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# The Influence of Random Noise Augmentation on the Predictive Accuracy of Ann and Anfis Models for Pet-Modified Concrete

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**Abstract**

The escalating challenge of plastic waste and the demand for sustainable infrastructure have prompted exploration into innovative construction materials. This study assessed the feasibility of using polyethylene terephthalate (PET) waste as a partial replacement for coarse aggregate in permeable concrete. An experimental program was conducted, examining constituent materials and key concrete properties such as workability, permeability, water absorption, and compressive strength. Due to a limited dataset, a novel data augmentation approach using controlled random noise in MATLAB expanded the original 32 data points to 352. This enriched dataset was used to train predictive models: an Artificial Neural Network (ANN) and an Adaptive Neuro Fuzzy Inference System (ANFIS). Results showed an inverse relationship between PET content and compressive strength. The 28-day strength dropped from 23.1 N/mm² in the control mix to 8.7 N/mm² at 20 percent PET, representing a 62.3 percent reduction. Both predictive models performed exceptionally well, with both ANFIS and ANN achieving nearly identical and high predictive accuracy ($R^2$ = 0.9990 and 0.9988, respectively). The study concludes that up to 10 percent PET waste replacement yields permeable concrete with acceptable strength for low-load applications, such as pedestrian walkways and landscaping.

Keywords: PET-modified, polyethylene, terephthalate, Permeable and data

## 1. Introduction

The construction industry is at a crossroads, simultaneously tasked with meeting the escalating demand for infrastructure while addressing its profound environmental footprint. The production of traditional concrete is a resource-intensive process that contributes significantly to global carbon emissions.

Concurrently, the proliferation of plastic waste, particularly polyethylene terephthalate (PET), has become a major environmental concern in urban areas. To address both challenges, researchers have explored the use of waste PET as a partial substitute for natural aggregates in concrete, which offers a sustainable and eco-friendly alternative for resource conservation and waste management (Nematzadeh et al., 2020; Assaad et al., 2022). Odeyemi et al (2024) demonstrated that the incorporation of Elephant Grass Straw (EGS) does not improve the quality of Coconut Shell Concrete (CSC).

Despite these environmental benefits, the incorporation of plastic waste can have a detrimental effect on the mechanical properties of concrete. Studies have shown that the lightweight nature and poor characteristic strength of PET, when compared to natural aggregates, often result in a degradation of concrete properties, including a decrease in compressive and tensile strength (Assaad et al., 2022). However, a body of research suggests that this degradation can be effectively mitigated or even overcome. For example, the reduction of the water-to-cement ratio or the inclusion of steel fibers and polymeric latexes has been shown to enhance the matrix porosity and improve the structural performance of PET-modified concrete, helping to reinstate its mechanical properties and reduce crack propagation (Assaad et al., 2022). Other studies have also demonstrated that specific mix designs and the use of supplementary cementitious materials (SCMs) can lead to satisfactory strength, with some mixes achieving target design strengths even with significant PET replacement levels (Chong & Shi, 2023).

Given that traditional laboratory experiments are often costly and time-consuming, predictive models rooted in artificial intelligence (AI) and machine learning (ML) have emerged as a promising and transformative solution for estimating concrete properties (Mouzoun et al., 2024; Kumar et al., 2025). However, a review of the existing literature reveals significant inconsistencies regarding the performance of different ML models for predicting the properties of concrete containing waste materials. For instance, while one study found that Support Vector Regression (SVR) models were more accurate than Artificial Neural Networks (ANNs) for predicting slump and compressive strength (Mouzoun et al., 2024), another concluded that a Decision Tree (DT) model was superior to both ANN and Multiple Linear Regression (MLR) for predicting compressive strength (Nadimalla et al., 2025). The latter study noted that the ANN model exhibited poor performance, partly due to the relatively small dataset, a common challenge in experimental research (Nadimalla et al., 2025). Conversely, other research has demonstrated the superior predictive capabilities of ANN models in different contexts, such as forecasting the bulk-specific gravity of asphalt mixtures (Kumar et al., 2025). These conflicting findings highlight the need for further investigation into strategies that can improve the predictive accuracy and robustness of AI models, particularly when working with limited datasets.

To address the inherent data limitations in experimental studies, this research investigates the influence of random noise augmentation on the predictive accuracy of Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models. The primary objective is to evaluate whether a controlled injection of random noise can enhance model generalization and reliability for predicting the mechanical properties of PET-modified concrete, thereby contributing to the development of more robust and efficient tools for sustainable construction practices. Table 1 shows the summary of relevant studies on PET-modified concrete and their key findings.



Table 1 Summary of relevant studies on PET-modified concrete and predictive modeling.

| Category | Author(s) & Year | Focus of Study | Key Findings |
|---|---|---|---|
| **Experimental Studies** | Nematzadeh et al. (2020) | Post-fire compressive strength of PET aggregate concrete with steel fibers | PET + steel fibers reduced strength after fire; GEP provided reliable predictions. |

| | | | |
|---|---|---|---|
| | Chong & Shi (2023) | Meta-analysis of PET aggregates on compressive strength | PET as fine aggregate more effective than coarse; up to 30% replacement viable. |
| | Xiong et al. (2024) | Physical & mechanical properties of PET concrete with predictive models | Low PET improved flexural strength; predictive models validated performance. |
| **Predictive Modeling (ANN, ML, AI)** | Mouzoun et al. (2024) | ANN & SVR models predicting slump and compressive strength | SVR outperformed ANN in accuracy for slump and compressive strength. |
| | Nadimalla et al. (2025) | ANN, DT, MLR predicting PET + M-sand concrete strength | Decision Tree gave best performance ($R^2 = 0.918$); ANN performed poorly. |
| | Kumar et al. (2025) | Comparative ML for bulk specific gravity of PET-modified asphalt | ANN achieved best prediction (CC = 0.9999, MAE = 0.0004). |
| | Khan et al. (2025) | ML models predicting stress–strain of PET FRP confined concrete | XGBoost outperformed RFR & KNN; fiber thickness & layers were critical. |
| **Hybrid / Optimization Approaches** | Basser et al. (2022) | RSM modeling of SCC with PET & steel fibers | Optimum mix: 4% PET + 0.23% fiber improved strength & ductility. |
| | Ofuyatan et al. (2022) | RSM & ANN predicting SCC with PET & silica fume | ANN showed higher accuracy ($R^2 > 0.93$); admixtures improved workability. |
| | Assaad et al. (2022) | Structural performance of PET-modified RC beams | Reduced w/c ratio and fibers/latexes improved beam strength. |



## 2.0 Materials and method

Figure 1 outlines the comprehensive methodological framework adopted for this study on concrete incorporating Polyethylene terephthalate (PET) waste. It details the sequential stages of the research, from material selection and mix design to experimental testing, data augmentation using MATLAB, and the final machine learning modeling for predictive analysis.

