Modelling of Compressive Strength of Concrete using Artificial Neural Network

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Abstract
Researchers were interested in finding solutions to the problems caused by the complexity and insufficiency of empirical relations in estimating compressive strength from its elements utilising soft computing technologies like MATLAB's Artificial Neural Network (ANN), etc.One cutting-edge method for predicting the compressive strength of composite and complicated materials like concrete made with a variety of constituents is the use of Artificial Neural Networks (ANN). In order to create this kind of tool, artificial neural network (ANN) models with various architectures were trained and fine-tuned using data collected from the RMC batching plant. The goal was to achieve test results with a minimum error between the expected and intended output. In addition to comparing the ANN models' performance with that of the Multiple Linear Regressions (MLR) model, we used the Cosine Amplitude Method (CAM) to determine the impact of each input variable on the compressive strength.The best-fitting model is the one that produced the lowest root-mean-squared error values during training and validation; this demonstrates that artificial neural networks (ANNs) are a practical tool for analysis and modelling, and they can also absorb the complexity of concrete's behaviour. Because concrete exhibits such complicated behaviour, it was determined that the MLR models could not provide the dependability and predictability that were required. The complicated character of composite materials might be understood via the relative significance assessments performed using CAM.

Keywords: *Artificial Neural Networks (ANN), Ready-Mix Concrete (RMC), Multiple Linear Regressions (MLR), Cosine Amplitude Method (CAM), Characteristic compressive strength.*

1. Introduction

1.1 General: -

For a long time now, concrete has been meeting the needs of contemporary civilization. Along these lines, concrete is a composite material that finds widespread usage in building projects throughout the globe. Up till 2017, it anticipates just 0.47 billion m3 in India.Engineers and contractors now choose concrete because of its numerous desirable properties, such as its moldability, low cost, durability, and abundant supply of raw materials. The characteristics of concrete change depending on whether it is wet or dry. When the material is wet, its workability, moldability, hydration rate, plasticity, and time to initial and final setting are its most important features. On the other hand, when it is dry, its main attributes include compressive strength, impermeability, fire resistance, abrasion, durability, and rate of strength increase. At each step of the process, the concrete's characteristics are influenced by the mineralogy, kind of material, additive, and mix composition. Researchers have taken a keen interest in concrete as a result of its widespread usage and complicated nature. Rapid infrastructure development and technical innovation in the manufacturing sector gave rise to a plethora of specialised materials; yet, engineers and contractors alike have come to choose Ready-Mix Concrete (RMC) for its superior the qualities mentioned before. The RMC is made in accordance with the specified recipe at the factory. Using transit mixers, it is transported to a construction site after production. It is possible to create and use speciality concrete mixes on building sites thanks to this method, which also produces a precise combination. building sites often employ RMC to increase quality and simplify activities, leading to hassle-free building in the end.

1.2 Why Compressive Strength Is Crucial for RMC Testing and Industry: -

To accomplish the intended results, the design mix procedure is dependent on the component types and quantities chosen. Globally, the most critical values for evaluating the desired concrete mix qualities are the slump during the wet stage and the compressive strength during the hardening stage. The quality of the concrete mix is indicated by these figures. To accomplish these desired results, a lot of experiments with various compositions are conducted. In some applications, such as seawater concreting or exposure to extreme weather, other properties, such as permeability and durability, take precedence over strength, which is still the most significant feature. They are crucial for quality control because the molecular structure inside the concrete determines its strength, which in turn relies on compaction and cement hydration. The concrete's typical compressive strength dictates the design of various structural components.

A 28-day compressive strength below which no more than 5% of samples are anticipated to fall is a good way to characterise the typical compressive strength. As a general rule, a conventional uniaxial compression test is used to measure the compressive strength of RMC after 7, 28, and sometimes even 3 days to guarantee its quality. When testing compressive strength, cubes or cylindrical moulds are used. Depending on the amount of concrete, standard size moulds measuring 150 mm x 150 mm x 150 mm are filled with the necessary amount of concrete and compressed to eliminate any air spaces. Cubes may be removed from moulds after 24 hours and left to cure at room temperature until testing date. Three, seven, and twenty-eight days after mixing, concrete is tested for strength. Until the sample breaks, a slow but steady pressure of 14 MPa is applied. Additionally, the compressive strength of concrete is determined by averaging the specimen areas of at least three concrete samples. For the purpose of acceptance, the compressive strength data from all three tests is used. The results of the 28-day compressive strength test are used in the design of all structural elements. Additionally, it provides a synopsis of the quality of concrete.

However, it is still important to consider the findings of the 3-day and 7-day tests. The former may help with early strength prediction, while the latter is estimated to account for 64% to 70% of the 28-day strength, respectively. If a contractor's projects are late, they will be out of business. Therefore, developers and engineers must anticipate the possibility of poor results from 3-day and 7-day compressive strength tests. This would allow them to keep a careful eye on the mix proportion, mixing, moulding, and testing processes, as well as take the necessary precautions to ensure the required quality on site. We can finally fix the problem of weak strength in the next batch. The findings of the early age test may also be used to predict the compressive strength in 28 days. Reducing project time and costs, early strength also aids in decision-making towards early framework removal.

