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Artificial Neural Network-Based Prediction of Concrete Compressive Strength with Experimental Validation

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Abstract - Estimating concrete compressive strength during mix development requires repeated laboratory testing and curing, particularly when supplementary cementitious materials such as Fly Ash and Ground Granulated Blast Furnace Slag (GGBS) are used. Due to the nonlinear interaction between concrete constituents, conventional empirical methods often provide inconsistent prediction across different concrete grades.

In the present investigation, an Artificial Neural Network (ANN)-based model was developed to predict the compressive strength of conventional cement concrete along with Fly Ash and GGBS blended mixes. Concrete grades ranging from M20 to M70 were considered. Experimental data obtained from published studies were used for ANN training, validation, and testing. The input parameters included cement, Fly Ash, GGBS, water, fine aggregate, coarse aggregate, and superplasticizer content, while compressive strength was considered as the output parameter.

A feed-forward backpropagation ANN model was developed using MATLAB Neural Network Toolbox. Experimental validation was carried out using standard concrete cube specimens tested under controlled laboratory conditions. The developed model showed reasonably close agreement between experimental and predicted compressive strength values, with most prediction deviations remaining within acceptable limits.

Lower-grade concrete mixes exhibited comparatively stable prediction behaviour, whereas slight variations were observed in higher-strength mixes due to the sensitivity of low water-binder ratio concrete to small variations in material proportioning and curing conditions.

A MATLAB-based graphical user interface (GUI) was also developed for rapid compressive strength prediction using user-defined mix parameters. The developed ANN model can assist preliminary mix evaluation and reduce repeated trial calculations during concrete mix design.

KEYWORDS

Artificial Neural Network (ANN); Concrete Compressive Strength; MATLAB; Machine Learning; Mix Design; Fly Ash; GGBS; Experimental Validation; Predictive Modeling

1. INTRODUCTION

Concrete compressive strength prediction becomes more complex when supplementary cementitious materials such as Fly Ash and GGBS are incorporated into the mix. Variations in binder composition, water-binder ratio, aggregate grading, and admixture dosage influence strength development in a nonlinear manner, particularly in higher-grade concrete where small changes during batching or curing can produce noticeable variation in compressive strength.

Traditional empirical relationships often become less reliable when multiple concrete grades and blended material systems are considered together. Artificial Neural Networks (ANNs) provide an alternative approach by learning hidden relationships directly from experimental datasets without requiring predefined mathematical equations. This characteristic becomes useful when predicting compressive strength across different binder combinations and strength levels.

In the present investigation, an ANN-based prediction framework was developed using MATLAB Neural Network Toolbox for concrete grades ranging from M20 to M70. The model was trained using literature-based datasets to improve prediction stability across cement-only, Fly Ash blended, and GGBS blended concrete mixes. Experimental validation was carried out using standard concrete cube specimens cured under controlled laboratory conditions.

The experimentally obtained compressive strength values were compared with ANN predictions to evaluate network performance under varying mix conditions. Particular attention was given to higher-strength mixes, since low water-binder ratio concrete generally exhibits greater sensitivity to curing condition, compaction quality, and admixture dosage. A MATLAB-based graphical user interface (GUI) was also developed to enable rapid preliminary strength estimation using user-defined mix parameters.

The developed framework is intended primarily for preliminary mix assessment and reduction of repeated trial calculations during early-stage mix development. However, the prediction capability remains dependent on the variability and quality of the training dataset, especially for input combinations approaching the limits of the trained data range

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2. OBJECTIVES OF THE STUDY

The present investigation aims to develop an ANN-based prediction framework capable of estimating the compressive strength of concrete mixes prepared using cement, Fly Ash, and GGBS combinations. The study considers a wide range of concrete grades from M20 to M70 in order to evaluate whether the developed model can maintain consistent prediction performance under varying mix compositions and strength levels.

The specific objectives of the study are as follows:

1. To prepare concrete mixes of different grades using conventional cement concrete, Fly Ash blended concrete, and GGBS blended concrete under controlled laboratory conditions.
2. To experimentally determine the 28-day compressive strength of concrete specimens and generate a reliable dataset for ANN modelling.
3. To develop a feed-forward backpropagation ANN model in MATLAB for predicting compressive strength using mix proportion parameters as input variables.
4. To assess the prediction capability of the developed ANN model through regression analysis, mean squared error evaluation, and comparison between experimental and predicted strength values.
5. To develop a GUI-based prediction tool for rapid estimation of concrete compressive strength using user-defined mix parameters, thereby reducing dependence on repeated preliminary trial calculations.