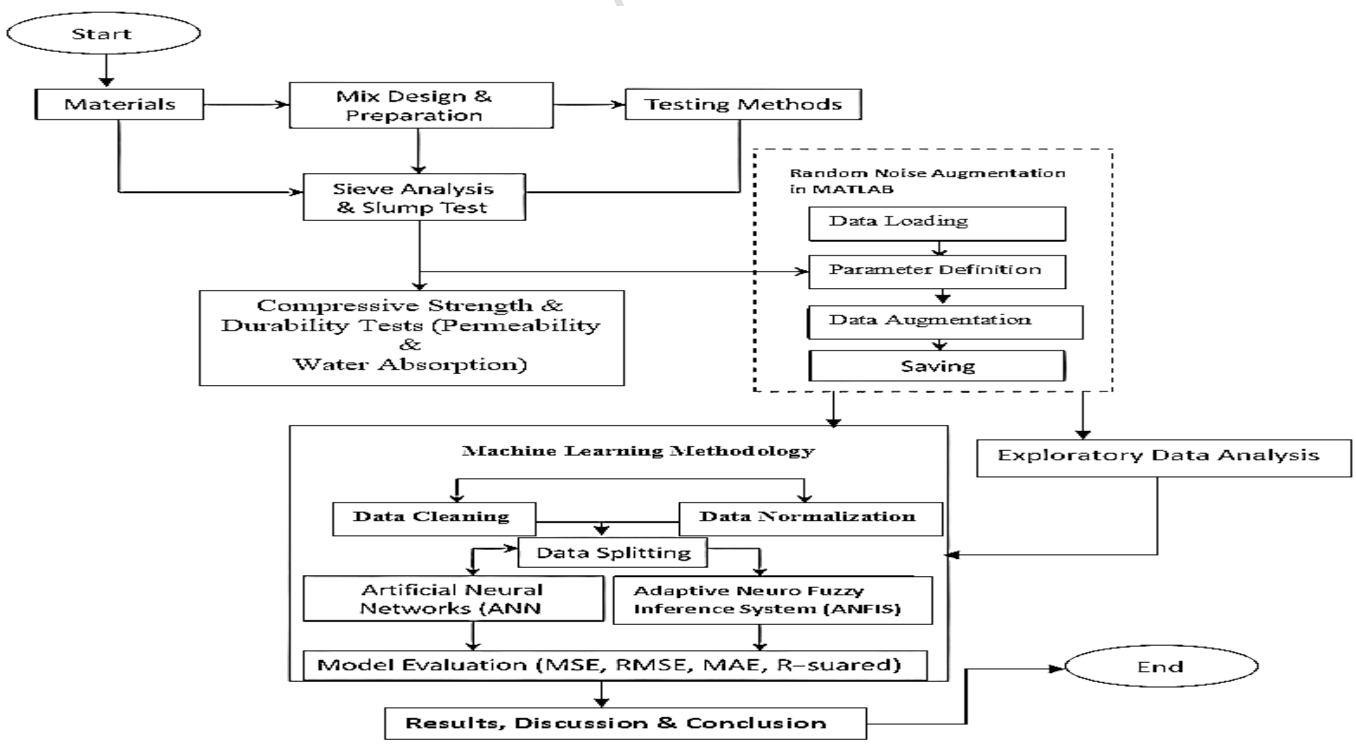


Figure 1 Methodology flowchart

## 2.1 Materials

Ordinary Portland Cement (OPC), CEM I 42.5N, conforming to BS EN 197-1:2011, was used as the primary binder. Crushed granite (10–20 mm) from Ishiagu Quarry, Ebonyi State, served as coarse aggregate, while Natural River sand from the Imo River was used as fine aggregate. Both aggregates complied with BS 882:1992 and were washed and sieved to remove impurities. Polyethylene terephthalate (PET) waste was collected from provision stores and waste bins within MOUAU, cleaned, shredded, and used as partial coarse aggregate replacement. Clean borehole water, meeting BS 8500:2015 requirements, was used for mixing and curing.

## 2.2 Mix design and specimen preparation

The concrete mixes were proportioned with a constant water–cement ratio of 0.50. A control mix (PET-0) was prepared using 158.5 kg/m$^2$ of water, 317 kg/m$^2$ of cement, 739 kg/m$^2$ of sand, and 1443 kg/m$^2$ of granite. In the experimental mixes, shredded PET waste replaced sand by mass at levels of 2%, 5%, 10%, 12%, 15%, 17%, and 20%. For example, at 2% replacement (PET-2), sand content was reduced to 724.22 kg/m$^2$, and 14.78 kg/m$^2$ of PET was added. At 5% replacement (PET-5), sand was reduced to 702.05 kg/m$^2$ with 36.95 kg/m$^2$ of PET incorporated. This ensured that the combined mass of sand and PET remained constant (739 kg/m$^2$) across all mixes, providing a consistent basis for comparison.

Cubic specimens (150 × 150 × 150 mm) were cast for each mix. At least four specimens were prepared per mix at testing ages of 7, 14, 21, and 28 days. After casting, specimens were covered to prevent moisture loss and cured in water at 20 ± 2 °C and >95% relative humidity, following BS EN 12390-2:2019.

## 2.3 Testing methods

All experimental tests were performed following relevant British Standards. The grading characteristics of granite and sand were determined by sieve analysis (BS 882:1992) to establish particle size distribution curves. Workability was assessed by slump test using a standard Abrams cone. Compressive strength was measured at 7, 14, 21, and 28 days in accordance with BS EN 12390-3:2019, using a compression machine conforming to BS EN 12390-4:2019. Durability-related tests were also carried out. Permeability was determined using a falling head permeameter, with coefficients calculated from Darcy's Law, adapting BS EN 12697-40:2006. Water absorption was evaluated as per BS EN 12390-2:2019, where oven-dried specimens were immersed in water for 48 hours and absorption was calculated as the percentage increase in weight relative to dry mass.

## 2.4 Random noise augmentation in MATLAB

The primary objective is to expand a limited, original dataset into a larger, synthetic one by introducing controlled random noise. Unlike Pchip Data Augmentation used by Ozioko and Eze (2025), this technique is valuable for enhancing the diversity of training data, thereby improving the robustness and generalization performance of subsequent machine learning or artificial intelligence models. In the current study, an original dataset of 32 data points was successfully augmented to 352 data points. The methodology is structured into five distinct phases: previous works that utilized similar augmentation process, data loading, parameter definition, data augmentation, and finalization.

### *2.4.1 Previous research on related data augmentation process*

Table 2 professionally synthesizes key research on data augmentation techniques that utilize noise. The selected studies demonstrate a range of applications, from seismic data and audio to medical imaging, highlighting the efficacy of strategically introducing noise to improve model performance and address data scarcity.

Table 2 Summary of relevant studies on noise-based data

| Study | Publication | Objective | Methodology | Key Findings |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| Feng, Q., Li, Y., & Wang, H. (2021) | *Geophysics* | Generate synthetic random noise for seismic data augmentation. | Improved Variational Autoencoder (VAE) with redefined Kullback-Leibler distance generates realistic noise. | Simulated noise matched real noise, boosting CNN denoising. |
| Abeysinghe, A., et al. (2023) | *Applied Acoustics* | Address the scarcity of labeled audio data for mechanical noise classification. | Evaluated augmentations, proposed novel class-specific combined technique. | Data augmentation reduced overfitting; combined method achieved highest precision. |
| Rai, S., Bhatt, J. S., & Patra, S. K. (2021) | *IEEE Access* | Enhance medical denoising by augmenting deep learning method limits. | Unsupervised noise learning framework with deep residue network (DRN) and patch dictionaries. | The augmented approach enhanced denoising performance with minimal signal leakage and artifacts. |

## 3.0 Results and Discussion

### 3.1 Material properties test results

Table 2 lists material properties. All met concrete standards. OPC had adequate strength and setting times. Aggregates showed good grading, density, low absorption. PET waste was characterized. Materials suit permeable concrete.