1.3 Why Now Is the Time to Do It: -

The traditional design mix approach is time-consuming and labor-intensive since it entails several trials with various mix proportions and mineral admixtures and takes at least 28 days to reach a decision about the strength of the concrete. Although experimental approaches are always a good bet in any field since they produce the most accurate results and provide the groundwork for future study and development, mathematical models may help estimate a mix's compressive strength and recommend appropriate proportions of unique ingredient to get the concrete quality that is needed. This manner, it's possible to get the appropriate percentage of RMC grade with fewer trials. A frequent mathematical connection for expressing the outcome using empirical formulas from the outcomes is a regression equation. However, these empirical formulas fail to provide the expected dependability and forecast since concrete governs are complicated and depend on many components, their sources, and quantities. Therefore, it is necessary to build an alternative modelling approach as this type of modelling utilising Non-Linear regression for concrete strength is a usual job. An effective auxiliary tool for establishing the

connection of compressive strength with the other components is ANN. Soft computing tools are a new set of approaches that aim to take advantage of people's tolerance for ambiguity and error. As far as soft computing technologies go, ANN is the way to go. An ANN is a computer model that mimics the behaviour of real-life neural networks. Due to its learning mechanism via input and output, an ANN's models are impacted by the information going through the neural network.
The first layer of an ANN contains input neurons, the second layer establishes relations between input parameters and output, and transfers the output neurons to the third layer. ANNs are tri-layered architectures. Taking into account the shortcomings of conventional approaches and the progress made by ANN, it is also noted that ANN has shown to be a computational tool for estimating the compressive strength of concrete using the mix design's component proportions.

1.4 Purpose of the Research:

In order to establish a functional relationship between the mix design components and the concrete's compressive strength, this research use Neural Networks to generate a model for both prediction and analysis of compressive strength. The concrete design mix proportions example data came from an RMC batching facility. These modelling data sets were used for training, validating, and testing artificial neural network (ANN) models. Predicting the compressive strength and analysing constituent qualities are the primary goals of constructing such a model. Additionally, it will be useful for comprehending the intricate relationship between the components of a concrete mix and its compressive strength, since it provides a sense of the weight that each variable carries.

2. Modelling of Compressive Strength of Concrete

2.1 Introduction

Cement, aggregate, and water are the three main components of concrete. The use of various additives, such as fly ash and admixtures, has allowed concrete to gradually improve in quality over the years. Concrete is made using carefully chosen materials to achieve a cheap cost while yet producing a material with great strength, excellent workability, and durability. It has been shown that utilising ANN for modelling the prediction of concrete compressive strength is a fantastic concept. This allows for the possibility of making the required adjustments to the material proportions in the event that the concrete does not achieve the target strength. The characteristic compressive strength of RMC is used to determine the design mix. This strength is important for all structural elements. However, there are many factors that influence this strength, including the concrete's design mix, material properties, compaction, curing conditions, temperature, and so on. This makes prediction and modelling more difficult. Because empirical relations are complicated and inadequate for predicting compressive strength from its constituents, researchers have been interested in finding a better solution that saves time and money using soft computing tools like MATLAB's Artificial Neural Network (ANN), among others. The research here models concrete's compressive strength using MATLAB 7.1 Version.

2.2. What You Need

Gathering Data Sets (2.2.1)

To decrease the likelihood of material variations in the physical and chemical attributes used to build the Neural Network model for strength prediction, this research relies on data acquired from a single Ready-Mix Concrete (RMC) factory. The data sets have compressive strength test results for concrete of varying ages (3, 7, and 28 days), as well as 1167 samples of design mixes containing cement, fly ash, fine and coarse aggregate (20mm and 10mm), superplasticizers (admixture), water, and the concrete's age. The grades of concrete in the sets range from M15 to M40. Using this data of compressive strength, the ANN models were created. Table 2.1 provides a detailed overview of the data: -

Table 2.1: Description of data used for modelling the compressive strength

Data collected for	Minimum Value	Maximum Value	Mean Value	Standard Deviation
Cement (kg/m^3)	158.00	525.00	294.5767	72.8228
Pulverized Fly Ash (kg/m^3)	0.00	165.00	50.1568	50.7867
Sand (kg/m^3)	467.00	935.00	728.2811	83.9066
CA(20 mm) (kg/m^3)	654.00	847.00	753.5673	42.1227
CA(10 mm) (kg/m^3)	253.00	450.00	368.1054	19.0200
Superplasticizers (kg/m^3)	0.00	6.45	3.2665	0.8905
Water (kg/m^3)	137.50	211.00	178.1882	12.3321
Age (days)	3.00	28.00	15.5398	11.2273
Compressive Strength (N/mm^2)	6.04	62.67	29.6246	10.9736