3. SCOPE OF THE STUDY

The present investigation is limited to prediction of 28-day concrete compressive strength using Artificial Neural Network (ANN) techniques combined with laboratory validation. Concrete grades from M20 to M70 were considered to evaluate whether the developed network could maintain stable prediction behaviour across both normal-strength and higher-strength mixes. Cement-only concrete along with Fly Ash and GGBS blended mixes were included to introduce variation in binder composition and hydration characteristics.

Experimental compressive strength testing was carried out on standard concrete cube specimens cured under controlled laboratory conditions. The ANN model was developed in MATLAB using input parameters such as cement content, Fly Ash content, GGBS content, water content, fine aggregate, coarse aggregate, and superplasticizer dosage. Experimental data together with selected literature-based datasets were used for network training, validation, and testing to improve prediction consistency over a wider range of mix combinations.

Prediction performance remained comparatively stable for lower and medium-strength concrete, whereas slight variation was observed in certain higher-grade mixes. Such behaviour is generally associated with the increased sensitivity of low water-binder ratio concrete to minor variations in curing condition, compaction quality, and admixture dosage. The developed model therefore performs more reliably within the trained data range and may exhibit reduced accuracy for input combinations outside the dataset limits.

A MATLAB-based graphical user interface (GUI) was also developed for practical implementation of the trained ANN model. The interface enables rapid preliminary strength estimation using user-defined mix parameters, reducing dependence on repeated trial calculations during initial mix proportion assessment. However, the developed framework is intended as a support tool for preliminary evaluation and not as a substitute for codal laboratory verification in structural applications.

4. MATERIALS USED

The materials selected for the present investigation were chosen to achieve consistent concrete performance under varying binder compositions. Ordinary Portland Cement (OPC), Fly Ash, Ground Granulated Blast Furnace Slag (GGBS), fine aggregate, coarse aggregate, potable water, and a polycarboxylate ether-based superplasticizer were used for preparation of concrete mixes. All materials satisfied relevant Indian Standard specifications to maintain uniformity during casting and testing.

Cement

OPC 53 grade conforming to IS 12269:2013 was used as the primary binding material. The cement exhibited a specific gravity of 3.15 and standard consistency of 31%. Initial and final setting times were observed as 35 minutes and 520 minutes respectively, indicating suitability for normal concrete production and controlled laboratory casting conditions. The fineness value of 5% contributed to stable hydration behaviour during early-age strength development.

Fly Ash

Class F Fly Ash obtained from a thermal power plant was used as partial cement replacement material. The material possessed a specific gravity of 2.20 and fine powdered texture, which improved particle packing and workability of blended concrete mixes. Compared with conventional cement mixes, Fly Ash mixes exhibited comparatively gradual strength development due to slower pozzolanic reaction.

Ground Granulated Blast Furnace Slag (GGBS)

GGBS with a specific gravity of 2.85 was incorporated as supplementary cementitious material. The finely powdered off-white material contributed to improved cohesiveness and denser matrix formation, particularly in lower water-binder ratio mixes. Its influence became more noticeable in higher-grade concrete where hydration behaviour governs strength gain more sensitively.

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Fine Aggregate

Locally available river sand conforming to Zone II of IS 383:2016 was used as fine aggregate. The material exhibited a specific gravity of 2.64, water absorption of 1.2%, and fineness modulus of 2.75. Proper grading of fine aggregate helped maintain workability and reduced segregation during casting.

Coarse Aggregate

Crushed angular coarse aggregate of 20 mm nominal maximum size was used throughout the investigation. The aggregate showed a specific gravity of 2.72 and water absorption of 0.5%. Angular particle geometry improved aggregate interlocking, which contributed to better load transfer within the concrete matrix.

Water and Superplasticizer

Potable water conforming to IS 456:2000 was used for mixing and curing operations. A polycarboxylate ether-based superplasticizer, SikaPlast®-3069 NS, with specific gravity of 1.08 was incorporated to maintain workability at lower water-cement ratios. The admixture dosage was varied depending on mix requirements, particularly for higher-grade concrete where workability loss and compaction difficulty become more critical.

5. EXPERIMENTAL PROGRAMME

The experimental programme was conducted to generate compressive strength data for development and validation of the ANN-based prediction model. Concrete grades ranging from M20 to M70 were considered to examine prediction behaviour across both normal-strength and higher-strength concrete. For each grade, three mix categories were prepared: conventional cement concrete, Fly Ash blended concrete, and GGBS blended concrete. The selected combinations introduced variation in binder composition and helped evaluate the adaptability of the ANN model under different material conditions.