#### *3.1.1 Grading characteristics of the fine and coarse aggregate*

Figure 2 presents the combined sieve analysis results for coarse and fine aggregates. The gradation characteristics of the aggregates, confirm their suitability for permeable concrete. The fine aggregate, with a Coefficient of Curvature ($C_{u)}$ of 3.93 and Coefficient of Uniformity (Cu) of 1.02, is moderately well-graded, promoting good packing and workability. In contrast, the coarse aggregate with a Cu of 1.8 and Cc of 1.09 is uniformly graded, which is ideal for creating the interconnected voids necessary for permeability. These values support the intended balance between strength and drainage in the concrete mix. Figure 3 presents the basic raw materials utilized in carrying out this study.

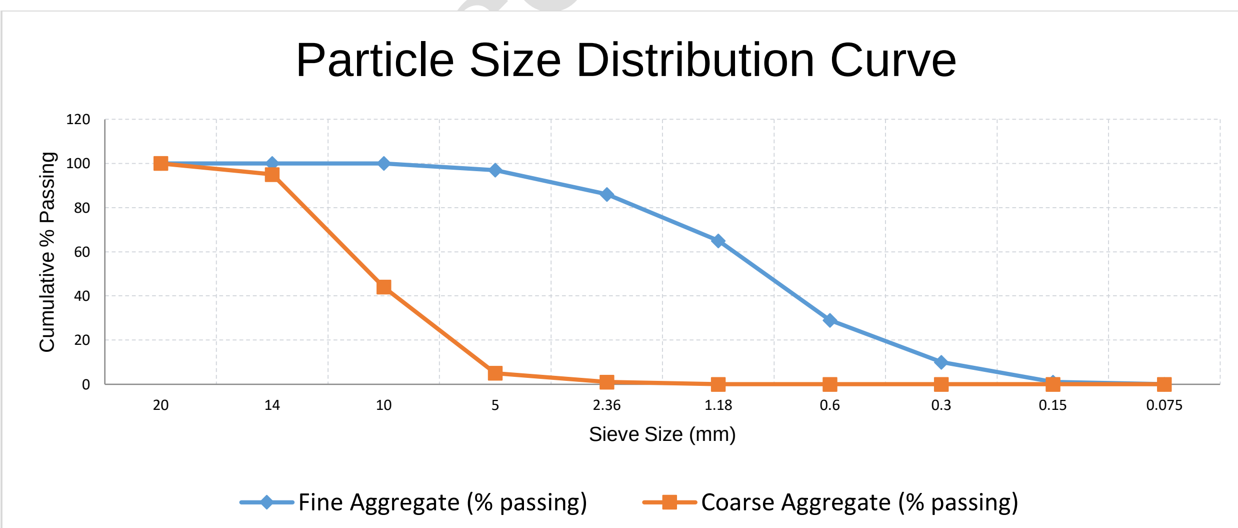


Figure 2 Particle size distribution curve

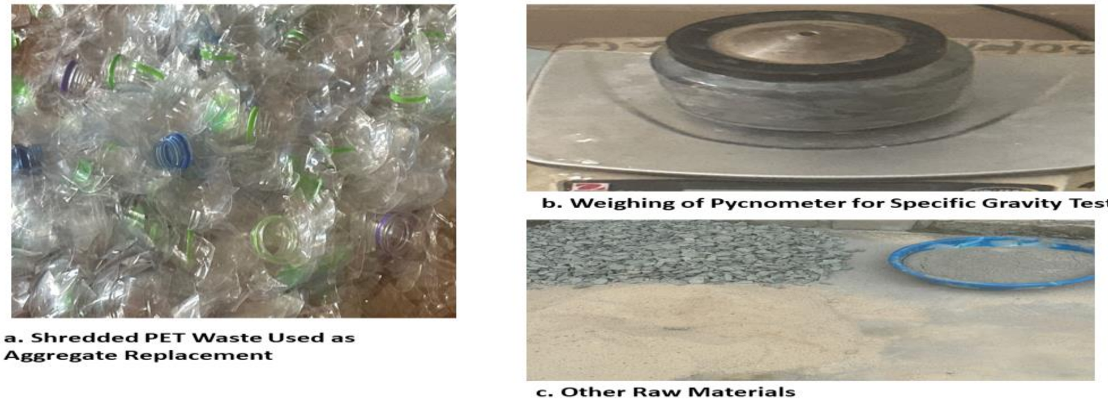

Figure 3 Raw materials used in the permeable concrete mix

**3.2 Workability of PET-modified concrete**

Figure 5 shows PET content inversely affects concrete slump. PET-0 had 66 mm slump; PET-20 dropped to 9 mm, due to PET particles disrupting flow. This aligns with Aocharoen & Chotickai (2023), Qaidi et al. (2023) and Hasan-Ghasemi & Nematzadeh (2021). However, Bamigboye et al. (2022) found workability increased up to 40% PET before decreasing, possibly due to particle shape or mix design. The very low slump at 20% PET likely increases porosity, hinders compaction, creates voids, and worsens mechanical strength beyond weak PET-cement bonding. Figure 4 shows slump testing.


Figure 4 Slump determination process

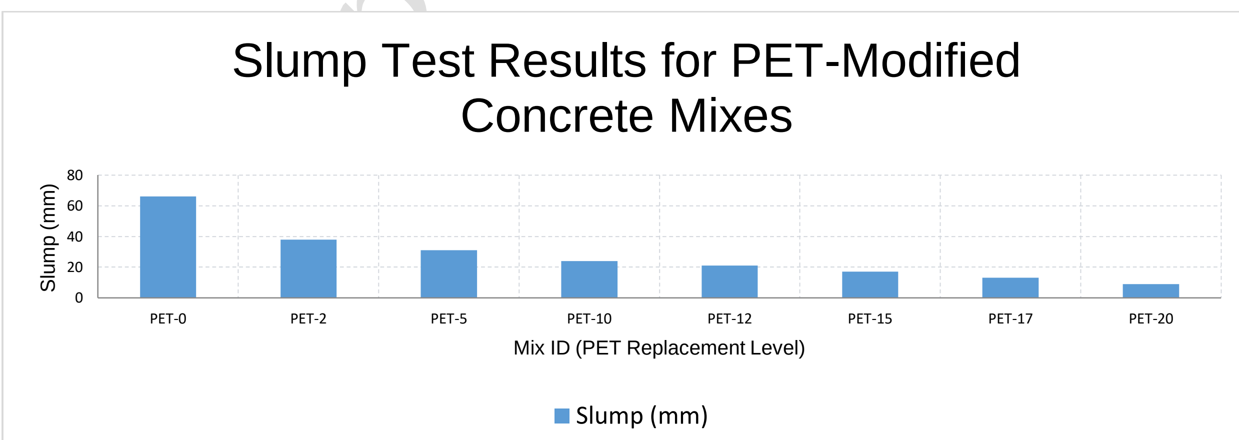

Figure 5 Slump test results for PET-modified concrete mixes

**3.3 Permeability characteristics durability assessment of pet-modified permeable concrete**

Table 3, Table 4 and Figure 6 show that increasing PET reduces permeability and water absorption. Control permeability: 0.87 cm/s; 20% PET: 0.54 cm/s. Absorption fell from 14.9% to 10.4%, indicating pore refinement. This contradicts Dawood et al. (2021), Qaidi et al. (2023), and Sau et al. (2024), who reported increased absorption or permeability with PET. Discrepancies may stem from PET particle size, shape or mix design. Findings align with Lazorenko et al. (2022) on geopolymer mortars. Reduced absorption is due to non-absorbent PET particles occupying pore space.