2.3 Modelling of Compressive Strength of concrete using ANN

Artificial Neural Networks (section 2.3.1)

The rise of computing has given rise to a brand-new area of study: artificial intelligence (AI). Computer science, physiology, and philosophy come together to develop AI. In an effort to build smarter robots modelled after humans, a number of AI methods have surfaced in the last half-century. One kind of artificial intelligence that mimics brain function is known as an artificial neural network (ANN). Machines that can learn and respond to new situations and problems in a way that humans can are the focus of artificial intelligence research and development. To do this, modelling neural networks using data derived from human reactions yields an electronic model capable of mimicking human behaviour in similar contexts. It is a potent instrument that provides the fundamental component for AI. Since concrete is a composite, there are no well-established empirical connections that can be used to simulate its material characteristics. To lessen the likelihood of compressive strength change caused by variation in the mix percentage, artificial neural networks (ANNs) trained using the data may learn from previous instances or experimental data.

We may classify neural networks according to their architecture, with wavelet neural networks, radial basis functions, self-organizing maps, and multilayer perceptrons being the most common. The Multi-Layer Feedforward Neural Networks (MFNNs) are a subset of MLPs that link neurons across layers in a single direction, forwards, and do not need a loop. In MFNNs, there are many hidden layers that process data, in addition to an input and output layer. Each layer has a number of neurons or nodes. Training and fitting functions in MFNNs often include back propagation, and the training procedure for neural networks consists of the following steps:-

1) Setting Weight and Bias to tiny, arbitrary values
Supplying supervised learning with input-output pairs
Thirdly, information is sent forward.
Fourthly, the difference between expected and actual outputs is used to calculate the accuracy via error.
5) Errors that propagate backwards
Altering biases and weights
7) Carry out steps 3–6 repeatedly until the target error rate or the maximum number of training cycles is reached.
8) Record the neural network's training data.

2.3.1 Selection of data sets for Training, Validation and Testing

The design of the model might be based on the information processing features of the human brain, which is the inspiration for artificial neural networks (ANN). In order to determine its generalizability, neural networks should be taught to learn from a variety of samples and test their findings. In order to detect the mistake, neural networks may be tested after training. It should be mentioned that there are no established guidelines or regulations for determining the proportion of data to be used for training, validation, and testing. Nonetheless, after dividing the data in half, about 55% to 60% may be set aside for network training, while the remaining data can be used for both training and validation.

2.3.2 Normalization of Data

When dealing with complicated or indefinite input/output relationships, the complexity of multi-layer perceptrons increases as a result of the activation or transfer functions. Activation functions that are not linear are used by the back propagation neural network. The data is transformed linearly to a fixed value within a predetermined range of -1 to 1 using min-max normalisation in this research.

2.3.3 Architecture of Neural Network and Parameters of Training

The fundamental building blocks of a Neural Network design are the input layer, the output layer, and a hidden layer or layers. A component of the MATLAB 7.1 software suite, the Toolbox of Neural Network is used in the development of the MFNN. The training procedure sets up the framework for updating the biases and weights of the ANN.
The amount of hidden layers and the neurons in each determine the network's complexity. Overfitting the training data becomes more common and the network's capacity to generalise diminishes as the number of neurons grows. As a result, choosing the hidden layers and the neurons inside them is an iterative process. A neural network design consisting of fifteen distinct single-hidden-layer layers (ANN1–ANN15) with neuron limits ranging from six to twenty is used in this research. The training and validation performance of each model can be evaluated using three performance metrics: root mean square error (RMSE), correlation coefficient (R), and mean absolute error (MAE). The models are then ranked according to the values of these metrics. The model that produces the highest ranking is selected and put to the test.

2.4 Evaluation of the Models Performance

Root mean square error (RMSE), correlation coefficient (R), and mean absolute error (MAE) are three performance measures that should be used to assess the accuracy and performance of ANN and MLR models in prediction.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(T_i - P_i)^2} \quad (2.2)$$

$$MAE = \frac{1}{N}\left(\sum_{i=1}^{N} abs(T_i - P)_i\right) \quad (2.3)$$

$$R = \frac{\sum_{i=1}^{N}(T_i - \bar{T})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{N}(T_i - \bar{T})^2 \sum_{i=1}^{N}(P_i - \bar{P})^2}} \quad (2.4)$$

where, T_i =Target or actual value

P_i = Predicted value of ANN.

$\bar{T}$ = Mean of actual values

$\bar{P}$ = Mean of predicted values

N = Number of data Sets.

