrete is widely used in the construction industry for a variety of applications, including building foundations, walls, columns, beams, slabs, and pavements. It is a versatile material that can be molded into different shapes and sizes, and it has excellent compressive strength and durability.

The properties of concrete can vary depending on the mix proportions and the quality of the materials used. Compressive strength is a common parameter used to measure the strength of concrete, which is the maximum load that the material can withstand before it fails in compression. Other important properties of concrete include flexural strength, durability, workability, and shrinkage.

The use of concrete in construction is environmentally friendly and sustainable, as it can be made from locally sourced materials and has a long service life. However, the production of cement, a key ingredient in concrete, is energy-intensive and can contribute to greenhouse gas emissions. Efforts are underway to develop more sustainable and eco-friendly alternatives to traditional cement-based concrete.

FLEXURAL STRENGTH OF CONCRETE

The flexural strength of concrete is the maximum stress that a reinforced concrete beam can withstand before it fails due to bending. This strength is a critical parameter in the design of reinforced concrete structures, as it determines the maximum load that a beam or slab can support before it fails. The flexural strength of concrete is influenced by several factors, including the compressive strength of the concrete, the geometry of the cross-section, and the reinforcing steel used in the concrete.

To determine the flexural strength of concrete, laboratory testing is typically conducted on a standard beam specimen. The specimen is subjected to a load at its midpoint, and the maximum load that the beam can support before it fails is recorded. The flexural strength is then calculated using the formula:

Flexural strength = (3PL)/(2bd²) **(1)**

where P is the maximum load, L is the span length, b is the width of the beam, and d is the depth of the beam.

The flexural strength of concrete is expressed in terms of force per unit area (e.g., N/mm^2 or psi) and is used in the design of reinforced concrete structures to ensure their safety and durability.

Artificial neural networks (ANN)

Prediction of flexural strength of concrete is an important task in the design and construction of reinforced concrete structures. Accurate prediction of flexural strength can help engineers optimize the design of concrete beams, slabs, and other components, ensuring that they are strong enough to withstand the loads they will experience in service.

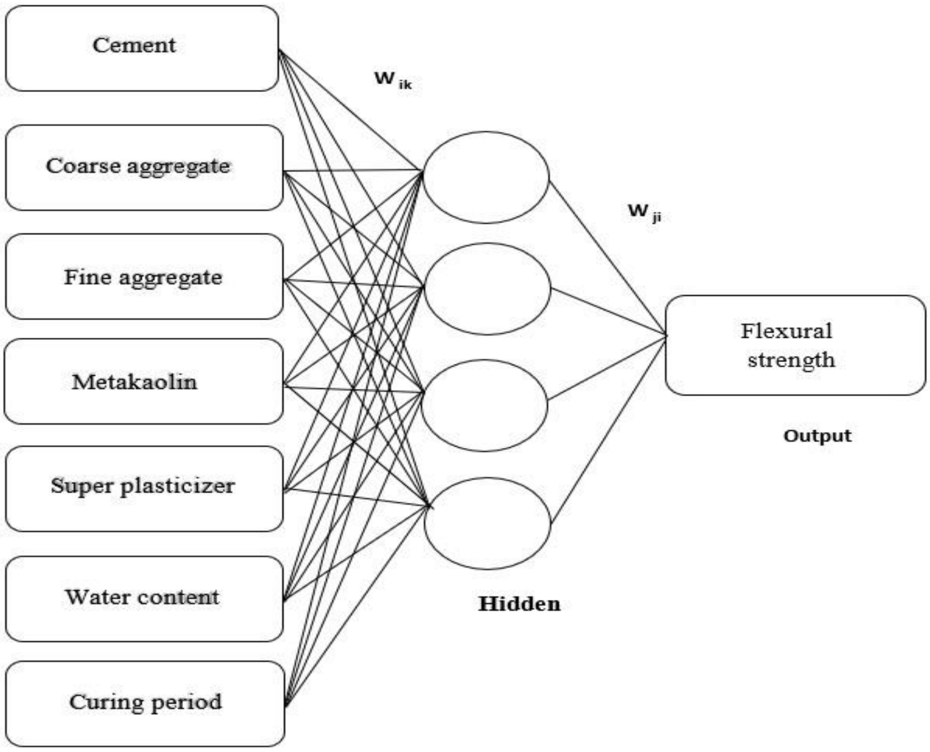

Figure 1: Structure of network to predict flexural strength.