Table 3 Permeability coefficient of PET-modified permeable concrete

| Mix Designation | PET Replacement Level (%) | Permeability Coefficient *(k)* (cm/s) |
|---|---|---|
| Control | 0 | 0.87 |
| PET-2 | 2 | 0.83 |
| PET-5 | 5 | 0.79 |
| PET-10 | 10 | 0.70 |
| PET-12 | 12 | 0.66 |
| PET-15 | 15 | 0.63 |
| PET-17 | 17 | 0.59 |
| PET-20 | 20 | 0.54 |

Table 4 Water absorption of PET-modified permeable concrete

| Mix ID | Dry Wt (g) | Sat. Wt (g) | Absorption (%) |
|---|---|---|---|
| Control | 7853 | 9027 | 14.9 |
| PET-2 | 7732 | 8833 | 14.3 |
| PET-5 | 7564 | 8615 | 13.9 |
| PET-10 | 7291 | 8246 | 13.1 |
| PET-12 | 7062 | 7945 | 12.5 |
| PET-15 | 6838 | 7639 | 11.7 |
| PET-17 | 6676 | 7440 | 11.5 |
| PET-20 | 6509 | 7189 | 10.4 |

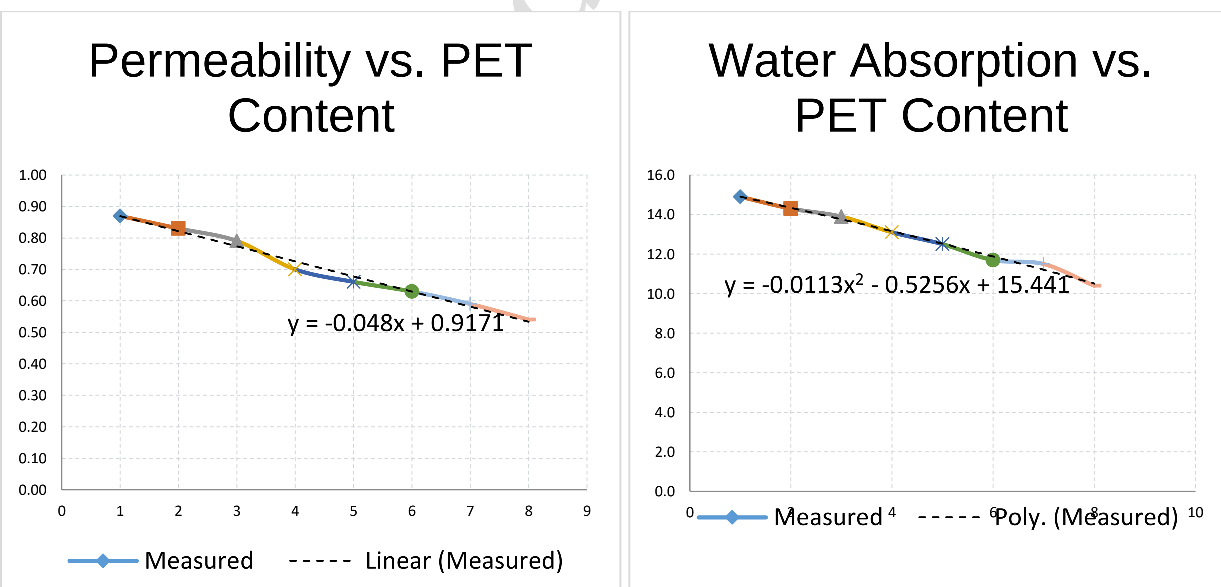


Figure 6 Permeability and water absorption of PET-modified concrete

### 3.4 Compressive strength test results

Compressive strength (Figure 7) decreased with higher PET content. Control: 23.1 N/mm²; 20% PET: 8.7 N/mm². This inverse trend held across 7–28 days. Supported by Assaad et al. (2022), Mwonga et al. (2022), Bamigboye et al. (2022), Hasan-Ghasemi and Nematzadeh (2021), and Qaidi et al. (2023) and others. Weak bond and poor ITZ cause strength loss. Dawood et al. (2021) saw gains only at low PET (5–12.5%). Abed et al. (2021) confirmed general strength reduction. Abu-Saleem et al. (2021) noted microwave treatment may improve ITZ.