Concrete ingredients were batched by weight and mixed to achieve uniform consistency prior to casting. Particular attention was given to workability in higher-grade mixes, since low water-binder ratio concrete exhibited greater sensitivity to segregation and inadequate compaction. Fresh concrete was placed in 150 mm × 150 mm × 150 mm steel cube moulds in layers and compacted properly to minimize entrapped air voids, which can influence compressive strength and cracking behaviour during loading.

After 24 hours, specimens were demoulded and cured under standard water curing conditions for 28 days. Compressive strength testing was carried out using a calibrated Compression Testing Machine (CTM) in accordance with IS 516 recommendations. The compressive strength was determined from the ratio of ultimate failure load to loaded surface area.

$$f_c = \frac{P}{A}$$

During testing, lower-grade specimens exhibited comparatively gradual crack development prior to failure, whereas several higher-grade mixes showed sudden crack propagation near the loaded faces with relatively brittle behaviour. This difference is generally associated with the denser internal matrix and lower deformation capacity of high-strength concrete. The experimentally obtained strength values were subsequently used for ANN training, validation, and performance assessment under varying mix conditions

6. MIX DESIGN

Concrete mix design was carried out in accordance with IS 10262:2019 guidelines for different concrete grades ranging from M20 to M70. Sustainable concrete mixes were prepared by partially replacing cement with Fly Ash and GGBS while maintaining the required workability and target compressive strength.

For each concrete grade, three categories of mixes were considered:

- Conventional cement concrete mix
- Cement + Fly Ash mix
- Cement + GGBS mix

The water-cement ratio, superplasticizer dosage, and aggregate proportions were adjusted appropriately to achieve desired strength and workability.

6.1 Mix Proportions

Concrete mix proportions for different grades of sustainable concrete were prepared using cement, Fly Ash, and GGBS as partial replacement materials. The detailed mix proportions adopted in the present study are given below.

Concrete Mix Design Data

Grade Mix Type	**Cement** kg/m^3	**Fly Ash** kg/m^3	**GGBS** kg/m^3	**Water** kg/m^3	**SP** kg/m^3	**Fine Aggregate** kg/m^3	**Coarse Aggregate** kg/m^3
M20Cement	320	0	0	160	3.2	750	1200
M20C+FA	280	40	0	160	3.2	750	1200

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M20C+ GGBS	280	0	40	160	3.2	750	1200
M30Cement	380	0	0	170	3.8	720	1150
M30C+ FA	320	60	0	170	3.8	720	1150
M30C+ GGBS	320	0	60	170	3.8	720	1150
M40Cement	420	0	0	180	4.2	680	1100
M40C+ FA	350	70	0	180	4.2	680	1100
M40C+ GGBS	350	0	70	180	4.2	680	1100
M50Cement	450	0	0	180	4.5	650	1080
M50C+ FA	360	90	0	175	4.5	650	1080
M50C+ GGBS	360	0	90	175	4.5	650	1080
M60Cement	480	0	0	175	4.8	630	1050
M60C+ FA	380	100	0	170	4.8	630	1050
M60C+ GGBS	380	0	100	170	4.8	630	1050
M70Cement	540	0	0	170	5.4	600	1020
M70C+ FA	420	120	0	165	5.4	600	1020
M70C+ GGBS	420	0	120	165	5.4	600	1020

.The above mix proportions were used for preparation of concrete cube specimens and generation of experimental data for ANN model training and validation.

6.2 Specimen Preparation and Curing

Concrete ingredients were batched by weight and mixed thoroughly to obtain uniform consistency. The fresh concrete was placed in cube moulds in layers and compacted properly using standard compaction procedures.

Figure 6.1 Concrete Cube Casting

The specimens were demoulded after 24 hours and cured in clean water for 28 days under standard laboratory conditions before testing.

A total of 54 concrete cube specimens were cast and tested under standard laboratory curing conditions. For each concrete grade and mix category, three cube specimens were prepared to ensure consistency and reliability of experimental result

7. ANN MODEL DEVELOPMENT

Artificial Neural Network (ANN) modelling was adopted to predict compressive strength of concrete mixes containing cement, Fly Ash, and GGBS. Since compressive strength depends on nonlinear interaction between binder composition, water-binder ratio, aggregate proportion, and admixture dosage, conventional regression approaches become less reliable when wider datasets and multiple mix categories are considered together.