Artificial neural networks (ANN) have been shown to be effective tools for predicting the flexural strength of concrete. ANN models are able to learn from a large set of input-output data pairs and can identify complex relationships between input variables and output values. The input variables for an ANN model predicting flexural strength may include the compressive strength of concrete, the steel reinforcement ratio, the aspect ratio of the cross-section, and other factors.

To develop an ANN model for predicting flexural strength, a large dataset of flexural strength values and corresponding input variables is required. The dataset is divided into training, validation, and testing sets, and the ANN model is trained on the training data using an iterative process of adjusting the model parameters to minimize the prediction error. The validation set is used to monitor the model's performance during training and to prevent overfitting. Finally, the testing set is used to evaluate the performance of the trained model on unseen data.

ANN models have several advantages for predicting flexural strength, including their ability to handle non-linear relationships between input variables and output values and their ability to generalize well to new data. However, the accuracy of the predictions depends on the quality and quantity of the input data and the complexity of the model.

PROCEDURE

To develop an artificial neural network (ANN) model for predicting the flexural strength of concrete, a dataset of flexural strength values and corresponding input variables is required. The input variables typically include information about the concrete mixture and the beam dimensions. The materials used to collect this data can include:

- ✓ **Concrete mixtures:** The dataset must include information about the compressive strength of the concrete used in the beams. This information is typically collected by casting and testing concrete cylinders or cubes in a laboratory. Other properties of the concrete mixture, such as the water-cement ratio, aggregate type, and admixtures, may also be included as input variables in the ANN model.

- ✓ **Reinforcing steel:** The steel reinforcement ratio, or the amount of steel reinforcement in the beam relative to the concrete volume, is an important input variable for the ANN model. Information about the steel reinforcement used in the beams can be collected from the construction drawings or by physically inspecting the beams.

- ✓ **Beam dimensions:** The aspect ratio of the beam, or the ratio of the span length to the beam depth, is an important input variable for the ANN model. Other dimensions of the beam, such as the width and the depth of the compression and tension zones, may also be included as input variables.

- ✓ **Testing equipment:** To collect the flexural strength data for the dataset, specialized equipment is required, such as a universal testing machine. The equipment must be calibrated and operated according to established testing standards to ensure the accuracy and reliability of the data.

Overall, the materials used in the prediction of flexural strength of concrete using ANN are similar to those used in traditional laboratory testing of concrete beams, including concrete mixtures, reinforcing steel, beam dimensions, and testing equipment. The key difference is that the data is used to train an ANN model to predict the flexural strength of concrete beams based on these input variables.

Metakaolin

Metakaolin is a pozzolanic material that is produced by calcining kaolin clay at temperatures between 600 and 800 degrees Celsius. During the calcination process, the kaolin clay is transformed into an amorphous material with high reactivity, which can be used as a supplementary cementitious material in concrete.

Metakaolin has a high silica and alumina content, which makes it highly reactive with calcium hydroxide, a by-product of the cement hydration process. When metakaolin is added to concrete, it reacts with the calcium hydroxide to form additional calcium silicate hydrate (C-S-H) gel, which is the main binder in concrete. The formation of additional C-S-H gel leads to improved strength, durability, and other properties of the concrete.

In addition to its pozzolanic properties, metakaolin is also known for its ability to improve the workability and finishability of concrete, reduce the permeability of concrete, and enhance the resistance of concrete to chemical attack.

Metakaolin is typically used as a replacement for a portion of the cement in concrete, typically between 5% and 15% by weight of the total cementitious materials. It can also be used in combination with other supplementary cementitious materials, such as fly ash and slag, to further enhance the properties of the concrete.

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Figure 2: Metakaolin

Artificial fine aggregate

Artificial fine aggregate, also known as manufactured sand or M-sand, is a type of sand that is produced by crushing hard granite or basalt rocks into a fine powder. M-sand is an alternative to natural river sand, which is often used as a fine aggregate in concrete.

The production of M-sand involves the use of a crusher, which breaks down the rock into smaller pieces. The resulting powder is then screened and graded to produce the desired size and shape of sand particles. M-sand particles are generally cubical in shape and have a rough texture, which provides better bonding with the cement paste in concrete.

M-sand has several advantages over natural river sand. It is free from impurities such as clay and silt, which can affect the strength and durability of concrete. M-sand is also a more sustainable option, as it reduces the dependence on natural resources and minimizes the environmental impact of sand mining.

