

Prediction of Sustainable Concrete Strength Incorporating Fly Ash and Recycled Aggregates Using Artificial Neural Networks

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ABSTRACT

Artificial Neural Networks (ANNs) have been used to predict the compressive strength of sustainable concrete as an alternative to large laboratory experiments. Sustainable concrete mixes were designed by replacing natural coarse aggregate (NCA) with recycled coarse aggregate (RCA) at varying percentages ranging from 0% to 100%. Ordinary Portland cement was replaced with fly ash at the rate of 0%, 5%, 10%, 15%, 20%, 25%, 30%, 35% and 40% to obtain samples. Twenty-five concrete mixes were tested for compressive strength at 3, 14 and 28 days. In contrast, for moderate fly ash replacement levels (10-20 percent), strength increased at later ages due to pozzolanic reactions. At high fly ash replacement levels, strength development was delayed during the curing period. Increasing RCA content decreased compressive strength because of the presence of unhydrated mortar, greater porosity, lower bonding between the aggregate and paste matrix, and greater water absorption compared to normal aggregate. An ANN model has been developed to predict the concrete strength, using five parameters as input (NCA content, RCA content, cement content, fly ash content and curing age) and the concrete compressive strength as an output parameter. Based on the seventy-five experimental results, the developed model is highly accurate, with R^2 -value of 0.9935 and RMSE (Root Mean Square Error) of 0.6465 MPa. These results show that the ANN can successfully predict the sustainable concrete compressive strength. The proposed model is very useful for mix proportion optimization with considerable reductions in the time, cost, and effort of experimental studies.

Keywords: Artificial Neural Network (ANN), Sustainable Concrete, Recycled Coarse Aggregate, Fly Ash and Compressive Strength

INTRODUCTION

Concrete is the most widely used construction material in the world because of its versatility, durability, and comparatively low production cost. However, the extensive consumption of natural resources and the large amount of carbon dioxide emitted during cement production have raised significant environmental concerns [1]–[3]. Ordinary Portland cement (OPC) production contributes substantially to greenhouse gas emissions, while excessive extraction of natural aggregates leads to depletion of natural resources and ecological imbalance. Consequently, the construction industry is increasingly focusing on sustainable alternatives capable of reducing environmental impact while maintaining structural performance [1], [4]. Sustainable concrete, incorporating industrial by-products and recycled materials, has therefore emerged as a promising solution for achieving environmentally responsible infrastructure development [2], [5]. Recycled concrete aggregates generally reduce strength because of residual mortar and higher porosity, while fly ash contributes to later-age strength and sustainability benefits.

Fly ash is the most commonly used supplementary cementitious material because of its pozzolanic properties and ability to partially replace cement in concrete [6][7]. Fly ash is an industrial by-product of the combustion of pulverized coal in thermal power plants. Fly ash reacts with the calcium hydroxide produced during cement

hydration to form calcium silicate hydrate (C-S-H) gel that improves concrete's long-term mechanical and durability-related properties [6]. A moderate level of fly ash replacement improves long-term compressive strength, reduces permeability, and improves durability in aggressive environments [7], [8]. Nevertheless, it has been shown that a large volume of fly ash can delay hydration, and thus slow the gain of early-age strength, due to the slow pozzolanic reaction [6], [9]. Fly ash concrete can provide increased workability and durability, but careful optimization of replacement level is required to produce a balance of early and long-term strength [7], [10]. Prediction of the strength of fly ash concrete using artificial neural network (ANN) technologies has been documented in Scopus-indexed literature.

Recycling and reuse of construction and demolition waste as recycled coarse aggregates (RCA), used as an alternative to natural coarse aggregates for concrete production, is another practice with meaningful potential to reduce the environmental impact and conserve natural resources [4], [11], with the aggregates themselves generated via crushed concrete waste. The use of RCA aids in reducing the use of landfill sites, virgin aggregate extraction, and promotes the circular economy concept in the construction sector [4] [12]. However, due to the presence of adhered old mortar, RCA produces higher water absorption, lower density, and poorer interfacial transition zones which reduce compressive strength, tensile strength, and elasticity [11] [13]. While the trend is clear that increasing the amount of recycled aggregate will decrease compressive strength, reasonable results have been obtained. The exact amount of recycled aggregate is subject to control [11], [14]. Studies involving the addition of fly ash alongside RCA indicate that it can offset the negative effects of RCA and improve long-term performance.

Concrete compressive strength is the most important design parameter for structural design and quality control [15]. It determines the serviceability, limit states, load-carrying capacity, and durability of concrete structures. However, a laboratory test for compressive strength requires a meaningful amount of time, expense, and concrete to be conducted. Various factors affect concrete properties, such as the cement content, aggregate properties, supplementary cementitious materials, water-to-binder ratio, curing conditions, and age. Due to these factors, it is complex and expensive to determine the compressive strength experimentally. Reliable computational models have been developed to accurately predict the concrete properties and reduce the amount of experimental work required.

More recently, the field of civil engineering has seen a great increase in the use of AI and machine learning techniques in modeling and predicting material behavior [17], [18]. Artificial neural networks (ANNs), computational models based on the structure and functionality of the human brain, have been widely used in nonlinear engineering applications [17]. As smart systems, ANNs have the ability to extract relationships between multiple input variables. They can predict concrete properties bounded by multiple interacting variables [18]. The advantage of ANNs over regression-based models is that there is no need to formulate a relationship between input variables and output response, as ANNs learn from experimental data obtained from the training process [17], [19].

Developed ANN models are also used for predicting the compressive strength, workability, durability, and other engineering properties of concrete [18], [20]. Another application is predicting compressive strength of self-compacting concrete and high-performance concrete using high-volume fly ash as a partial replacement for cement. The study by Prasad et al. suggested a good agreement between predicted values and experimental results [18]. Or researchers developed ANN models for recycled aggregate concrete with accurate predictions of compressive strength based on mix and curing parameters [19]. Similar ANN models were developed for concrete containing construction and demolition waste and industrial by-products including supplementary cementitious materials. The resulting models had high correlations and low prediction errors [17], [20]. ANN techniques are well suited to predict the compressive strength of recycled aggregate concrete in large datasets.