The ANN model was developed using MATLAB Neural Network Toolbox. Experimental data obtained from laboratory testing, along with selected literature-based datasets, were used for network training and validation. Input parameters included cement content, Fly Ash content, GGBS content, water content, fine aggregate, coarse aggregate, superplasticizer dosage, and curing age, while the output parameter was 28-day compressive strength.

The developed network consisted of one input layer, two hidden layers containing 10 and 5 neurons respectively, and one output neuron for strength prediction. The adopted configuration was selected after several trial runs. Networks with fewer neurons produced unstable prediction behaviour for higher-grade mixes, whereas larger hidden layers increased computational effort without noticeable improvement in prediction accuracy.

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A feed-forward backpropagation algorithm with the Levenberg–Marquardt training function was used for iterative learning. Compared with conventional gradient-based methods, the selected algorithm provided comparatively stable convergence and handled nonlinear variation in blended concrete datasets more effectively. The available dataset was divided into 70% training data, 15% validation data, and 15% testing data to improve generalization capability and minimize overfitting during training.

During network training, lower and medium-strength mixes exhibited comparatively stable prediction behaviour. Slightly higher deviations were observed in certain M60 and M70 mixes, mainly due to the increased sensitivity of low water-binder ratio concrete to curing condition, compaction quality, and superplasticizer dosage. Such variations become more pronounced in high-strength concrete because of its denser internal matrix and lower tolerance to minor batching inconsistencies.

Regression analysis and mean squared error evaluation indicated that most predicted values remained reasonably close to experimental results. However, prediction consistency reduced slightly near the extreme limits of the training dataset, highlighting the dependency of ANN performance on dataset variability and range of input parameters.

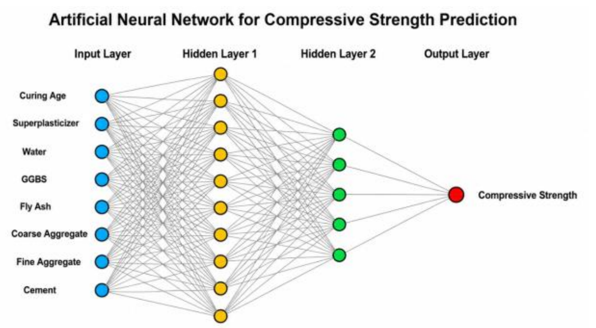

Figure 7.1 ANN Network Architecture

Feed-forward backpropagation ANN architecture developed in MATLAB consisting of one input layer, two hidden layers containing 10 and 5 neurons respectively, and one output neuron representing predicted compressive strength.

7.1 Training and Validation

Regression analysis was carried out to evaluate the correlation between experimental and ANN predicted compressive strength values.

The obtained regression coefficients were:

- Training Performance: R=0.9553
- Validation Performance: R=0.9475
- Testing Performance: R=0.9449
- Overall Performance: R=0.9526

The regression plots indicate strong agreement between target values and ANN predicted values. Most of the data points were concentrated near the ideal fit line, confirming good prediction capability of the developed model.

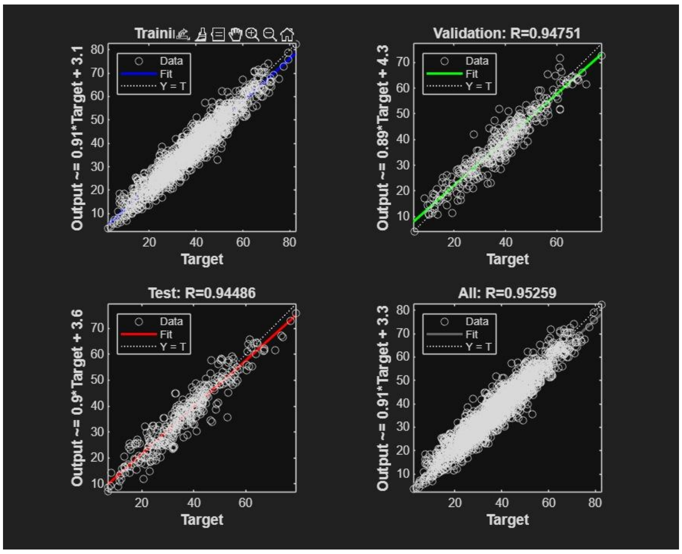

Figure 7.2 Regression Analysis Plots

Regression plots for training, validation, testing, and overall ANN performance.