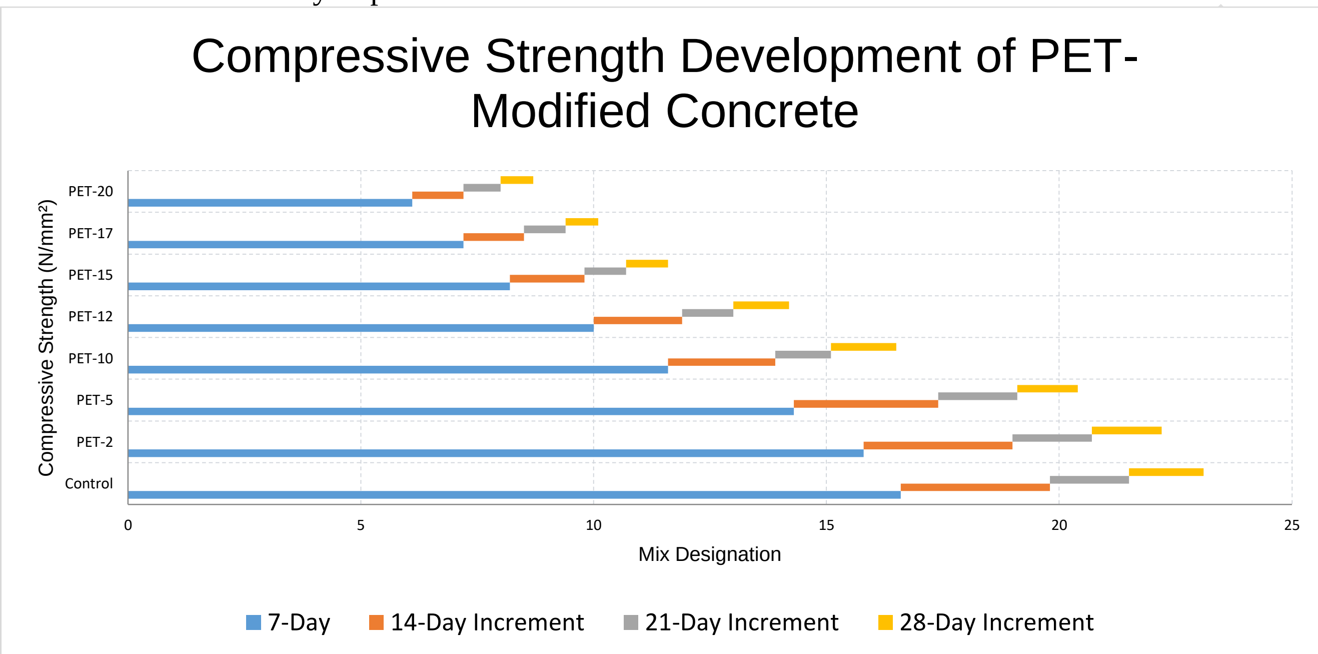


Figure 7 Compressive Strength Development of PET-Modified Concrete

### 3.5 EDA output results

Table 5 shows Cement, Granite, W/C, Water are constant. Days, PET, Sand vary. Figures 8–10 confirm: Days and Sand positively affect strength; PET negatively affects it. Constant variables show no correlation with strength.

Table 5 Descriptive statistics for numerical variables

| Variable | Mean | Standard Deviation | Min | Max | Range |
|---|---|---|---|---|---|
| Cement (kg/m$^3$) | 317.0000 | 0.0000 | 317.0000 | 317.0000 | 0.0000 |
| Days | 17.5049 | 7.8243 | 6.6571 | 28.3401 | 21.6830 |
| Granite (kg/m$^3$) | 1443.0000 | 0.0000 | 1443.0000 | 1443.0000 | 0.0000 |
| PET (kg/m$^3$) | 74.8626 | 50.1392 | -2.5283 | 149.9488 | 152.4771 |
| Sand (kg/m$^3$) | 664.1858 | 50.1182 | 589.3943 | 740.8900 | 151.4957 |
| W/C | 0.5000 | 0.0000 | 0.5000 | 0.5000 | 0.0000 |
| Water (kg/m$^3$) | 158.5000 | 0.0000 | 158.5000 | 158.5000 | 0.0000 |