While many researchers have studied concrete sustainability, there are few studies that utilize ANN to predict concrete with fly ash and RCA over the course of various curing ages. This is because the effect of fly ash replacement and RCA contents on strength development is complex and difficult to represent with a linear model. Other prediction models have been developed using artificial neural networks, which combine multiple input parameters to predict nonlinear trends in concrete performance [17], [20]. In this research, a sustainable concrete was prepared by partially substituting natural coarse aggregates and ordinary Portland cement with

recycled coarse aggregate (RCA) and fly ash, respectively. Twenty-five concrete mixtures were prepared by varying the percentage of RCA from 0% to 100% and fly ash from 0% to 40%. Furthermore, the compressive strength of the specimens was determined at the curing ages of 3, 14 and 28 days. An ANN model was then developed with five input parameters: percentage of natural coarse aggregate, percentage of recycled coarse aggregate, percentage of cement, percentage of fly ash, and curing age, and compressive strength as the output parameter. The developed model is expected to predict the performance of sustainable concrete more rapidly, accurately and economically, helping to reduce experimental work, material usage, construction waste and ultimately contribute to sustainable engineering.

Materials And Methods

Materials Used

The materials used for the present study are Ordinary Portland Cement (OPC), fly ash, fine aggregate (sand), natural coarse aggregate, recycled coarse aggregate and potable water. For the present study Ordinary Portland Cement is used as a binder as per the specification recommended by IS codes. Fly ash has been successfully used as a portion of the cement component of concrete to make concrete more sustainable by reducing the amount of cement and the related carbon footprint of concrete. Well graded fine aggregate was used to improve workability and packing. Natural coarse aggregate was used as control material. The sustainable material was recycled aggregate made from construction and demolition waste; the water used was potable water free from any impurities, used for mixing and curing purpose.

However, adhered mortar from hardened concrete to recycled coarse aggregate causes increases in the absorption and decreases in the density of the recycled coarse aggregate particles. Fly ash may improve the packing density of the particles, and strength of the concrete, via pozzolanic action. The physical and chemical properties of all materials were determined from standard laboratory tests prior to concrete preparation [22]. Table 1 and Table 2 summarize the physical properties and the chemical compositions of the cement and the fly ash used in this study, respectively.

Table 1: Physical Properties of Materials Used

Property	Cement (OPC 53 Grade)	Fly Ash (Class F)	Fine Aggregate (M-Sand)	Natural Coarse Aggregate (NCA)	Recycled Coarse Aggregate (RCA)
Specific Gravity	3.15	—	2.45	2.72	2.65
Bulk Density (kg/m ³)	—	—	2450	1550 (Compacted) / 1316 (Loose)	2354
Water Absorption (%)	—	—	—	1.90	5.65
Fineness / Fineness Modulus	15%	—	2.98	—	—
Standard Consistency (%)	31	—	—	—	—
Initial Setting Time (min)	36	—	—	—	—
Maximum Aggregate Size (mm)	—	—	—	20	20
Aggregate Type	—	—	Manufactured Sand	Crushed Granite Aggregate	Crushed Demolished Concrete

The physical characteristics of the cement, fly ash, fine aggregate, natural coarse aggregate (NCA), and recycled coarse aggregate (RCA) were determined based on the relevant Indian Standard specifications before the preparation of the concrete mix to confirm the suitability of the materials in producing eco-friendly concrete [23]. The specific gravity, standard consistency, and initial setting time of the cement used in this study were 3.15, 31%, and 36 minutes, respectively. The fineness modulus of the fine aggregate was 2.98. The recycled

coarse aggregate had higher water absorption than the natural coarse aggregate because the mortar remained attached to the surface of the recycled coarse aggregate.

Table 2: Chemical Composition of Cement and Fly Ash

Material	SiO ₂ (%)	Al ₂ O ₃ (%)	Fe ₂ O ₃ (%)	CaO (%)	MgO (%)	SO ₃ (%)	LOI (%)
Cement (OPC 53 Grade)	20.8	5.4	3.6	63.5	2.5	2.3	1.8
Fly Ash (Class F)	55	25	7	6	2	—	3

The chemical composition of Ordinary Portland Cement (OPC) and fly ash used in the present investigation is presented in Table 2. OPC primarily consisted of calcium oxide (CaO), silica (SiO₂), alumina (Al₂O₃), and iron oxide (Fe₂O₃), which contribute to cement hydration and strength development. The fly ash was classified as Class F fly ash and contained higher silica and alumina contents, indicating strong pozzolanic characteristics. The presence of reactive silica and alumina in fly ash contributes to secondary hydration reactions and long-term strength enhancement in concrete.

Mix Design and Material Proportioning

Based on the experimental study, concrete mixes of M30 grade were prepared and the role of fly ash and recycled concrete aggregate (RCA) on compressive strength of green concrete was investigated by replacing 0%, 10%, 20%, 30%, and 40% of ordinary Portland cement (OPC) with fly ash and 0%, 25%, 50%, 75%, and 100% of natural coarse aggregate (NCA) with RCA.

The water to binder ratio of the mixes remained constant at 0.45 throughout the test period. The base water content of all concrete mixes was fixed at 0.629 L, with additional water provided for the RCA mixes to counteract the higher water absorption of the RCA compared with the natural aggregate mix to ensure adequate and consistent workability of the mixes [24]. The amount of fine aggregate (sand) was kept constant.

To achieve batching convenience and uniformity of specimen preparation, the proportions of the constituent materials were based on the volume of a concrete cube of size 150 mm x 150 mm x 150 mm. The mix proportions arrived for this experimental work are given in Table 3.