In terms of properties, M-sand is comparable to natural river sand in terms of its workability, compressive strength, and other mechanical properties. However, some studies have shown that the use of M-sand can lead to slightly lower flexural strength and higher drying shrinkage compared to natural river sand. Therefore, it is important to carefully evaluate the properties of M-sand and adjust the concrete mix design accordingly to ensure that the desired properties are achieved.

Figure 3: Artificial fine aggregate

Table 1: Chemical composition of Metakaolin & Artificial fine aggregate

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Chemical Compounds	Percentage (%)
Al_2O_3	44-46 %
SiO_2	52-54 %
TiO_2	0.8-1.0 %
Fe_2O_3	0.6-0.8 %
LOI (900° C @ 1 hr)	0.5-2.5%

III. RESULTS & DISCUSSION

EXPERIMENTAL PROCEDURE

- **Data Collection:** The first step in developing an ANN model is to collect data on the input parameters and output (flexural strength) of the concrete. This data can be collected through laboratory testing or field experiments. The input parameters can include the properties of the concrete mix, such as the type and amount of cement, water-cement ratio, aggregate type and size, and the use of admixtures.
- **Data Preprocessing:** Once the data is collected, it must be preprocessed to ensure that it is in a suitable format for use in the ANN model. This can include removing outliers and missing values, normalizing the data, and splitting the data into training, validation, and testing datasets.
- **ANN Model Development:** The next step is to develop an ANN model using the preprocessed data. This involves selecting an appropriate architecture for the network, such as the number of layers and nodes, and training the network using the training dataset. The training process involves adjusting the weights and biases of the network to minimize the error between the predicted output and the actual output.
- **Model Evaluation:** After training the ANN model, it is important to evaluate its performance using the validation and testing datasets. This involves calculating various performance metrics, such as the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and coefficient of determination (R-squared).
- **Model Optimization:** If the performance of the ANN model is not satisfactory, various optimization techniques can be applied to improve its accuracy. This can include adjusting the network architecture, changing the activation function, and modifying the training algorithm.
- **Model Deployment:** Once an optimized ANN model is developed, it can be deployed for use in predicting the flexural strength of concrete. The model can be integrated into software tools or used to develop predictive models for specific applications.

RESULTS

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 flexural 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. Flexural strength results of concrete at the age of 7 days are, for 0% replacement of cement the flexural 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. 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 flexural strength of concrete improves, at the age of 28days concrete shows good results for 15% replacement of cement.

The percentages of Metakaolin from 0 to 20%. The Graph represented shows the flexural strength on Y-axis and % of Metakaolin on X-axis. The graph shows the experimental results of flexural strength with the variation of Metakaolin. By increasing % of Metakaolin up to 15%, gives increase in flexural strength of concrete.