7.2 Validation Performance Analysis

The ANN model achieved stable convergence during training with gradual reduction in mean squared error. The best validation performance was achieved at epoch 26.

The minimum validation mean squared error obtained was approximately:

MSE=18.1686

The gradual reduction in MSE during training confirms stable learning behavior and proper convergence of the network.

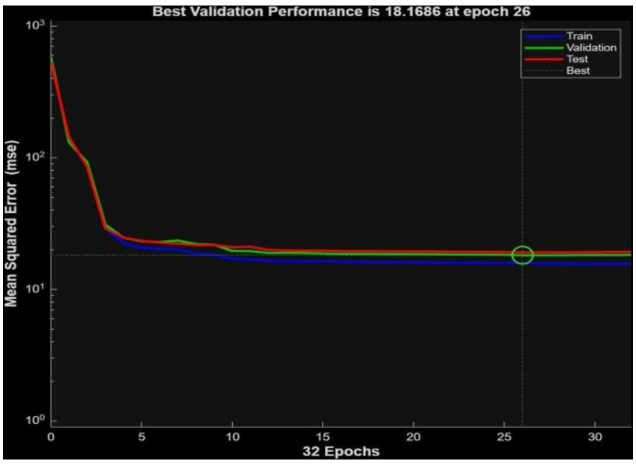

Figure 7.3 Best Validation Performance Curve

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Validation performance curve showing minimum validation error achieved during ANN training.

7.3 ANN Performance Statistics

The ANN performance statistics obtained from training and testing indicate good prediction capability and reduced prediction error.

The obtained statistical indicators confirm the reliability and effectiveness of the developed ANN model for predicting compressive strength of sustainable concrete mixes.

	Observations	MSE	R
Training	1650	15.8103	0.9553
Validation	353	18.1686	0.9475
Test	353	19.1540	0.9449

Table 7.1 ANN Performance Statistics

Mean squared error and regression coefficients obtained during ANN training and validation.

7.4 Prediction Accuracy Analysis

Prediction accuracy analysis was carried out to compare experimental and ANN predicted compressive strength values. Most data points were concentrated near the ideal fit line indicating high prediction accuracy.

The ANN model achieved an overall coefficient of determination:R2=0.956

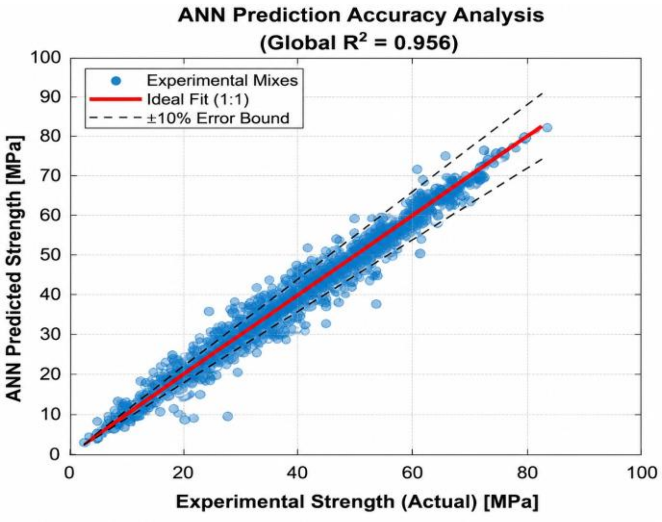

Figure 7.4 Prediction Accuracy Analysis

which confirms excellent agreement between experimental and predicted values.

7.5 Experimental vs ANN Predicted Strength Comparison

Comparison between laboratory experimental results and ANN predicted values indicates good agreement with acceptable prediction deviation.

The percentage prediction error for most concrete mixes was observed within ±5%, which is considered acceptable for ANN-based predictive models in concrete technology.

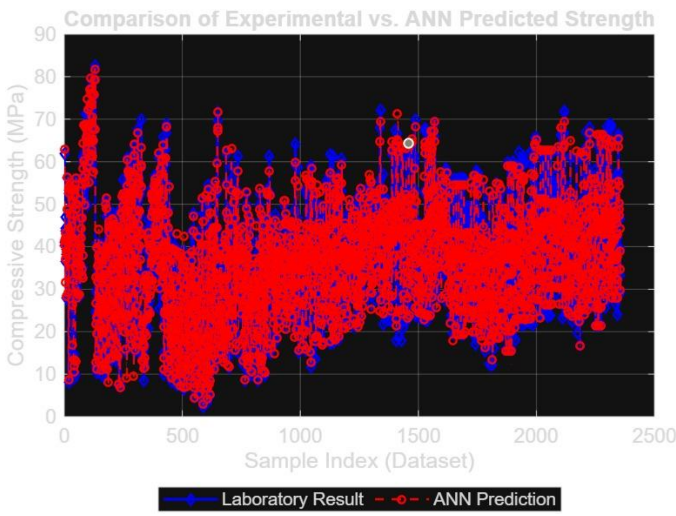

Figure 7.5 Experimental vs ANN Predicted Strength Comparison

Comparison between experimental compressive strength and ANN predicted strength values.