Finding the variance and bias degree allows one to quantify the model's accuracy in prediction using RMSE. As the inverse of the RMSE number represents the accuracy of the forecast, a smaller RMSE value indicates more accuracy. To achieve the intended prediction, it is desirable to have a low mean absolute percentage error (MAE) since it lends a significant weight to the model's absolute mistakes when comparing them. A model with a correlation coefficient (R) near to 1 indicates strong prediction accuracy and a fine link between the actual or target value and the anticipated values; R values may vary from -1 to +1.

2.5 Input Variables Importance on the Compressive Strength

In order to determine how comparable the relevant factors are, the Cosine Amplitude Method (CAM) may be used to analyse the relationship between compressive strength and the input variables. This approach, shown below, makes advantage of the X-space data array: -

$$X = [X_1, X_2, ...X_m] \quad (2.5)$$

Where, X_i = Elements in the data array,

X =Vector lengths of m,

$$X_i = (x_{i1}, x_{i2}, ... ,x_{im})_1 \quad (2.6)$$

3. Results and Analysis

3.1 Training and Validating of Models

Information on the compressive strength of concrete with various ingredients, such as cement, fly ash, sand, coarse aggregate 20 and 10 mm, additives, and water, as well as data at3,7, and 28 days of age, was collected from a ready-mixed concrete factory in order to build ANN models. The research used a multilayer feed forward neural network (MFNN) with the following input variables: age, admixture, cement, fly ash, sand, aggregate 20 and 10 mm, water, and the matching compressive strength value.While developing the input-output connection, the hidden layer relied on trial and error. The neural network design used in the research consists of fifteen distinct single-hidden-layer layers, with neuron limits ranging from six to twenty. You may find the model's architecture in Table 3.1.

Table 3.1: Details of ANN Models

Model	Input layer Neurons	Hidden layer Neurons	Output layer Neurons	Transfer function		Neural network architecture	Size of weight and bias matrix
				Hidden layer	Output layer		
ANN1	8	6	1	logsig	purelin	8-6-1	61
ANN2	8	7	1	logsig	purelin	8-7-1	71
ANN3	8	8	1	logsig	purelin	8-8-1	81
ANN4	8	9	1	logsig	purelin	8-9-1	91
ANN5	8	10	1	logsig	purelin	8-10-1	101
ANN6	8	11	1	logsig	purelin	8-11-1	111
ANN7	8	12	1	logsig	purelin	8-12-1	121
ANN8	8	13	1	logsig	purelin	8-13-1	131
ANN9	8	14	1	logsig	purelin	8-14-1	141
ANN10	8	15	1	logsig	purelin	8-15-1	151
ANN11	8	16	1	logsig	purelin	8-16-1	161
ANN12	8	17	1	logsig	purelin	8-17-1	171
ANN13	8	18	1	logsig	purelin	8-18-1	181
ANN14	8	19	1	logsig	purelin	8-19-1	191
ANN15	8	20	1	logsig	purelin	8-20-1	201

For each training epoch of the model, 233 datasets were utilised for validation to check its generalisation ability and avoid overfitting. The Levenberg Marquardt back-propagation algorithm was used for model training, with 60% of the data (701 datasets) allocated for training. The neural network model training and validation plots (ANN1–ANN15) showing the evolution of the Root Mean Square Error (RMSE) throughout training epochs.

3.2.1 Training, Validation and Test Performance of ANN Models

Three distinct performance measures, namely Root Mean Square Error (RMSE), Correlation Coefficient (R), and Mean Absolute Error (MAE), were used to assess the training and validation performance of artificial neural network (ANN) models ANN1–ANN15. Tabulated in Table 3.2 are the specific performance measures and their ranking for each ANN model during training, whereas Table 3.3 displays the same information during validation.

The performance measures reveal that when the number of hidden layer neurons grows, the complexity of the ANN models rises, leading to significant improvements in training performance.

following that. As the number of hidden layer neurons increases from 6 to 20, the RMSE value drops from 2.7735 N/mm2 to 1.3028 N/mm2. The increase of the ANN model's learning capacity is also shown by the lowering of MAE and the enhancement of the correlation coefficient R. At 16 hidden layer neurons, validation performance is at its lowest, but it rises and falls again as the number of neurons in the layer grows.

Table 3.2: Training performance and ranking of ANN models

Model	Performance metric (training)			Rank			Rank
	RMSE (N/mm^2)	R	MAE (N/mm^2)	RMSE	R	MAE	
ANN1	2.7735	0.9671	2.1054	1	1	1	3
ANN2	2.3523	0.9764	1.8420	2	2	2	6
ANN3	2.0967	0.9813	1.6457	3	3	3	9
ANN4	2.0448	0.9823	1.5585	4	4	4	12
ANN5	1.8661	0.9853	1.4496	5	5	5	15
ANN6	1.7592	0.9869	1.3795	6	6	6	18
ANN7	1.6578	0.9884	1.3073	7	7	7	21
ANN8	1.5604	0.9897	1.2371	8	8	8	24
ANN9	1.4652	0.9909	1.1505	9	9	9	27
ANN10	1.3480	0.9923	1.0289	11	11	11	33
ANN11	1.3536	0.9923	1.0629	10	10	10	30
ANN12	1.2894	0.9930	0.9857	13	13	13	39
ANN13	1.2862	0.9930	0.9769	14	14	15	43
ANN14	1.2793	0.9931	0.9811	15	15	14	44
ANN15	1.3028	0.9928	1.0037	12	12	12	36