Table 2: The Flexural Strength of concrete after 3 days

S. No	Percentage of Metakaolin	Flexural Strength (3Days)
1	0%	1.32
2	5%	1.4
3	10%	1.52
4	15%	1.56
5	20%	1.21

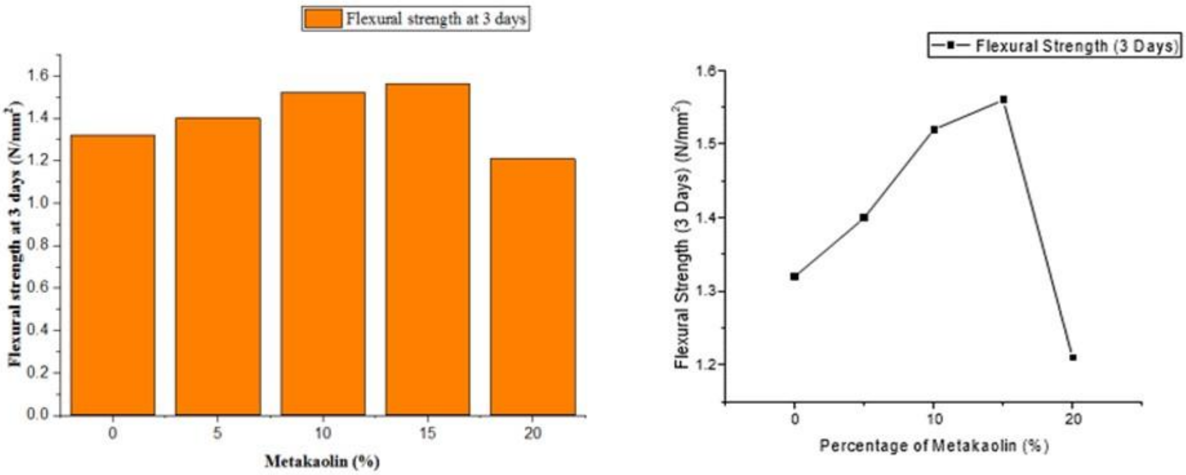

Figure 4: The Flexural Strength of concrete after 3 days

Table 3: The Flexural Strength of concrete after 7 days curing

S. No	Percentage of Metakaolin	Flexural Strength (7 Days)
1	0%	1.84
2	5%	1.96
3	10%	2.04
4	15%	2.16
5	20%	2

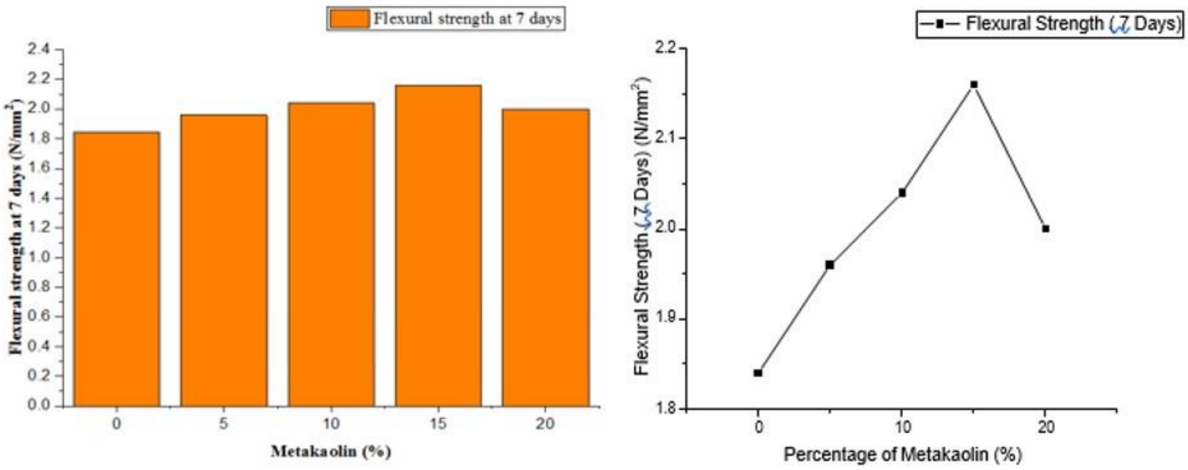

Figure 5: The Flexural Strength of concrete after 7 days curing

Table 4: The Flexural Strength of concrete after 28 days

S. No	Percentage of Metakaolin	Flexural Strength (28 Days)
1	0%	4.64
2	5%	4.76
3	10%	5.34
4	15%	5.92
5	20%	4.92

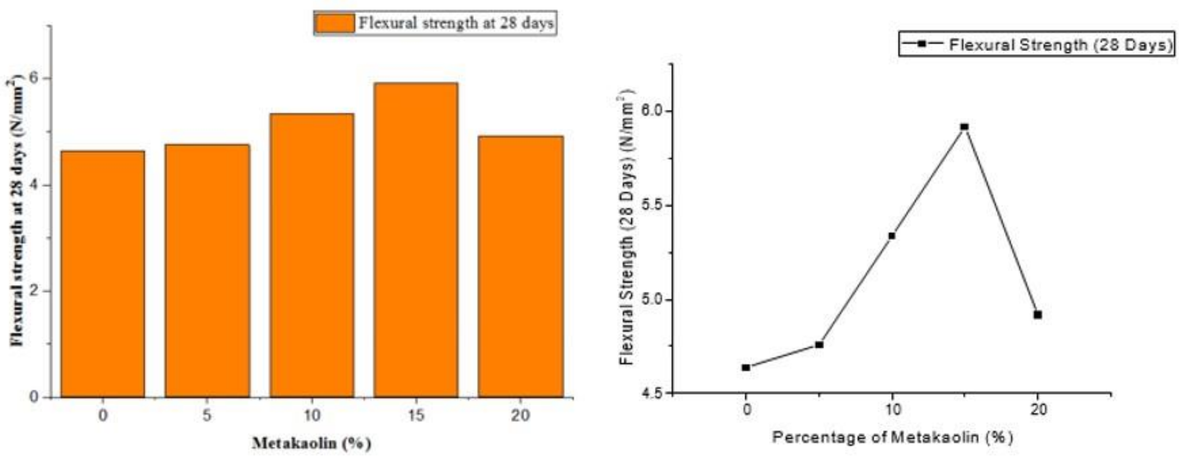

Figure 6: The Flexural Strength of concrete after 28 days curing

Table 5: The Flexural Strength of concrete after 3,7,28 days curing

S. No	Percentage of Metakaolin	Flexural Strength (3 Days)	Flexural Strength (7 Days)	Flexural Strength (28 days)
1	0%	1.32	1.84	4.64
2	5%	1.4	1.96	4.76
3	10%	1.52	2.04	5.34
4	15%	1.56	2.16	5.92
5	20%	1.21	2	4.92