7.6 Residual Error Analysis

Residual error analysis was conducted to evaluate prediction deviation and uncertainty associated with ANN outputs.

The residual histogram indicates that most prediction errors are concentrated near zero with very low dispersion. This confirms that the ANN model provides reliable and accurate prediction results with minimum uncertainty.

The obtained statistical values were:

- Mean Error = 1.86 MPa
- RMSE = 2.61 MPa

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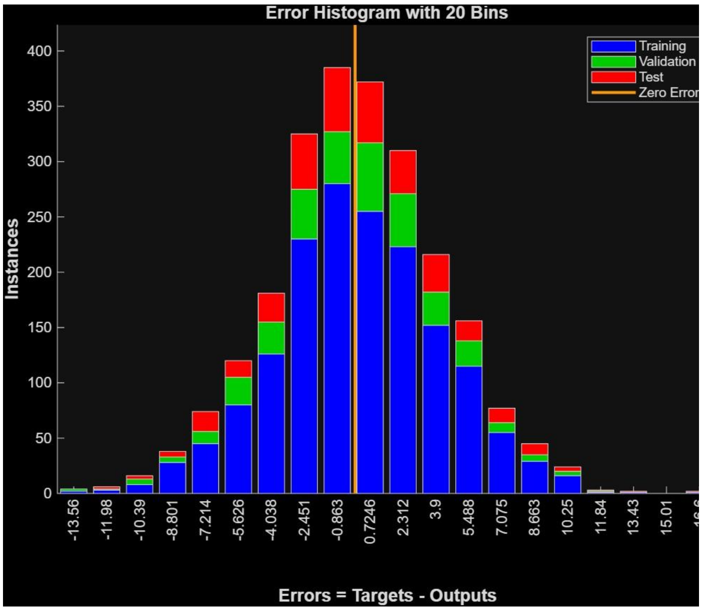

Figure 7.6 Residual Error Distribution Histogram

Distribution of residual prediction errors for the developed ANN model.

7.7 GUI Development

A graphical user interface (GUI) was developed using MATLAB for user-friendly prediction of concrete compressive strength.

The developed GUI allows users to input:

- Cement content
- Fly Ash content
- GGBS content
- Water content
- Fine aggregate quantity
- Coarse aggregate quantity
- Superplasticizer dosage

Based on the provided mix parameters, the GUI predicts the compressive strength of concrete instantly using the trained ANN model.

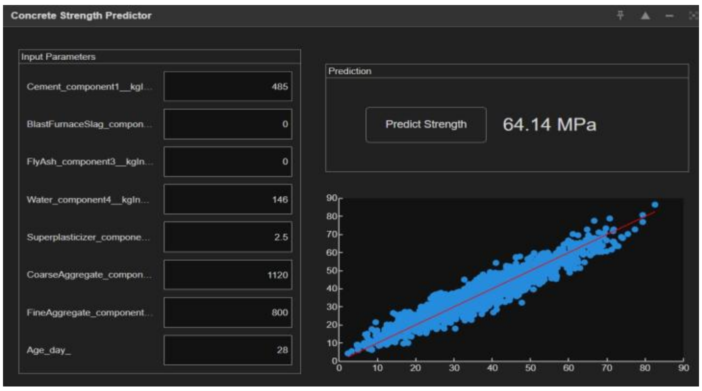

Figure 7.7 ANN-Based GUI for Strength Prediction

MATLAB-based GUI developed for rapid prediction of concrete compressive strength based on mix parameters.

8. EXPERIMENTAL VALIDATION AND DISCUSSION

8.1 Compressive Strength Test Results

The compressive strength test was conducted after 28 days curing period using a compression testing machine (CTM). The experimental results obtained for different concrete grades and mix categories were compared with ANN predicted values.

The ANN model showed strong agreement with laboratory experimental results. The percentage error between experimental and predicted values was found within acceptable limits, confirming the reliability of the developed ANN model.