Table 3: Representative Material Quantities for One 150 mm Cube Specimen

Parameter	Range Used
Cement (kg)	0.838 – 1.397
Fly Ash (kg)	0.000 – 0.559
Base Water (L)	0.629
Extra Water (L)	0.079 – 0.170
Total Water (L)	0.708 – 0.799
M-Sand (kg)	2.665
Natural Coarse Aggregate (kg)	0.000 – 4.150
Recycled Coarse Aggregate (kg)	0.000 – 4.150

For all concrete mixtures, the total coarse aggregate content was maintained constant while varying the proportion of natural coarse aggregate and recycled coarse aggregate according to selected replacement levels. Similarly, fly ash was introduced by replacing an equivalent proportion of cement while maintaining total binder content nearly constant. The adopted material proportioning enabled systematic investigation of both the individual and combined effects of fly ash incorporation and recycled aggregate utilization on sustainable concrete performance.

Specimen Preparation and Testing

The concrete raw materials were weighed for the different compositions and mixed to obtain a homogeneous mixture. The dry mixed materials consisting of Ordinary Portland Cement (OPC), fly ash, manufactured sand

(M-sand), natural coarse aggregate (NCA), and recycled coarse aggregate (RCA) were first mixed dry until a homogeneous mixture was obtained. Water was carefully added and mixed to produce a homogenous and workable concrete mix. Due to the high water absorption capacity of the RCA, owing to mortar residue remaining on the surface, water was added to each mix according to the percentage of RCA replacement in order to ensure the same workability for each matrix [25]. The concrete was mixed until a homogeneous material was obtained, with no visible segregation.

The freshly prepared concrete was immediately subjected to the slump cone test for assessment of workability. For testing concrete for compressive strength, it was filled into steel cube moulds of 150 mm × 150 mm × 150 mm dimensions and poured in layers compacted by a poker to disperse air bubbles and achieve full compaction. Specimens were cast in the laboratory, demoulded after approximately 24 h and cured in water until 3, 14 and 28 days of testing. The complete sequence of specimen preparation and casting are shown in Fig. 1(a)-(c).



Fig 1(a) Mould Preparation



Fig 1(b): Casting



Fig 1(c): Specimen and Curing

Artificial Neural Network (ANN) Modeling

The Artificial Neural Network (ANN) model is proposed to predict the sustainable concrete compressive strength made of fly ash and RCA. ANN is a computational technique, which can effectively model and predict the complex nonlinear relationships amongst input variables and target variables for estimating the mechanical behavior of concrete materials [26], [27]. The measured values of compressive strength were used to train and validate the prediction model developed in this study. The input variables to the model were the natural coarse aggregate (NCA) content, the recycled coarse aggregate (RCA) content, the cement content, the fly ash content and the curing age. The output variable was the compressive strength. The database comprised 75 experimental observations corresponding to 25 concrete mix combinations tested at 3, 14 and 28 days of curing.

A feed-forward backpropagation neural network was chosen for the prediction model, as it is composed of an input layer, one or more hidden layer(s), and one output representing the compressive strength. The number of hidden neurons was determined by trial-and-error to be the minimum to achieve maximum prediction accuracy and minimum model error. To reduce prediction time and the effect of several orders of magnitude, the data inputs were normalized before training [28].

The dataset was randomly divided into training, validation, and test sets in order to allow learning, validation of generalization, and prevention of overfitting. Then, the model was trained until the prediction error became constant and the predicted and measured compressive strength values exhibited an acceptable level of agreement. Coefficient of determination (R^2) and root mean square error (RMSE) were used to check the performance of the model in order to understand the accuracy and reliability of developed ANN model.

The complete ANN model was developed using the MATLAB Neural Network Toolbox. The predicted compressive strength values were compared with the experimental compressive strength values to validate the performance of the developed prediction model.

ANN Model for Concrete Strength Prediction

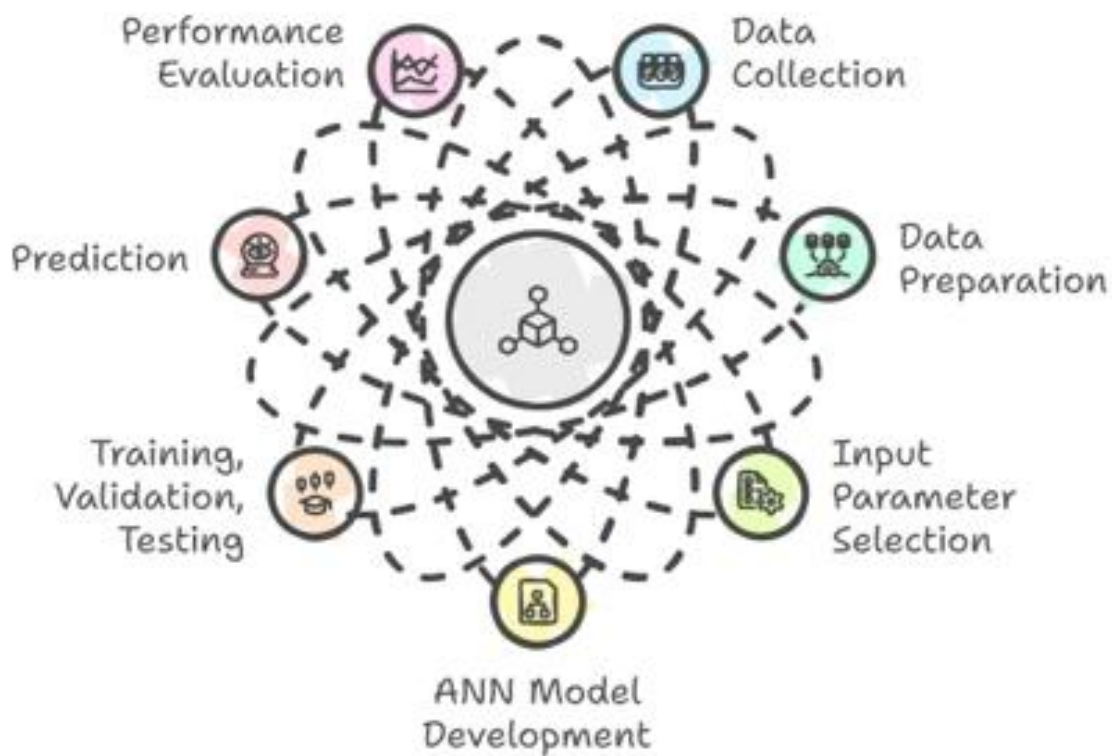


Fig. 2. Workflow of Artificial Neural Network (ANN) modeling adopted for compressive strength