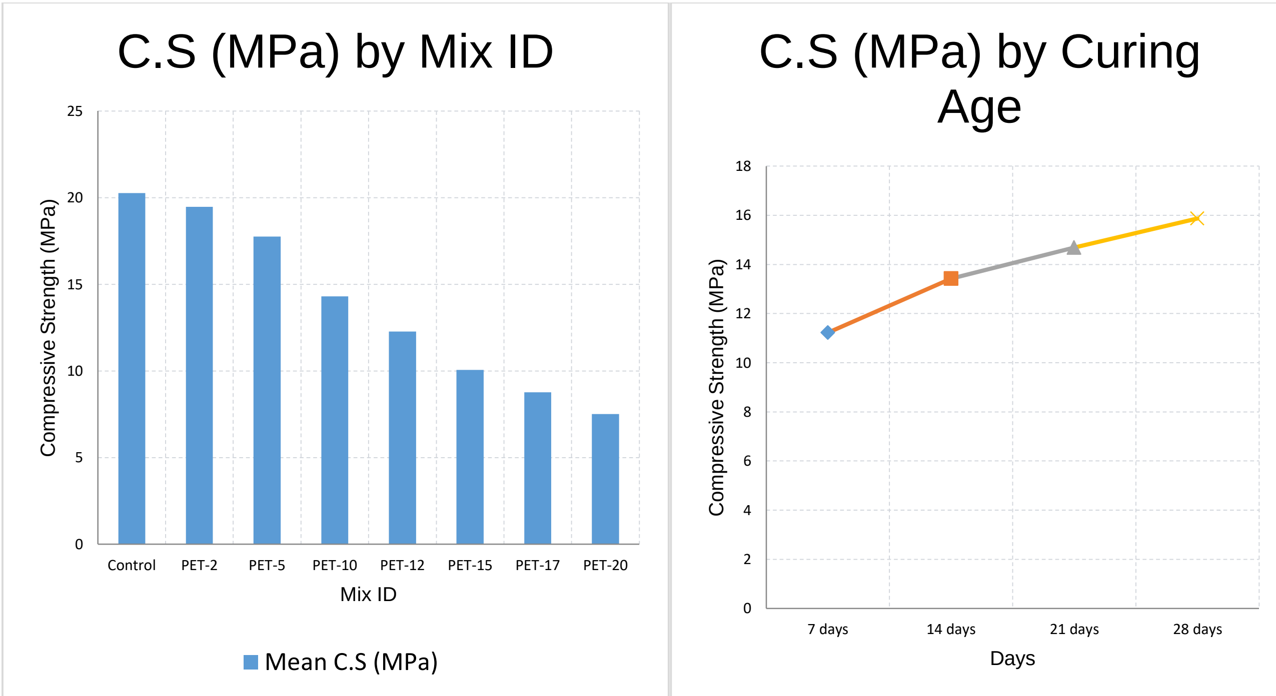


Figure 8 Compressive strength by category

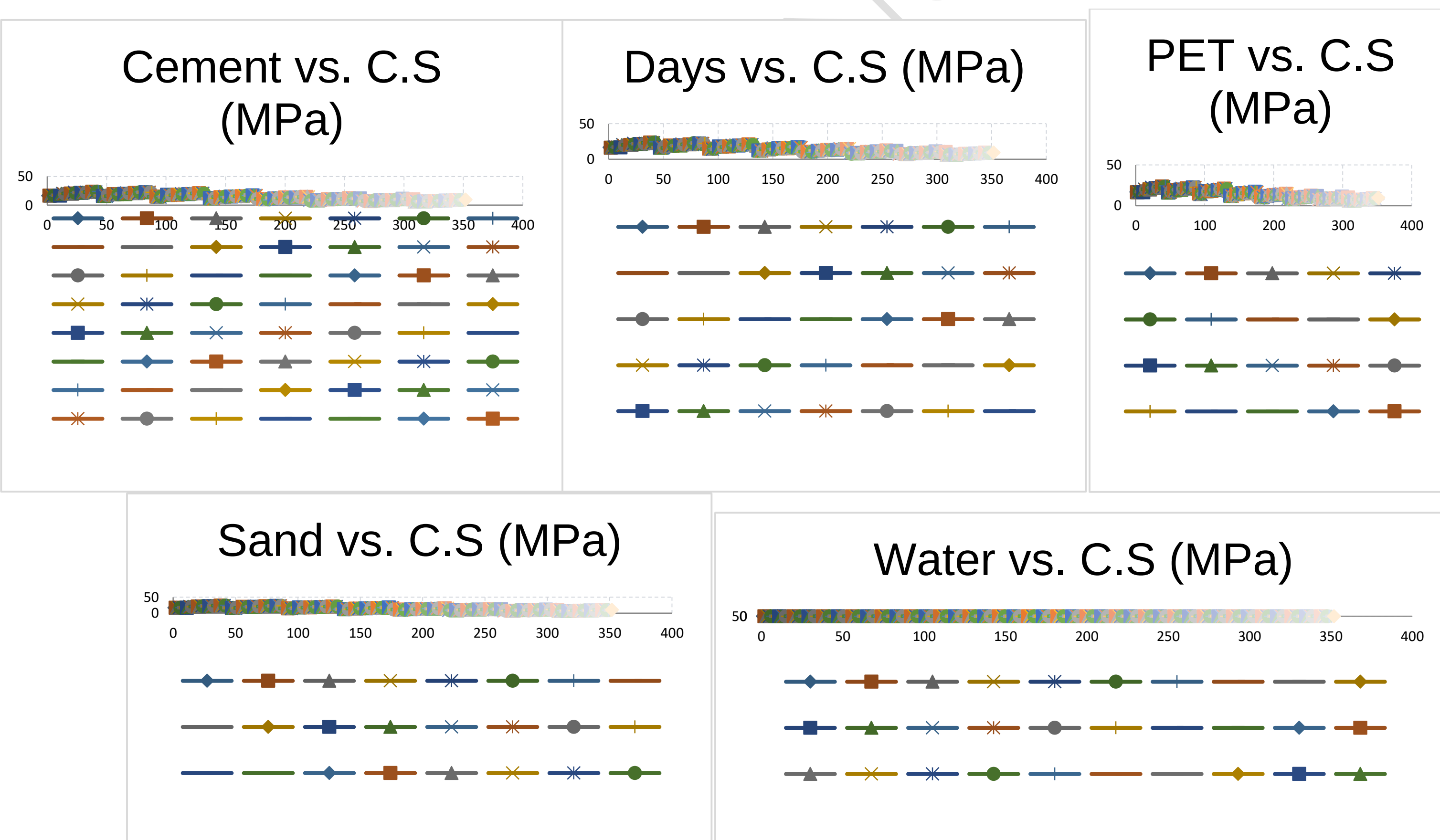


Figure 9 Relationships of input variables with the Compressive Strength

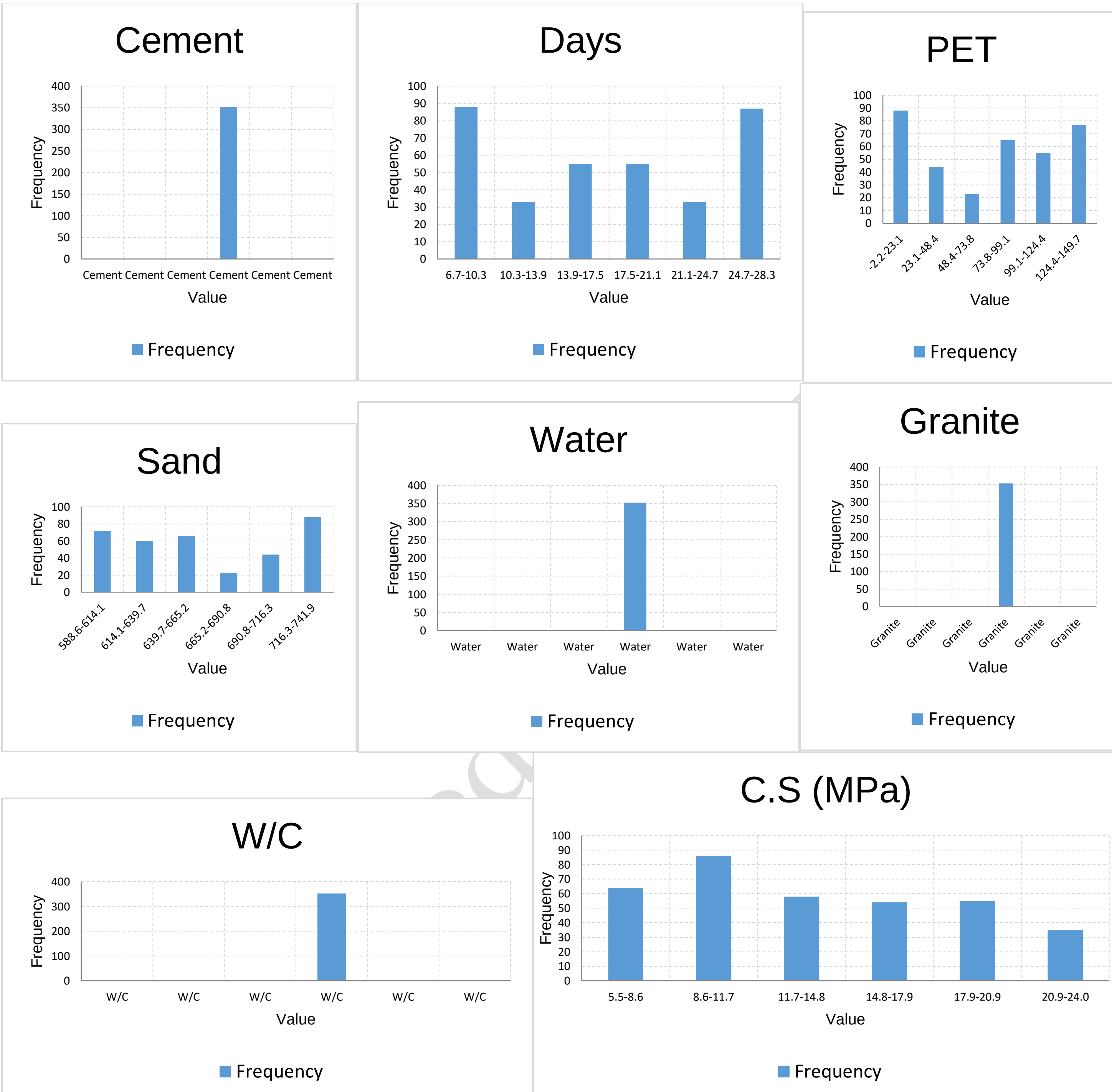


Fig 10 Histogram distribution of variables

### 3.6 ANN model architecture and training progress

Figure 11: ANN with 8 inputs, 10 hidden neurons, 1 output. Figure 12: Training stopped after 30 epochs. Performance reached $4.61\times10^{-5}$ (goal $1.00\times10^{-5}$). Validation checks stopped training to prevent overfitting before goal met.