Grade	Mix Type	Experimental (MPa)	Predicted (MPa)	Error (MPa)	% Error
M20	Cement	26.5	26	-0.5	1.89%
M20	Fly Ash	26	25.5	-0.5	1.92%
M20	GGBS	25.8	26.3	0.5	1.94%
M30	Cement	38.2	39.8	1.6	4.19%
M30	Fly Ash	37.8	36.4	-1.4	3.70%
M30	GGBS	37.5	39.1	1.6	4.27%
M40	Cement	44.6	42.8	-1.8	4.04%
M40	Fly Ash	44	45.7	1.7	3.86%
M40	GGBS	43.8	41.9	-1.9	4.34%
M50	Cement	52.8	54.9	2.1	3.98%
M50	Fly Ash	52.3	50.4	-1.9	3.63%
M50	GGBS	51.9	54	2.1	4.05%
M60	Cement	60.5	58	-2.5	4.13%
M60	Fly Ash	60	62.4	2.4	4.00%
M60	GGBS	59.2	56.9	-2.3	3.89%
M70	Cement	72.4	75.1	2.7	3.73%
M70	Fly Ash	71.8	68.9	-2.9	4.04%
M70	GGBS	71	73.8	2.8	3.94%

Table 8.1 : Comparison of Experimental and ANN Predicted Results

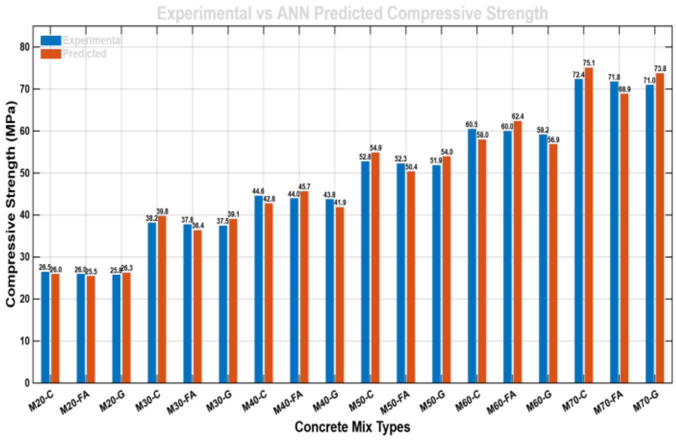

Figure 8.1 — Experimental vs ANN Predicted Strength

The comparison between experimental and ANN-predicted compressive strength values indicated reasonably stable prediction behaviour across most concrete grades and mix categories. Lower and medium-strength mixes exhibited comparatively smaller deviations, suggesting that the ANN model captured the primary nonlinear relationship between mix parameters and strength development with acceptable consistency.

Slightly higher variation was observed in certain M60 and M70 mixes. High-strength concrete is generally more sensitive to small changes in water-binder ratio, superplasticizer dosage, curing condition, and compaction quality due to its denser matrix and lower deformation tolerance. Consequently, minor inconsistencies during batching or curing influenced compressive strength more noticeably than in normal-strength concrete.

Fly Ash and GGBS blended mixes also showed some variation in prediction behaviour across different grades. Fly Ash mixes exhibited comparatively smoother prediction trends at lower grades, which may be associated with gradual pozzolanic activity and progressive strength development. GGBS mixes demonstrated relatively cohesive behaviour in several cases; however, slight fluctuations were observed in higher-grade mixes where binder interaction and curing sensitivity become more dominant.

Although minor deviations were observed in some higher-strength mixes, the overall prediction pattern remained reasonably consistent throughout the dataset, indicating that the developed ANN framework was capable of handling different concrete grades and binder combinations within a unified prediction model.

8.2 Prediction error analysis

Prediction error analysis was carried out to examine the deviation between experimental and ANN-predicted compressive strength values for different concrete grades and mix categories. The assessment considered both absolute error and percentage error values to evaluate prediction consistency under varying mix conditions.

Most prediction errors remained within ±5%, indicating reasonably stable ANN performance for preliminary strength estimation. Lower-grade mixes such as M20 and M30 exhibited comparatively smaller deviations, whereas certain M60 and M70 mixes showed slightly higher variation. This behaviour is generally associated with the increased sensitivity of high-strength concrete to minor changes in curing condition, superplasticizer dosage, and compaction quality due to its lower water-binder ratio and denser microstructure.