RESULTS AND DISCUSSION

Workability

Figure 3 shows slump values for all mixtures. It can be seen that both the fly ash content and the percentage of replacement with recycled coarse aggregate (RCA) had a meaningful effect on the workability of fresh concrete mixtures. With the increase in RCA content, slump was found to decrease gradually. The control concrete mix (M1) had maximum slump of 88 mm while the minimum slump was observed in 100% RCA concrete mix (M5) with slump value of 66 mm.

Decreased workability of recycled coarse aggregate concrete is mainly associated with the recycled aggregate properties (the amount of attached mortar). Recycled aggregate typically has a considerably higher water absorption and rougher surface texture compared to natural aggregates. This causes an increased amount of mixing water to be sorbed by the RCA, thus reducing the amount of mixing water available for lubricating and plasticizing the concrete matrix. Likewise, the high surface roughness of the RCA increases interparticle friction, which in turn causes a reduction in slump values with an increase in replacement level.

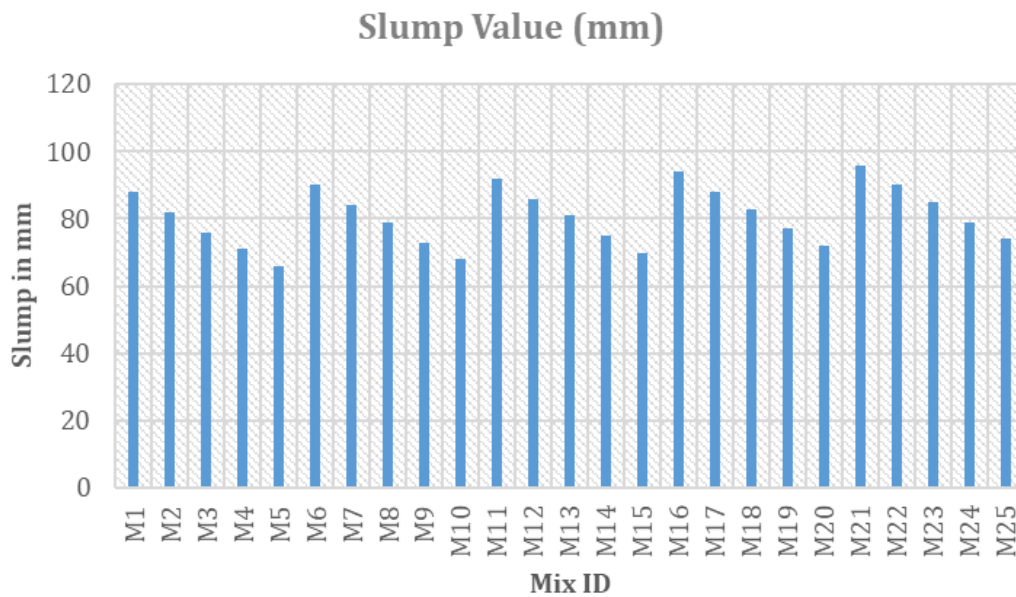


Fig 3: Variation of slump value for different concrete mixes

In contrast, the incorporation of fly ash improved workability characteristics. Mixes containing higher fly ash percentages exhibited comparatively higher slump values at corresponding RCA replacement levels. The maximum slump value of 96 mm was recorded for mix M21 containing 40% fly ash and 0% RCA. The improvement in workability is associated with the spherical particle morphology and finer particle size of fly ash, which enhanced particle packing and reduced interparticle friction.

Although RCA incorporation reduced slump values, all concrete mixes exhibited medium workability suitable for casting and compaction operations. The results demonstrate that fly ash effectively compensated for the adverse effects of RCA on fresh concrete behavior.

COMPRESSIVE STRENGTH

All the concrete mixes were subjected to compressive strength tests to investigate the effects of fly ash replacement level, recycled coarse aggregate (RCA) content and curing period as independent variables on the compressive strength performance of the concrete mixes. The 3-, 14- and 28-day results were summarized in a bar chart and a line chart (shown in figure 4), to help with comparing the material results for different curing ages. The results showed that the compressive strength increased continuously as the curing age of all concrete mixes increased due to continuous cement hydration and the pozzolanic reaction between fly ash and cement which was delayed for a while. However, an increase in the content of RCA decreased the compressive strength. The highest 28-day compressive strength was achieved for the M11 mix, which used a combination of fly ash and RCA in the concrete mix, showing its effectiveness. The M25 mix had the lowest 28-day compressive strength due to the combination of the highest fly ash replacement and the use of 100% recycled coarse aggregate, which reduced the mechanical properties of the concrete mixes.

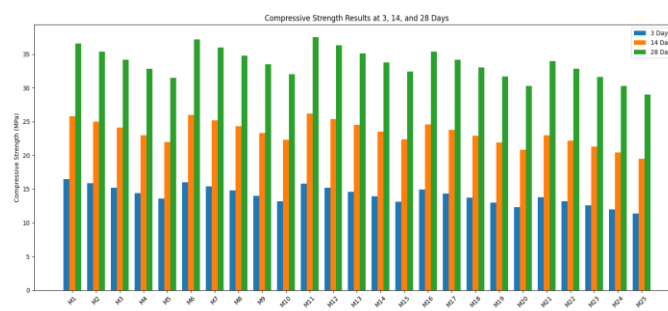


Fig 4 : Compressive Strength Results at 3, 14, and 28 Days

Figure 5 presents the relationship between the compressive strength at 28 days and the amount of recycled coarse aggregate (RCA) where the compressive strength decreases as the RCA percentage of substitution increases. This reduction can be attributed to factors such as the increased porosity and water absorption of the recycled aggregate and the weaker interfacial transition zone of the aggregate-cement paste. In spite of this, moderate use of RCA in concrete has reached compressive strengths adequate for many sustainable concrete applications.