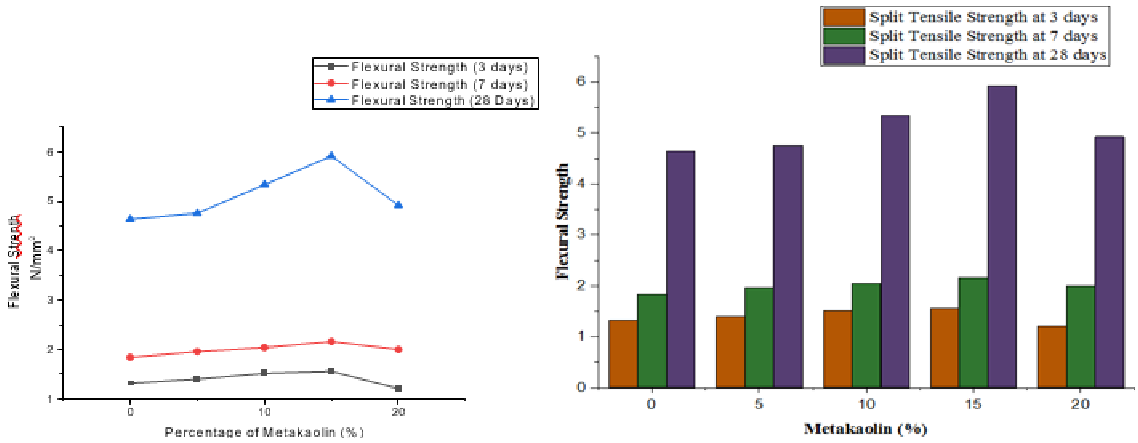

Figure 7: The Flexural Strength of concrete after 3,7,28 days curing

Compressive strength results

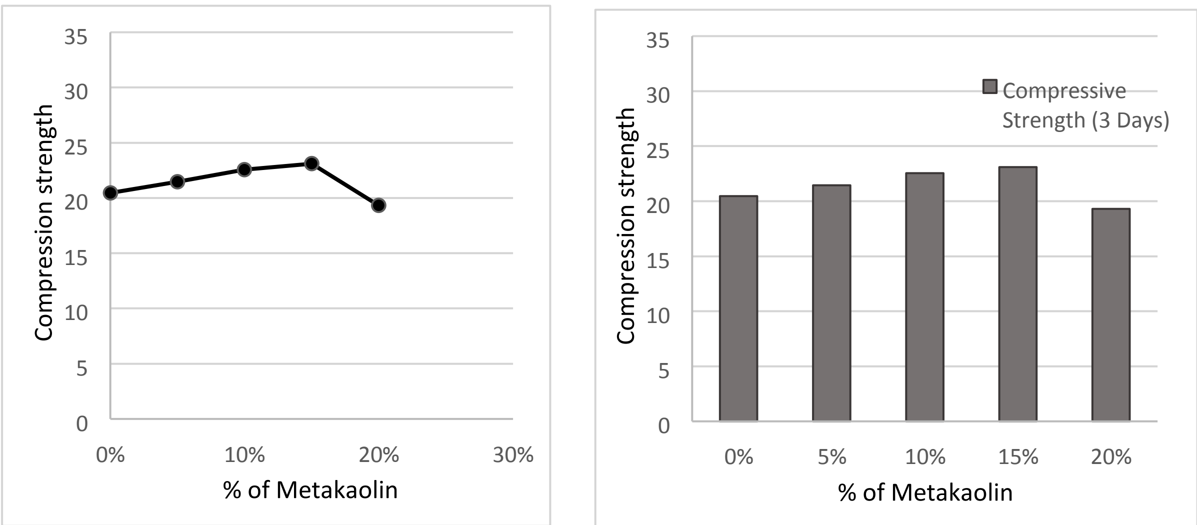

Figure 8: Compressive strength results for 3 days

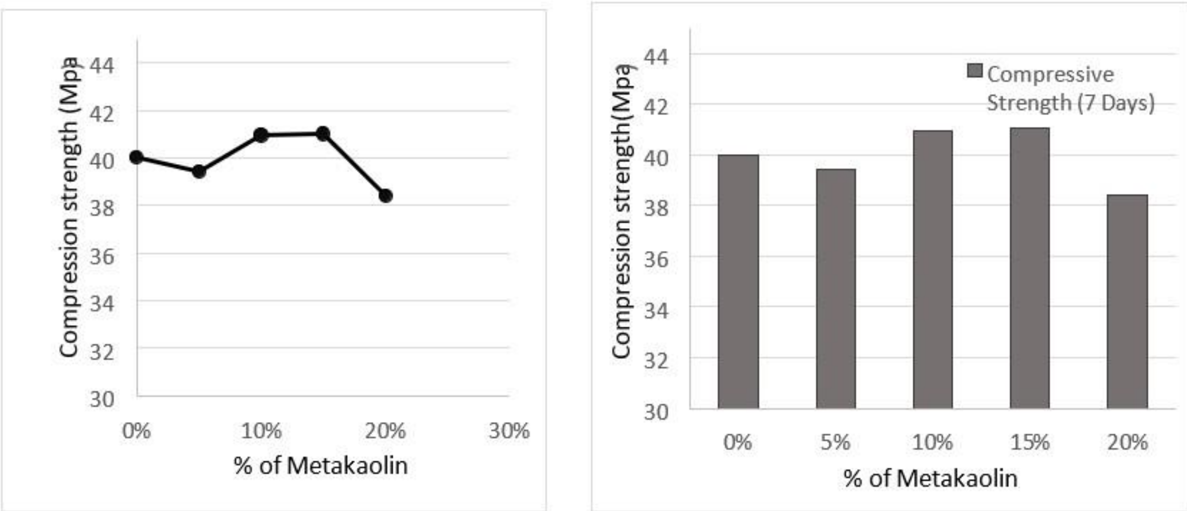