Table 3.3: Validation performance and ranking of ANN models

Model	Performance metric (validation)			Rank			Rank
	RMSE (N/mm^2)	R	MAE (N/mm^2)	RMSE	R	MAE	
ANN1	2.9998	0.9641	2.2370	1	1	1	3
ANN2	2.7638	0.9697	2.1521	2	3	2	7
ANN3	2.7605	0.9695	2.0751	3	2	3	8
ANN4	2.5207	0.9749	1.9502	4	4	4	12
ANN5	2.4024	0.9770	1.8331	6	6	5	17
ANN6	2.4259	0.9766	1.7549	5	5	7	17
ANN7	2.2748	0.9794	1.7629	10	10	6	26
ANN8	2.2349	0.9803	1.7073	12	12	8	32
ANN9	2.2326	0.9806	1.5915	13	13	14	40
ANN10	2.1738	0.9813	1.6283	14	14	11	39
ANN11	2.0202	0.9839	1.5443	15	15	15	45
ANN12	2.2649	0.9800	1.6070	11	11	13	35
ANN13	2.3814	0.9777	1.6096	7	7	12	26
ANN14	2.3214	0.9786	1.6658	8	8	9	25
ANN15	2.3165	0.9788	1.6410	9	9	10	28

Figure 3.1 displays the overall ranking of all ANN models according to their performance metrics, which describe their training and validation performance. Based on the ranking diagram, we know that the model with the greatest learning and generalisation capacity is ANN11, which uses 16 neurons in its hidden layer.

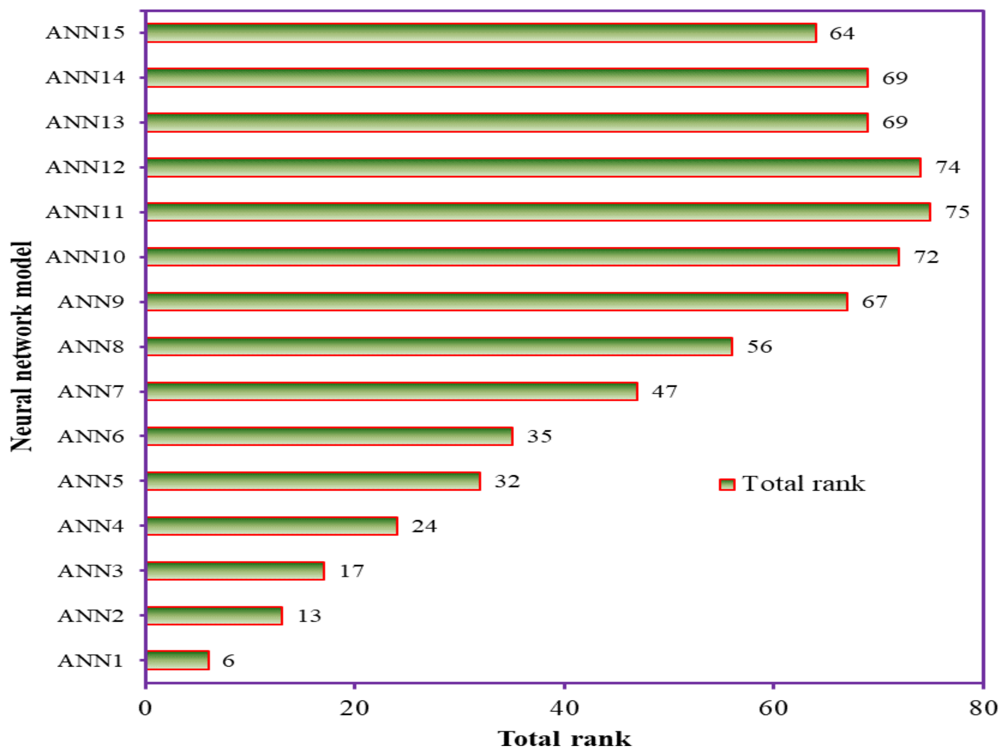

Fig. 3.1: Total ranking of neural network models.

The datasets that are designated for testing are used to evaluate the best-trained Neural Network Architecture ANN11, which has 16 neurons in its hidden layer. Table 3.4 displays the results of the ANN11 model's test on the test dataset. We get an RMSE of 2.2088 N/mm2, a R of 0.9808, and an MAE of 1.6314 N/mm2 in our tests.