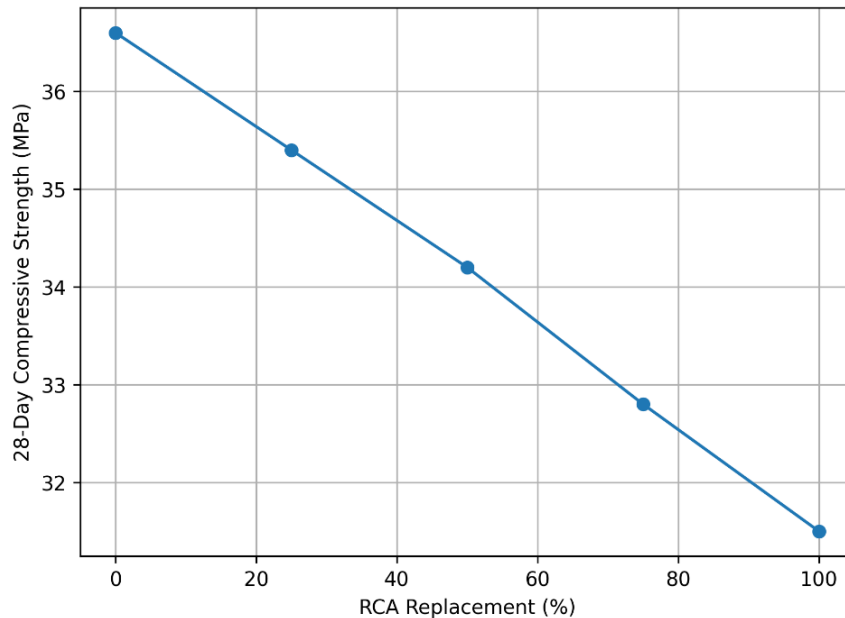


Fig 5 Variation of 28-Day Strength with RCA Content

Figure 6 also shows that 10-20% fly ash replacement has been seen to increase the 28-day compressive strength due to further pozzolanic reaction and refinement of the pore structure (i.e. lower porosity) of the concrete. In contrast, higher replacement levels of fly ash (>30%) showed a decrease in compressive strength, potentially due to the reduction in cement content and the slower rate of hydration.

Figure 7 shows that the compressive strength continued to increase from 3 to 28 days of curing for all concrete mixes, indicating that the reaction of the cementitious materials continued over this period. The strength gain is more pronounced during the first 14 days and less so from 14 days to 28 days as the processes of hydration are nearly complete.

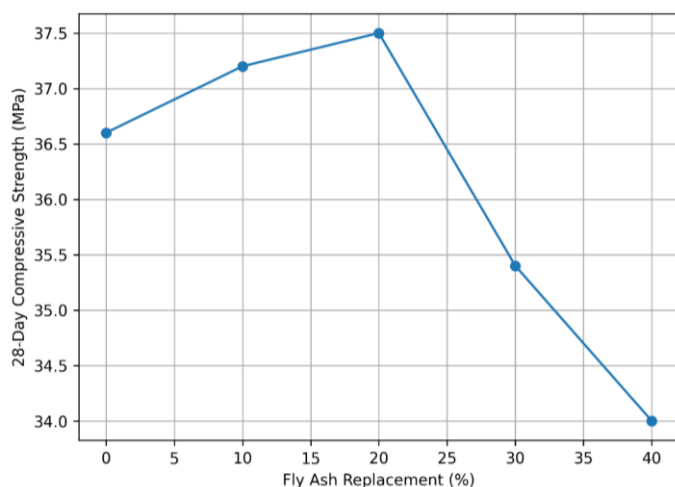


Fig 6: Effect of Fly Ash on Compressive Strength

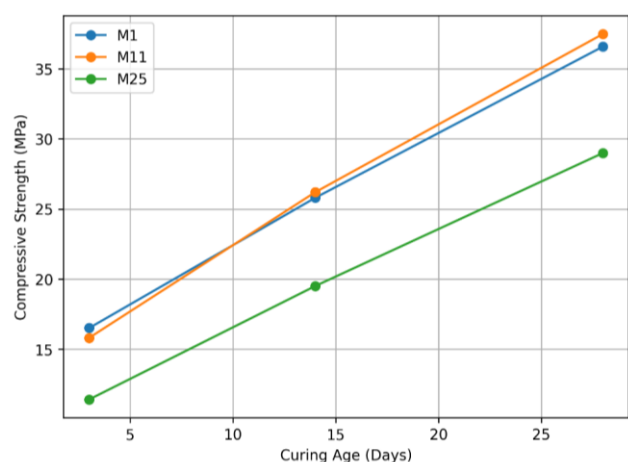


Fig 7 Strength Development with Curing Age

ANN Performance Analysis

ANN Training Performance

The ANN model was developed in MATLAB R2026a using a feed-forward backpropagation architecture trained with the Levenberg–Marquardt (trainlm) algorithm for predicting compressive strength of sustainable concrete containing RCA and fly ash. The dataset was randomly divided into training, validation, and testing subsets using dividerand, and MSE was used as the performance metric. As shown in Fig. 8, the training performance curve indicates a rapid reduction in MSE during initial epochs, followed by gradual stabilization[29]–[30]. The best validation performance of 0.0076424 at epoch 18 (Fig. 8 indicates optimal generalization of the network. Beyond this point, validation error slightly increased while training error continued to decrease, indicating early signs of overfitting. MATLAB automatically terminated training using early stopping, ensuring optimum model selection.