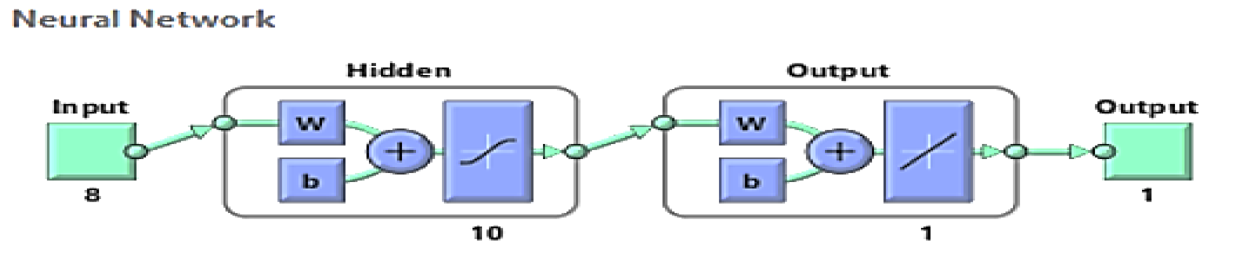


Figure 11 ANN Architecture

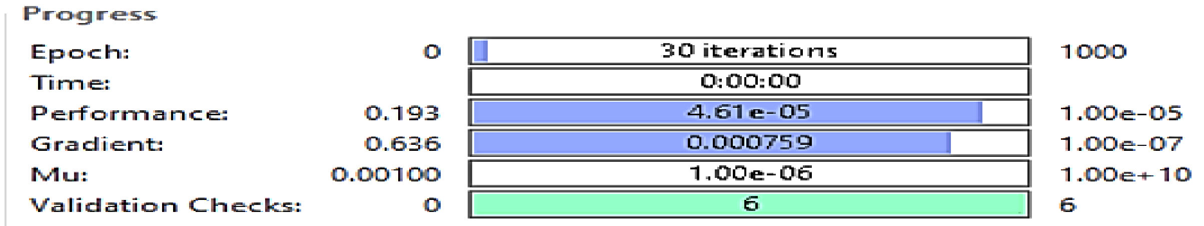


Figure 12 ANN Training Progress

***3.6.1 Comparative discussion of ANN performance***

Current ANN model (PET-modified concrete, augmented data) achieved a high $R^2$ of 0.9988, contrasting with Nadimalla et al. (2025) (negative $R^2$ due to small dataset). It aligns with Ofuyatan et al. (2022) ($R^2 > 0.93$), Khan et al. (2022) ($R \geq 0.91$), and Çolak et al. (2021). Data augmentation expanded dataset from 32 to 352 points, overcoming small-data limitations.

***3.6.2 Neural network performance during training***

Figure 13 shows neural network MSE over 30 epochs. Training, validation, test errors dropped rapidly. Best validation MSE ($6.9877\times10^{-5}$) at epoch 24, indicated by dotted line and green circle. Curves align, confirming good generalization without overfitting. Performance surpassed the goal.

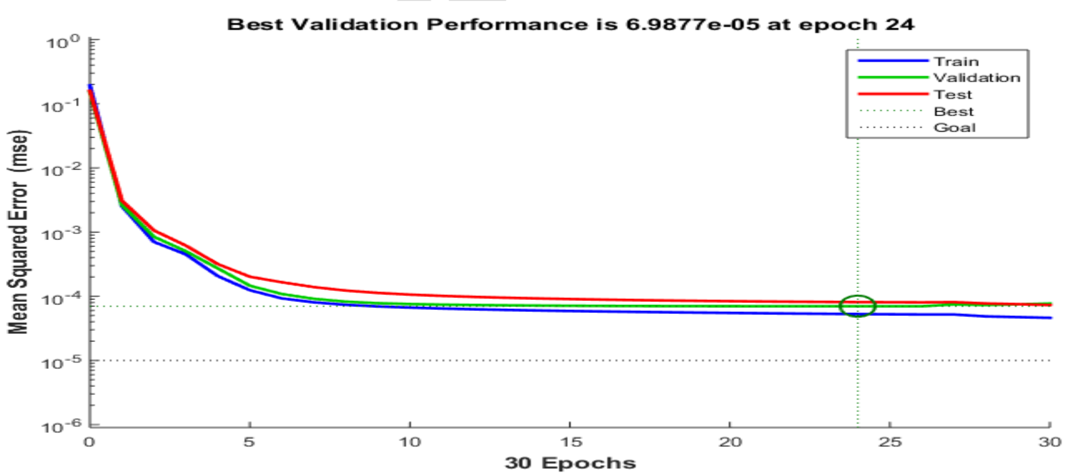


Figure 13 ANN Performance Plots

***3.6.3 Neural network training parameters and stopping criteria***

Figure 14 shows training over 30 epochs. Top: gradient decreased to 0.00075894, indicating convergence. Middle: Mu (μ) ended at $1\times10^{-6}$, suggesting efficient optimization. Bottom: Validation checks rose to 6 after epoch 24, triggering early stop to prevent overfitting.

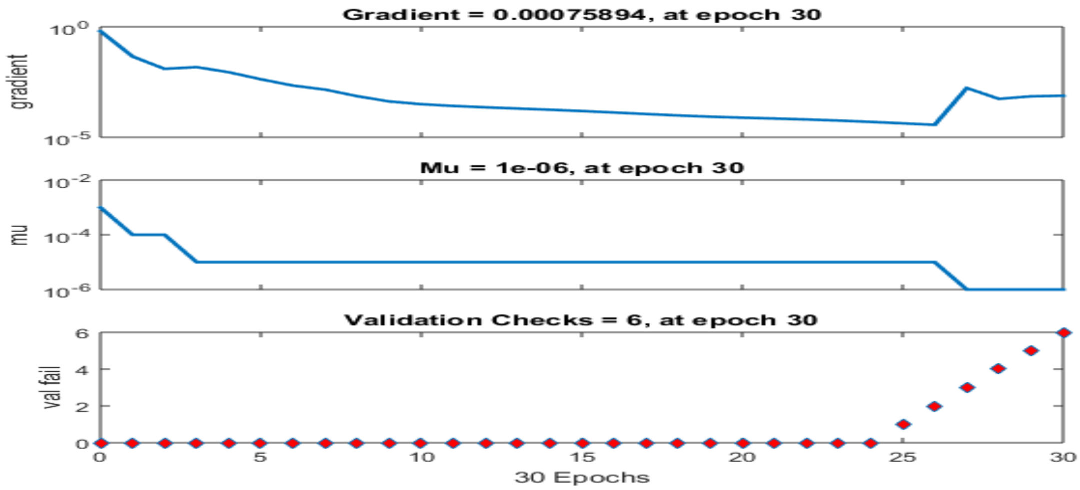


Figure 14 Neural network training plots

### *3.6.5 Neural network error histogram and distribution analysis*

Figure 15 shows error distributions for training, validation, test sets. Most errors cluster near zero (orange line), indicating accurate predictions. Symmetrical, bell-shaped distribution suggests unbiased, random errors. Large errors are rare. Model performs well.