Model	Architecture	Performance metric (validation)		
		RMSE (N/mm^2)	R	MAE (N/mm^2)
ANN11	8-16-1	2.2088	0.9808	1.6314

Table 3.4: Results of selected ANN model

Step 3.3: Instructing and Verifying an MLR Model

Using the designated datasets for training and validation, we model and analyse compressive strength using a first-order multiple linear regression (MLR) model with eight independent variables and one dependent variable.
Task 3.3.1: MLR Model Training, Validation, And Testing

Three distinct performance metrics—Root Mean Square Error (RMSE), Correlation, and Test Performance—are used to assess the MLR model's training, validation, and test phases.

Model	Performance metric		
	RMSE (N/mm^2)	R	MAE (N/mm^2)
MLR (Training)	4.4426	0.9132	3.4311
MLR (Validation)	4.8239	0.9047	3.6480
MLR(Test)	4.6052	0.9060	3.6586

Coefficient (R) and Mean Absolute Error (MAE). The values of test results of the performance metrics are exhibited in **Table 3.5**.

Table 3.5: Performance of the MLR model

3.3 Comparison of neural network and MLR model

Thirdly, we compare the neural network model with the MLR model. In terms of RMSE, R-value, and MAE, the ANN11 model outperformed the MLR model in training, validation, and testing for the given datasets, with values of 1.3536 N/mm2, 2.0202 N/mm2, and 2.2088 N/mm2 for the corresponding sets of datasets, and 0.9923, 0.9839, and 0.9808 for the corresponding sets of datasets. In addition, the MLR model's performance was much lower—RMSE=4.4426 N/mm2, 4.8239 N/mm2, and 4.6052 N/mm2, R=0.9132, 09047, and 0.9060, and MAE=3.6480 N/mm2, 3.6586 N/mm2, and 3.6480 N/mm2 for the training, validation, and test datasets, respectively. Figure 3.2 shows the MLR model's regression plot and Figure 3.3 shows the ANN model's. Figure 3.2 shows that the actual and predicted lines overlap for the ANN model, which has the best fit with an R2 value of 0.9761 and can predict 97.61% of the data. The data points are positioned closely together so that the best fit line may be seen. As a result, the actual compressive strength and the anticipated values from the neural network model are shown in a regression plot.

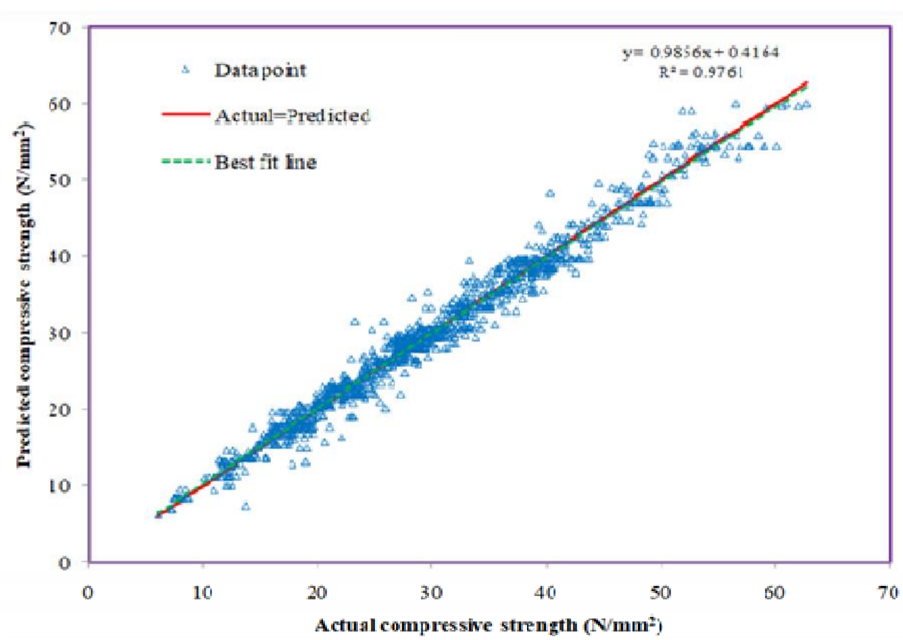

Fig. 3.2: Regression plot of actual and predicted ANN model of compressive strength