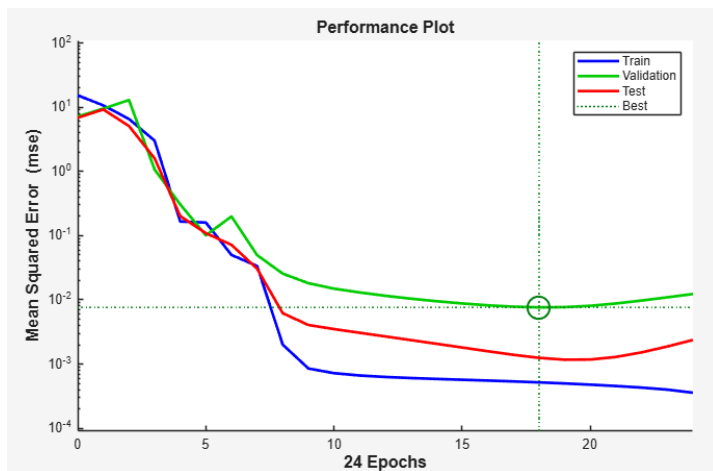


Fig 8: Performance Plot

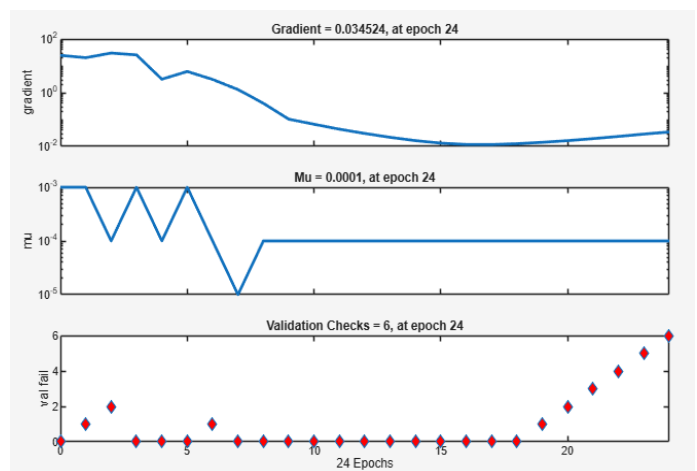


Fig 9: Training State / Epoch Graph

The training state plot (Fig. 5.7) shows stable convergence within 24 epochs with an elapsed time of ~ 7 seconds. The performance value reduced from 15.3 to 0.000358, indicating significant learning improvement. The gradient decreased from 24.6 to 0.0345, confirming stable convergence of weight updates. The Mu parameter reduced from 0.001 to 0.0001, indicating controlled adjustment during optimization. Validation checks reached the limit of 6, triggering automatic stopping to avoid overfitting. Overall, Figs. 8 and 9 confirm stable learning behavior, fast convergence, and good generalization capability of the ANN model.

Regression Analysis

The regression performance of the ANN model is presented in Fig. 10, which compares experimental and predicted compressive strength values for training, validation, testing, and overall datasets. The obtained correlation coefficients are: Training: $R = 1.0000$, Validation: $R = 0.99995$, Testing: $R = 0.99999$, Overall: $R = 0.99999$. The data points in Fig. 10 are closely aligned along the 45° line ($y = x$), indicating near-perfect agreement between predicted and experimental values. The very high R-values confirm that the ANN model has successfully captured the nonlinear interaction between input variables (fly ash %, RCA content, and curing age) and compressive strength output[31].