Figure 9: Compressive strength results for 7 days

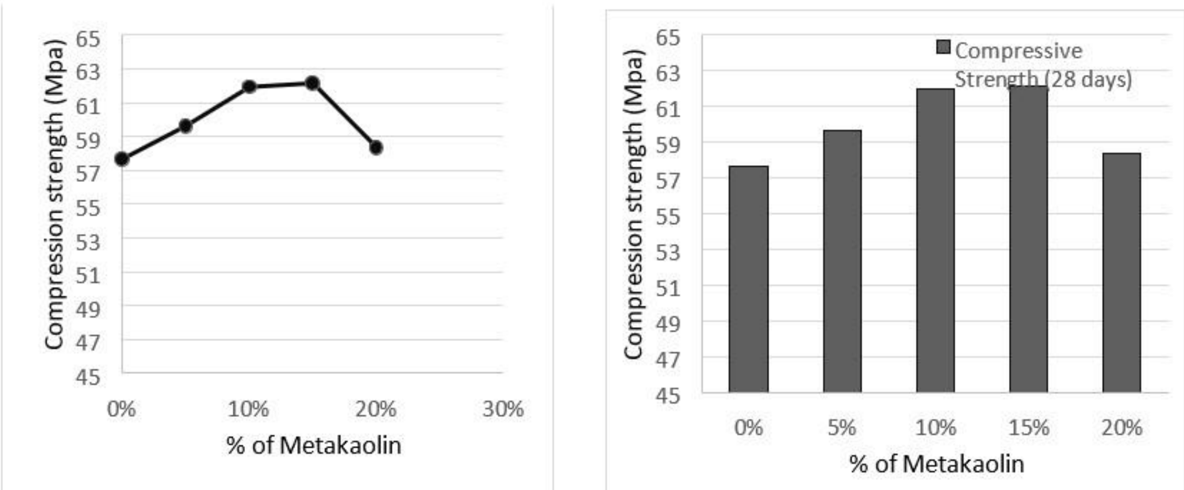

Figure 10: Compressive strength results for 28 days

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 flexural 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.