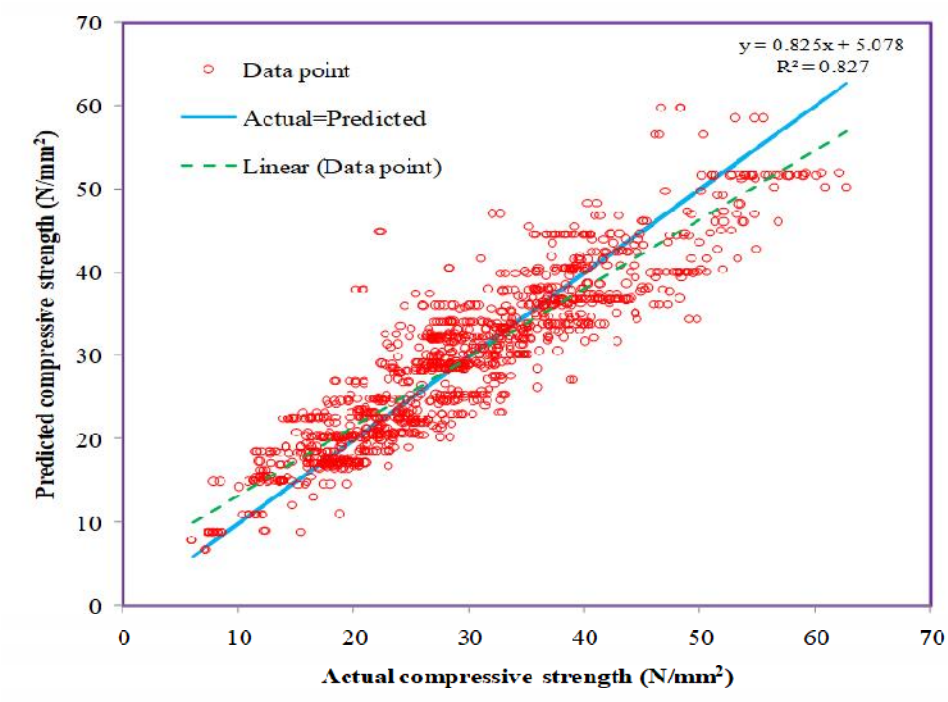

Fig. 3.3: Regression plot of actual and MLR model to predict the strength

Based on the MLR model's regression plot, it's clear that the line representing actual and projected data is not in the best fit. The model accurately predicts 82.70% of the data. Additionally, the data is widely scattered around the best-fit regression line, indicating that the MLR model's prediction accuracy is extremely poor. Thus, the findings have shown that the ANN model can accurately forecast the strength even when dealing with a large number of factors whose interactions are difficult to uncover or are unknown.

3.4 How Important Different Input Variables Are Concrete, sand, fly ash, additive, water, age, and aggregates (20 and 10 mm) are the eight variables used in this investigation. Table 4.5 shows the results of normalising the input variables to the interval [-1,+1] and then quantifying and ranking their relevance using the Cosine Amplitude Method (CAM). Figure 3.20 illustrates the significance of the input variables on the concrete.

Table 3.6: Importance of input variables relatively and their rank

Input variables	Relative Importance	Rank
Cemen3	0.7314	2
PFA	0.1405	6
Sand	-0.6213	3
CA(20mm)	0.1007	8
CA(10mm)	-0.1293	7
SP	0.4358	4
Water	-0.1600	5
Age	0.9253	1

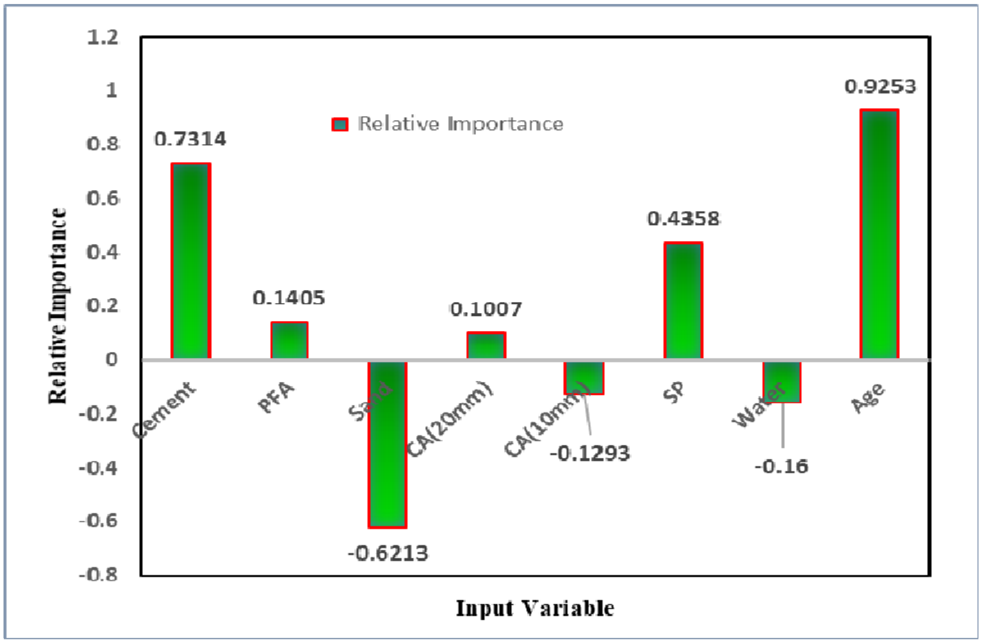

Fig. 3.4: Relative importance of input variables on the concrete compressive strength