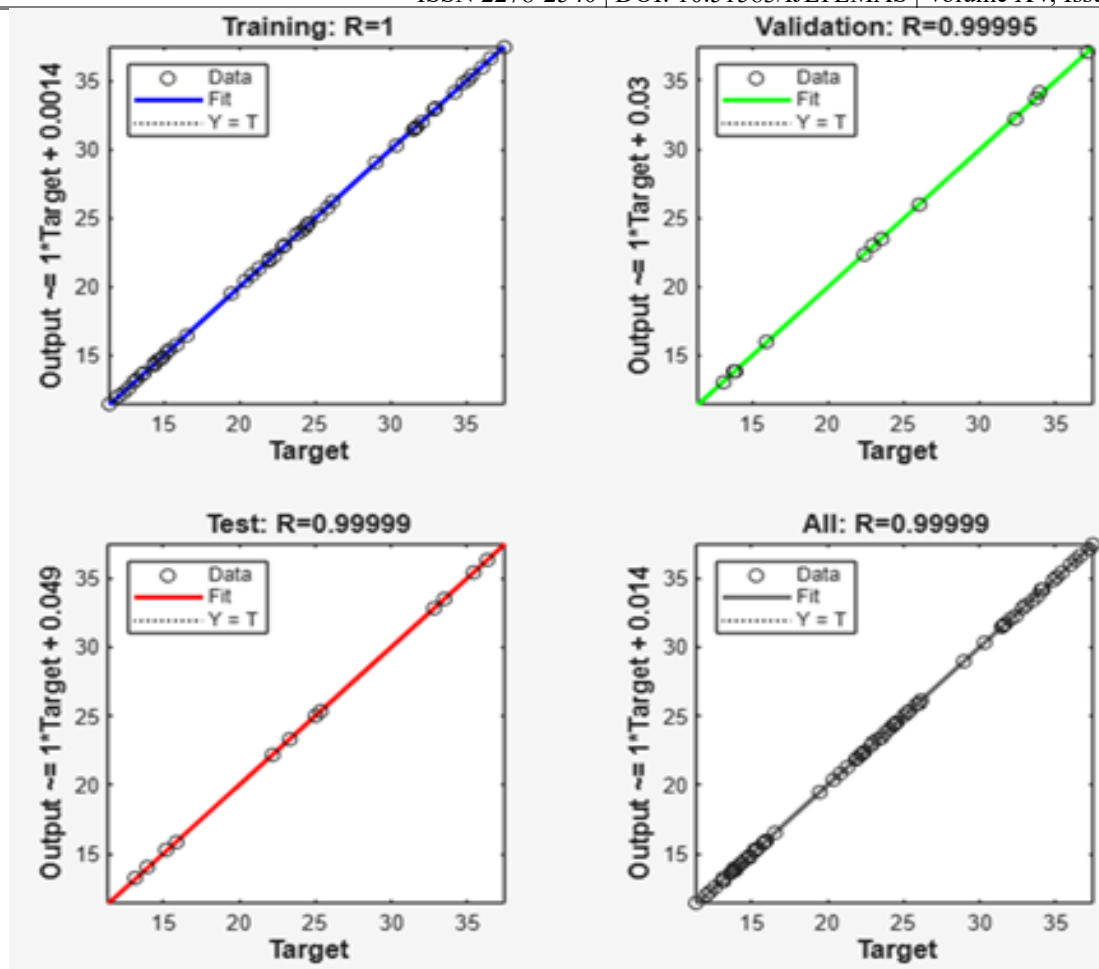


Fig 10: Regression Plot

Error Analysis

The error distribution is shown in Fig. 11, where residuals are highly concentrated around zero. The histogram exhibits a narrow spread with near-symmetric distribution, indicating minimal bias in prediction. The majority of errors fall within a small range, confirming high prediction stability. Minor deviations observed at higher error values can be attributed to material heterogeneity in recycled aggregates and variability in fly ash reactivity. Overall, Fig. 11 confirms strong prediction consistency and low model uncertainty.

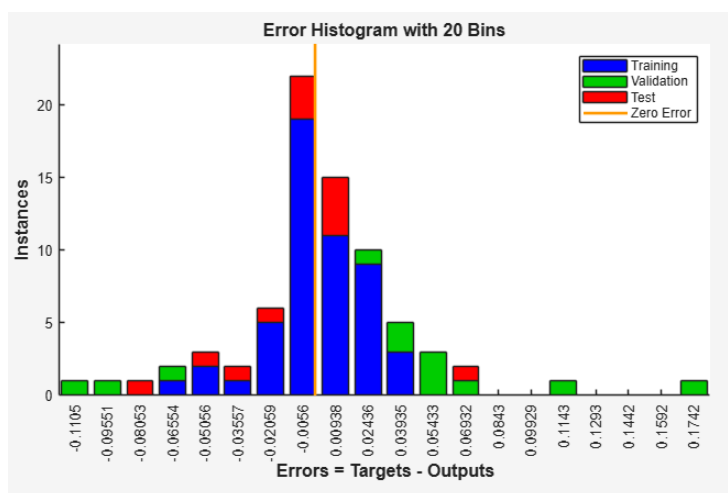


Fig 11: Error Histogram

Comparison Between Experimental and ANN Predicted Results

The comparison between experimental and ANN-predicted compressive strength values for all mixes (M1–M25) at 3, 14, and 28 days is presented through graphical illustrations. The predicted values closely follow the experimental results across all curing ages, indicating strong predictive capability of the developed ANN model. The deviation between experimental and predicted values is minimal, confirming high model accuracy and robustness.

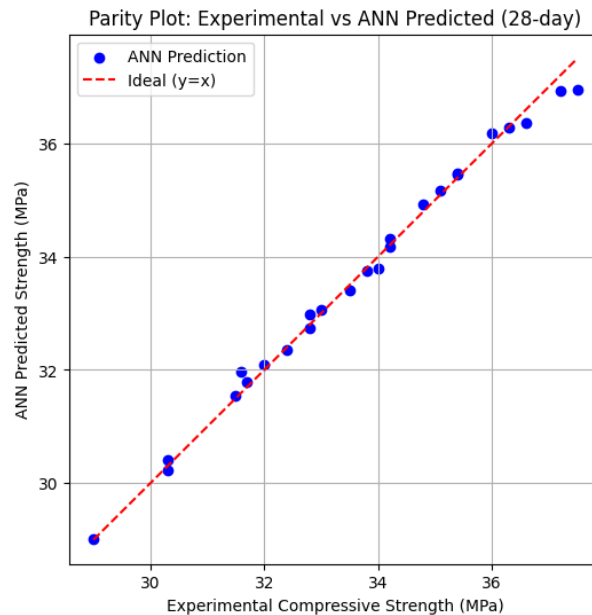


Fig 12 : Parity plot for 28-day compressive strength

The ANN model successfully captured the influence of mix constituents such as recycled coarse aggregate (RCA) and fly ash. The results indicate that increasing RCA content leads to a reduction in compressive strength due to the weaker interfacial transition zone and higher porosity. In contrast, moderate replacement of fly ash enhances later-age strength due to pozzolanic reactions and additional calcium silicate hydrate (C–S–H) formation. The parity plot for 28-day compressive strength clearly illustrates a strong correlation between experimental and ANN-predicted values. The data points are closely distributed along the ideal 45° line ($y = x$), indicating excellent prediction accuracy and minimal error dispersion. This confirms the reliability of the ANN model in predicting the compressive strength of sustainable concrete mixes.