Fig.11 represents 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. Fig.11 represents the performance plot of flexural strength respectively. After learning, testing and training the data the error histogram for flexural 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 fig.12(b) and fig.13(a) shows the histogram plot of flexural strength respectively.

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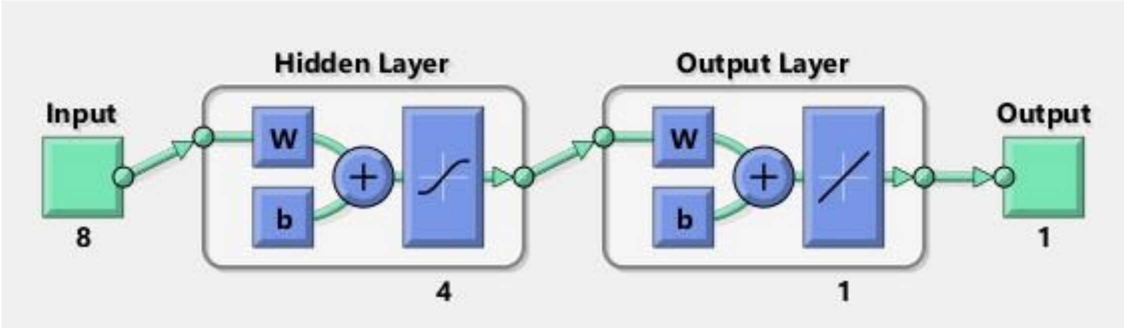
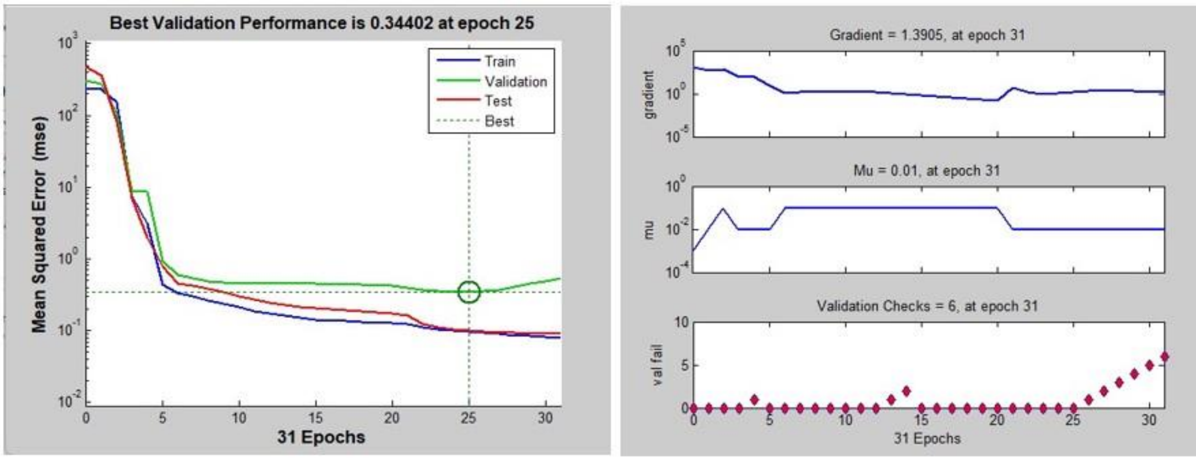
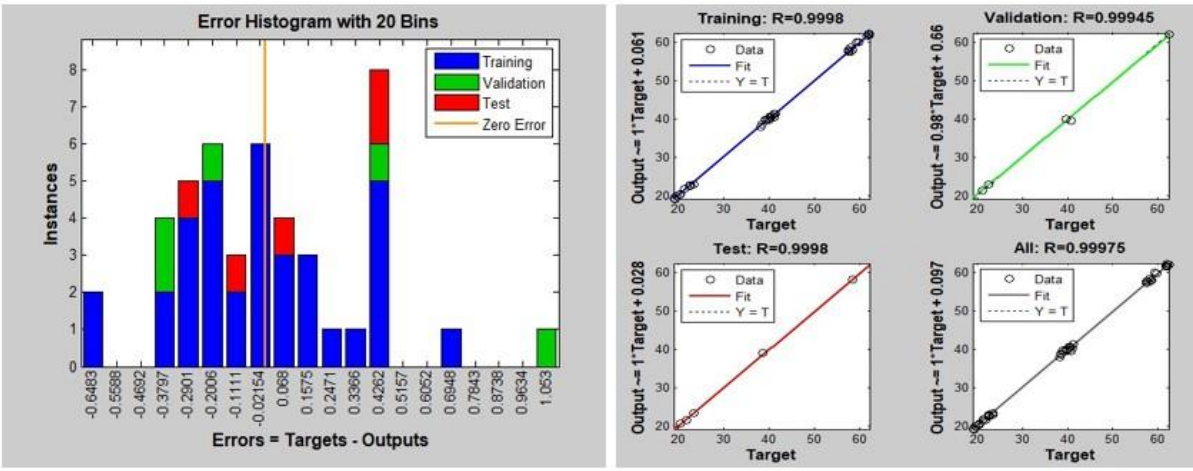