The error distribution further indicated that the ANN model did not exhibit consistent overprediction or underprediction for any specific mix category. Fly Ash blended mixes showed comparatively stable prediction behaviour, while some GGBS mixes exhibited moderate fluctuation at higher strength levels, likely due to differences in hydration rate and later-age strength development characteristics.

From a practical engineering standpoint, the obtained error range suggests that the developed ANN model can assist preliminary mix evaluation and compressive strength estimation prior to detailed laboratory verification.

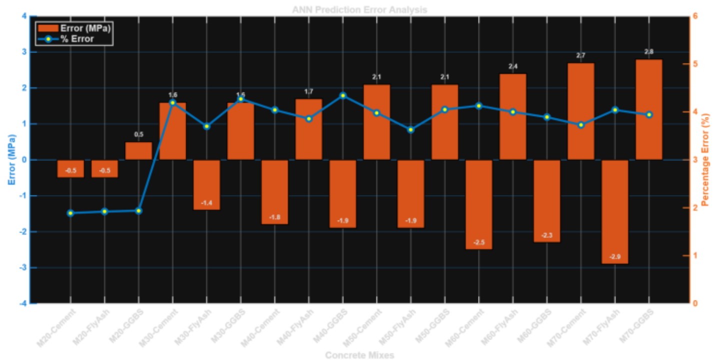

Figure 8.2 Prediction Error Distribution for Experimental and ANN Results

Comparison of prediction error and percentage error between experimentally obtained and ANN-predicted compressive strength values for different concrete mixes.

9. CONCLUSION

The ANN-based prediction framework developed in the present investigation demonstrated reasonably consistent performance for estimating compressive strength of concrete mixes containing cement, Fly Ash, and GGBS. The network was trained using experimental and literature-based datasets covering concrete grades from M20 to M70, allowing the model to capture nonlinear interaction between binder composition, water content, aggregate proportion, and admixture dosage.

Regression analysis indicated stable correlation between experimental and predicted values, with an overall regression coefficient close to 0.95. Most prediction deviations remained within ±5%, which is acceptable for preliminary material assessment and mix evaluation applications. Lower and medium-strength concrete mixes exhibited comparatively stable prediction behaviour, whereas certain M60 and M70 mixes showed slightly higher deviation. This behaviour is likely associated with the increased sensitivity of high-strength concrete to small variations in water-binder ratio, curing condition, and compaction quality.

The developed ANN model handled Fly Ash and GGBS blended mixes within the same prediction framework without requiring separate empirical equations for each material system. Fly Ash mixes generally showed smoother prediction trends at lower grades, while some fluctuation was observed in higher-strength GGBS mixes due to variations in hydration response and binder interaction.

Residual error analysis indicated that prediction errors were concentrated near zero with limited dispersion, suggesting that the network generalized reasonably well within the trained data range. The developed MATLAB-based GUI further improved practical usability by enabling rapid compressive strength estimation using user-defined mix parameters.

The present framework can assist preliminary mix proportion assessment and reduce repeated trial calculations during initial stages of concrete mix development. However, the model remains dependent on the quality and variability of the training dataset. The predictions therefore should be treated as support estimates and not as a substitute for codal laboratory verification in structural applications.

10. FUTURE SCOPE

The present investigation was limited to prediction of 28-day compressive strength under controlled laboratory conditions. Although the developed ANN model maintained reasonably stable prediction behaviour across different concrete grades and binder combinations, prediction accuracy remains dependent on dataset variability and input parameter range.

Future investigations may incorporate larger experimental datasets with wider variation in aggregate properties, curing environments, and supplementary cementitious material combinations to improve ANN generalization capability, particularly for higher-strength concrete mixes where prediction sensitivity becomes more pronounced.

The current framework considered compressive strength as the primary output parameter. Further extension of the ANN model toward prediction of flexural strength, split tensile strength, modulus of elasticity, creep, shrinkage, and durability characteristics may improve its applicability for structural engineering assessment and long-term serviceability evaluation.

Hybrid prediction approaches combining ANN with optimization techniques, genetic algorithms, or fuzzy logic systems may further improve prediction stability for nonlinear concrete behaviour. In addition, inclusion of field curing conditions, temperature variation, and moisture fluctuation can provide better understanding of ANN performance under practical site environments.

The developed MATLAB-based GUI may also be extended into a standalone or web-based platform for rapid concrete mix evaluation and preliminary quality assessment. Future work may additionally examine advanced deep learning models and larger ANN architectures for handling complex datasets associated with sustainable and high-performance concrete systems.

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