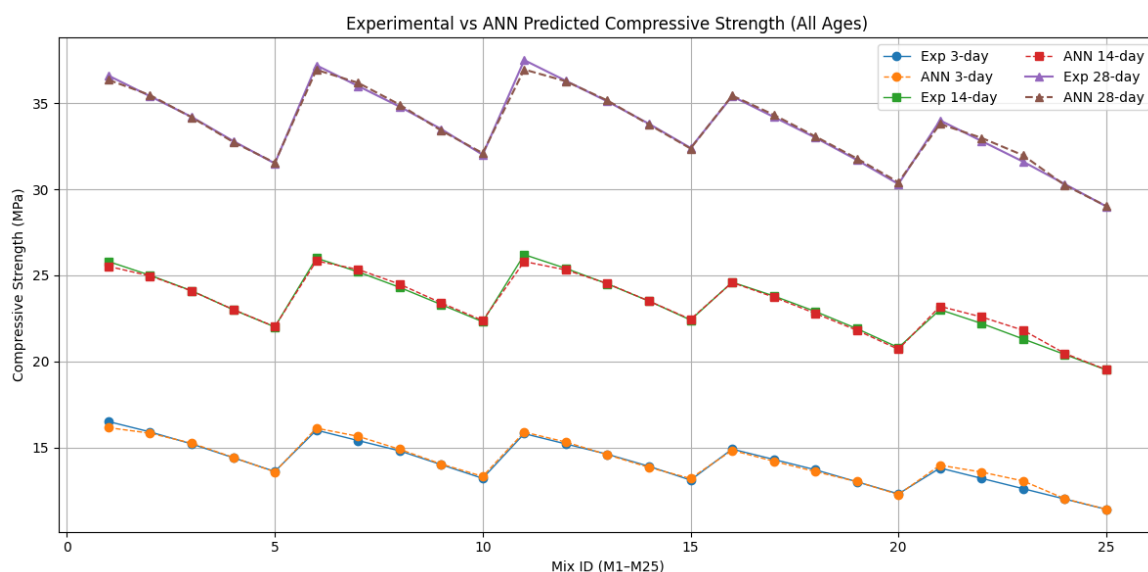


Fig13: Subplot comparison of experimental and ANN predicted results

The subplot comparison presents the variation of compressive strength at 3, 14, and 28 days for all mixes. In all cases, the ANN-predicted values closely follow the experimental trends. The overlapping nature of the curves demonstrates that the model effectively captures the curing-age-dependent strength development and mix composition effects.

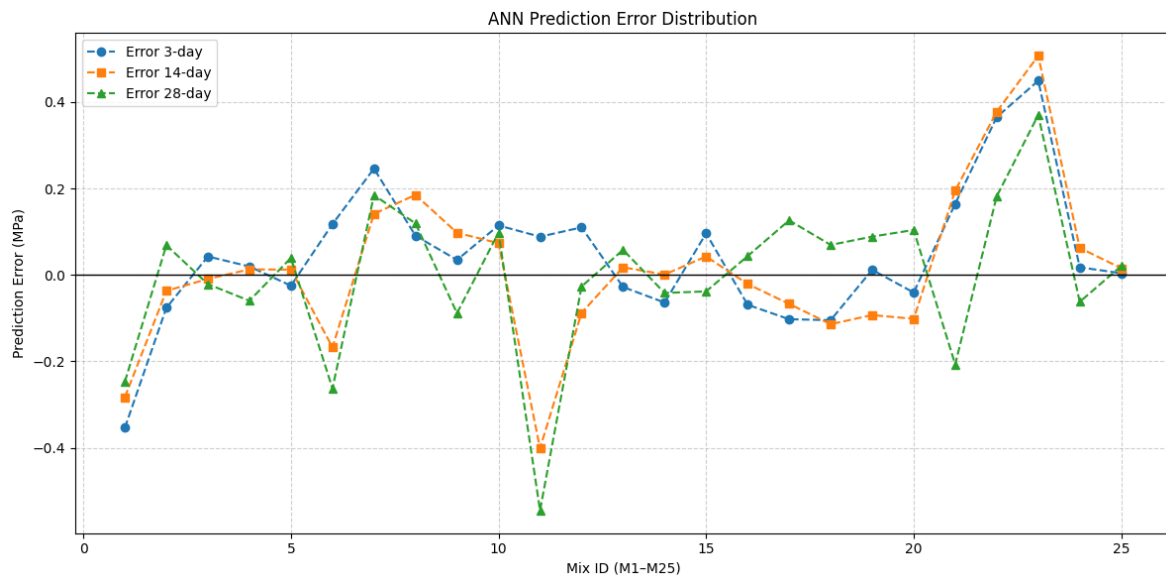


Figure14: Error distribution plot

The error plot represents the difference between ANN-predicted and experimental compressive strength values for 3-day, 14-day, and 28-day curing periods. The errors are distributed around zero with minimal fluctuation, indicating the absence of systematic bias. The low magnitude of errors confirms the high generalization capability and stability of the ANN model.

Summary

The ANN model exhibited strong convergence behavior, high regression accuracy, and minimal prediction error. Figures 5.10 to 5.12 collectively confirm stable learning performance, excellent correlation, and reliable predictive capability. The model effectively captures nonlinear relationships between input variables (cement, RCA, fly ash, and curing age) and compressive strength output.

Overall, the developed ANN model is highly suitable for predicting and optimizing sustainable concrete mixes, significantly reducing the need for extensive experimental trials and saving both time and cost in material design.

CONCLUSIONS

The present study investigated the compressive strength behavior of sustainable concrete incorporating fly ash and recycled coarse aggregate (RCA), along with the development of an Artificial Neural Network (ANN)-based prediction model. Based on the experimental investigation and analytical results, the following conclusions are drawn:

- The incorporation of recycled coarse aggregate resulted in a gradual reduction in compressive strength due to the presence of adhered mortar, higher porosity, and weaker interfacial transition zones compared to natural aggregates.
- Partial replacement of cement with fly ash up to an optimum range (10–20%) improved later-age compressive strength due to enhanced pozzolanic reactions and improved microstructural densification. However, higher replacement levels beyond the optimum reduced strength because of reduced cement content and slower hydration.

- All concrete mixes exhibited continuous strength development with curing age, with significant strength gain observed between 3 and 14 days, followed by a gradual increase up to 28 days.
- The combined use of fly ash and recycled aggregates demonstrated that sustainable concrete with acceptable mechanical performance can be achieved when proper replacement levels are selected.
- The ANN model developed using five input parameters (cement, fly ash, NCA, RCA, and curing age) accurately predicted compressive strength with high reliability. The model achieved a coefficient of determination (R^2) of 0.9935 and a low root mean square error (RMSE) of 0.6465 MPa, indicating excellent agreement between experimental and predicted results.
- The study confirms that ANN-based modeling is an effective and efficient tool for predicting compressive strength of sustainable concrete, significantly reducing the need for extensive experimental trials and supporting optimized mix design.

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