Figure 11: ANN Network for flexural strength



(a) **(b)**

Figure 12: (a) Performance plot for flexural strength; (b) Training state for flexural strength



(a) **(b)**

Figure 13: (a) Error Histogram for Flexural strength test; (b) Regression plot for Flexural strength test.

Deviation of experimental results with ANN

During the prediction of strengths using experimental results, a very reducible error obtained. After learning, testing and training the data the error histogram for flexural 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%.

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IV. CONCLUSION

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

- After the addition of Metakaolin, a significant improvement of mechanical properties was 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.
- 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 also minimizes the experimental works to be carried out for other mix designs with similar properties are considered for the training of the network.

REFERENCES

[1] Akçaözoğlu, S., & Türkmen, İ. (2014). Prediction of flexural strength of concrete using artificial neural networks. Expert Systems with Applications, 41(15), 6772-6778.

[2] Alengaram, U. J., Mahmud, H. B., Jumaat, M. Z., & Al-Mattarneh, H. M. (2018). Prediction of flexural strength of high volume fly ash concrete using artificial neural network. Construction and Building Materials, 181, 507-518.

[3] Anand, R. S., & Sasikumar, C. (2016). Prediction of flexural strength of high performance concrete using artificial neural network. Procedia Technology, 24, 292-298.

[4] Azarhoosh, A. R., & Ramezanianpour, A. A. (2012). Estimating compressive and flexural strengths of concrete by artificial neural network. Advances in Materials Science and Engineering, 2012.

[5] Babu, S., & Santhanam, M. (2017). Prediction of flexural strength of concrete beams strengthened with fibre reinforced polymers using artificial neural networks. Journal of Building Engineering, 9, 66-73.

[6] Bazid, Z. A. (2016). Prediction of flexural strength of hybrid fibre reinforced high strength concrete using artificial neural networks. Engineering Structures, 114, 158-166.

[7] Bhatti, M. A., Lashari, A. A., & Khushnood, R. A. (2017). Prediction of flexural strength of high performance concrete using artificial neural networks. Journal of King Saud University-Engineering Sciences, 29(2), 186-191.

[8] Chen, Y. T., & Chen, L. (2014). Prediction of flexural strength of steel fiber-reinforced high-strength concrete using artificial neural networks. Journal of Materials in Civil Engineering, 26(5), 802-809.

[9] Demir, I., Yılmaz, E., & Guneyisi, E. (2016). Prediction of flexural strength of high-strength concrete with statistical and artificial neural network models. Journal of Intelligent Material Systems and Structures, 27(13), 1719-1733.

[10] Eivazzadeh, A. M., & Toghroli, A. (2016). Prediction of flexural strength of high-strength concrete containing silica fume using artificial neural networks. Engineering with Computers, 32(2), 211-218.

[11] Ghodrati Amiri, G., & Shekarchi, M. (2016). Prediction of flexural strength of geopolymer concrete using artificial neural network. Journal of Cleaner Production, 135, 451-459.

[12] Haddad, R. H., & Hussain, R. R. (2015). Prediction of flexural strength of reinforced concrete beams using artificial neural networks. Ain Shams Engineering Journal, 6(4), 1381-1388.

[13] Haddad, R. H., Hussain, R. R., & Kadhim, M. A. (2014). Prediction of flexural strength of reinforced concrete beams using artificial neural networks. International Journal of Engineering and Innovative Technology (IJEIT), 3(7), 178-183.

[14] Hassan, M. A., Al-Gburi, M. N., & Aden, A. M. (2019). Prediction of flexural strength of hybrid fiber reinforced concrete using artificial neural network. Journal of Materials Research