The following can be concluded on the basis of results presented in **Table 3.5** and **Fig. 3.4** can be drawn:

a) The hydration rate is directly proportional to the age of concrete, which in turn determines the strength of the concrete. Thus, the compressive strength of concrete grows as its age does.

b) Hydration has a profound effect on compressive strength, which is the second most significant variable after water in concrete; consequently, increasing the amount of cement causes the strength of the material to grow.

b) Fine aggregate, such as sand, has an effect on the strength of concrete. The surface area of aggregates is increased with an increase in fine aggregates, which means that more water is needed to provide the appropriate workability. Requiring more water for workability raises the w/c ratio, which in turn lowers the compressive strength.

d) The water-to-cement ratio (w/c) is decreased because the dispersing and deflocculating effects of the superplasticizer (SP) in concrete lower the water content needed to maintain the flowability of the concrete. A lower water-to-cement ratio is associated with an increase in strength.

e) Concrete's water content makes it easier to deal with and speeds up the hydration process of the cement. The compressive strength of concrete is shown to be reduced. It has been noted, however, that this impact is minimal since the workability criterion is met by raising the dose of the superplasticizer.

f) One mineral additive used in RMC is pulverised fuel ash (PFA). Improving the workability of concrete, decreasing the water demand to maintain workability, and increasing the compressive strength are all benefits of using this product. The glassy particles, which have a "ball bearing" structure, contribute to this. Plus, since PFA has cementitious characteristics, it boosts concrete's compressive strength when added to the mix.

g) The increase in compressive strength is attributed to the coarse aggregate, which is greater in size (20mm). Coarse aggregate with a smaller size (CA, 10 mm) has a lower compressive strength because more water is needed to keep the aggregates workable when their surface areas are larger. As the water-cement ratio increases, the strength decreases over time.

4. Conclusions

The purpose of the desired green and set concrete qualities determines the amount of each element used in the mix proportions. With a lot of variables that might change on a daily basis, it's best to figure out the mix's proportions via trial and error. It takes a lot of time, materials, and needless design expense to attempt a bunch of trial nixes to get the concrete mix to operate the way you want it to. In an effort to streamline the process, artificial neural network (ANN) models were sought after to create a complicated network of concrete compressive strength with a non-linear connection between input and output parameters. Fifteen models of varied levels of complexity were developed for the research. Accurate training, validation, and testing were performed to provide the most suitable ANN model. Because of its complex composition and non-linear behaviour, concrete makes it difficult to determine the relative importance of individual ingredients in determining the concrete's compressive strength. To solve this problem, researchers employ the Cosine Amplitude Method (CAM) to determine the relative importance of each input variable in determining the strength.

This research presents the results of an initial test of a neural network model on 1167 data sets. The following is the study's conclusion: - A 1) The study's best-fitting ANN model has the following numbers for training, validation, and testing: RMSE 1.3536 N/mm2, 2.0202 N/mm2, and 2.2088 N/mm2, R 0.9923, 0.9839, and 0.9808, and MAE 1.0629 N/mm2, 1.5443 N/mm2, and 1.6314 N/mm2, respectively. Beyond this, the MLR model performed much worse in the training, validation, and testing datasets, with RMSE values of 4.4426 N/mm2, 4.8239 N/mm2, and 4.6052 N/mm2, R values of 0.9132, 09047, and 0.9060, and MAE values of 3.4311 N/mm2, 3.6480 N/mm2, and 3.6586 N/mm2, respectively. The findings disprove the dependability and accuracy of commonly used generalised regression models. In addition, the ANN models provided a dependable and simpler method for simulating these unknown, intricate relationships.

2) The suggested model may be used as a tool to assist with concrete design mixes, accurately predicting compressive strength based on design mix and concrete age. This will aid the technical team in making informed judgements, cutting down on the need for trial and error to get the appropriate design mix.

3) The Cosine Amplitude Method (CAM) was used to assess the relative impact of each input variable on the compressive strength value. As a result, the factors' effects on the strength have been significantly decreased. By comparing their respective significance, we may deduce concrete's complicated conduct. The compressive strength of RMC is determined by its cement and superplasticizer content, rather than its age.

Section 5.2: The Project's Future Scope

Cement, Fly Ash, Water, Sand, Coarse Aggregates, Super-plasticizer, and Age are the input variables used in the research to calculate the compressive strength of concrete. We utilised the Cosine Amplitude Method (CAM) to rank the variables in order of significance. The results demonstrate that neural networks may outperform regression models in terms of accuracy. This system for forecasting compressive strength may be expanded to include other elements like glass powder, silica, blast, and so on.

Material from a furnace, artificial sand, repurposed stones, etc. Neural networks may be used to represent the outcomes of workability and compressive strength values. For the purpose of forecasting the slump and compressive strength values for the RMC proportions, this kind of model may be used as a decision assistance tool.

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