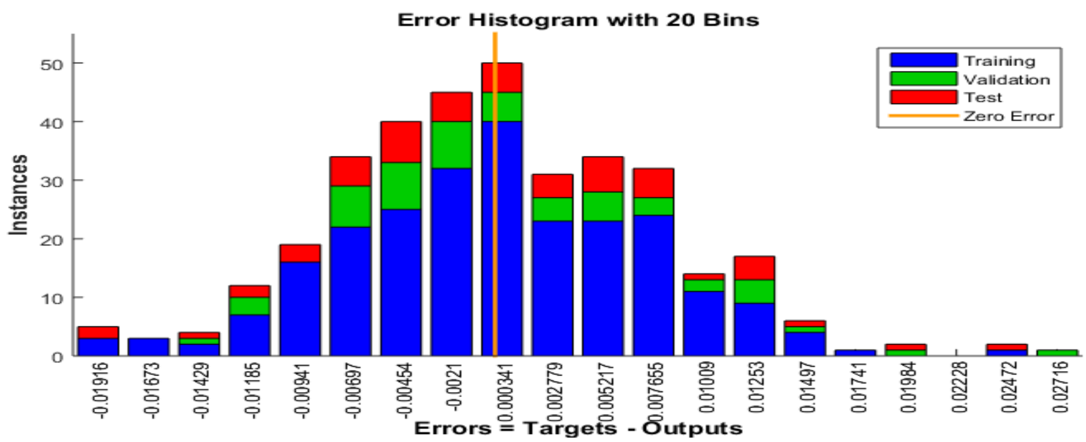


Figure 15 ANN error histogram

### *3.6.6 Analysis of ANN regression and performance metrics*

Figure 16 shows strong agreement between predicted and actual outputs, with data clustering around the one-to-one line. Correlation coefficients (R) were exceptionally high: training 0.99967, validation 0.99959, test 0.99941. Coefficients of determination ($R^2$) were 0.9993 (training), 0.9992 (validation), and 0.9988 (test). Consistency across datasets indicates good generalization without overfitting. Low test RMSE (0.1554) further confirms robust predictive performance.

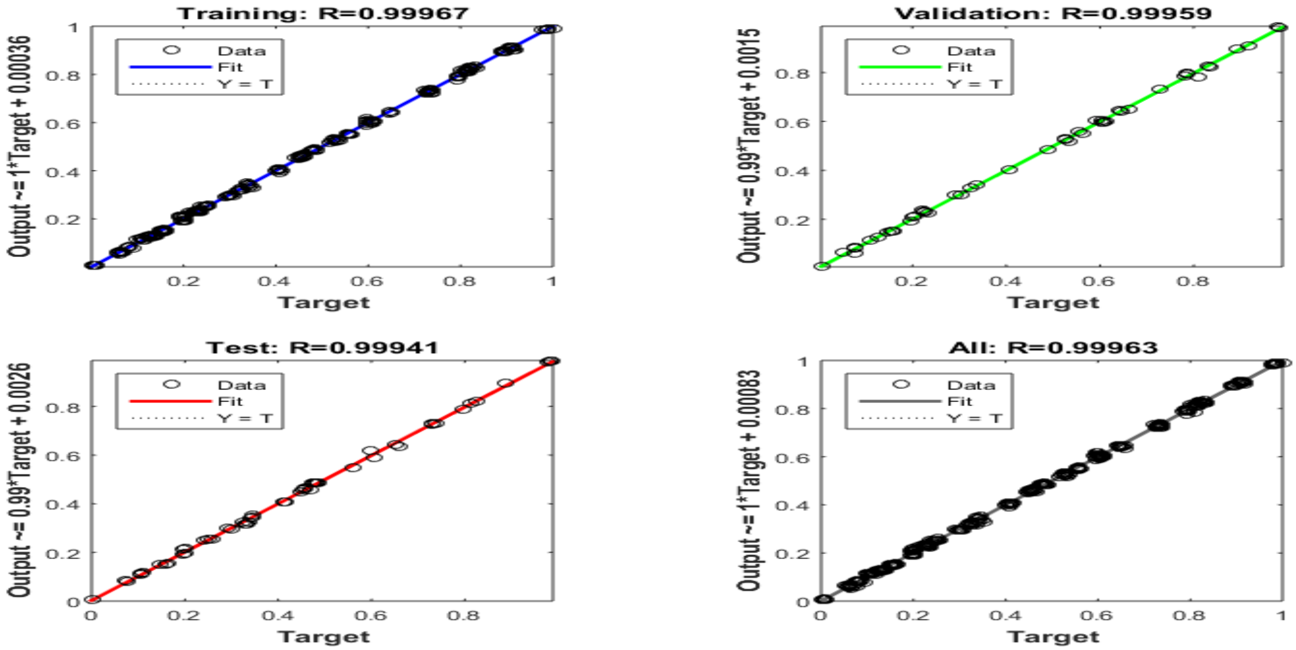


Figure 16 Neutral network regression plots

### *3.6.7 Analysis of ANN predicted compressive strength surface*

Figure 17 shows ANN-predicted compressive strength vs. days and PET. Strength increases with curing time (5–30 days) and decreases with higher PET (0–150 kg/m³). Surface transitions from high strength (yellow: many days, low PET) to low strength (blue: few days, high PET).

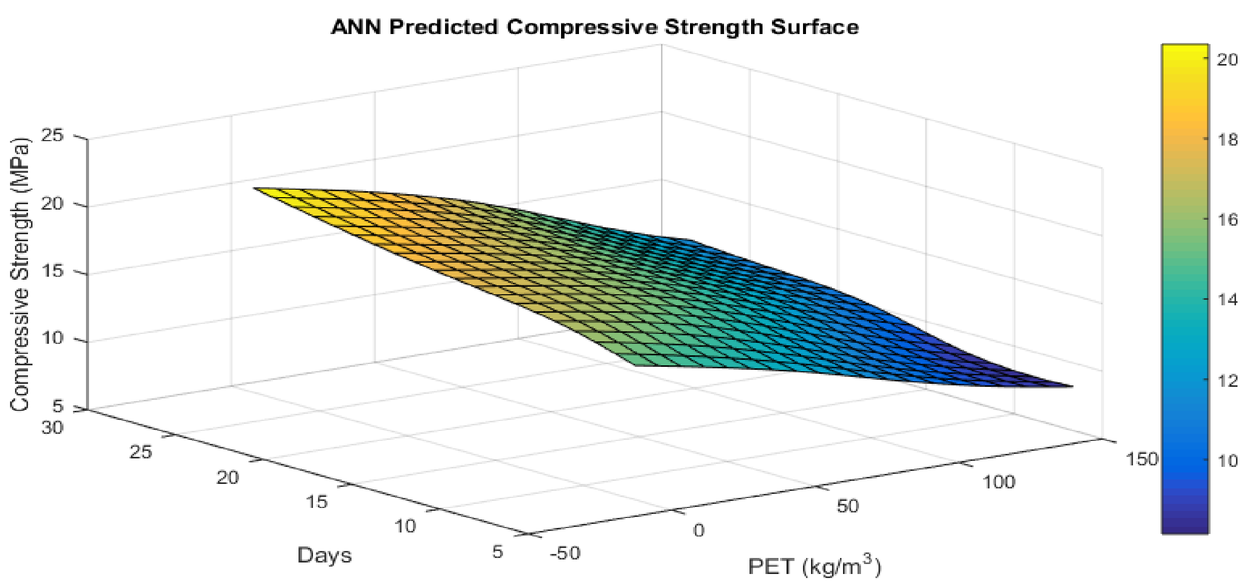


Figure 17 ANN 3D predicted compressive strength surface

## 3.7 ANFIS model architecture

Figure 18 shows Sugeno-type ANFIS with 8 inputs, membership functions, fuzzy rules, and weighted average output. Training over 100 epochs reduced error from 0.0903 to 0.0853. Though parameters (375) exceed training pairs (246), high validation/test $R^2$ suggests no overfitting. Table 6 lists specifications.

Table 6 ANFIS model specifications

| Parameter | Value |
|---|---|
| Number of Nodes | 281 |
| Number of Linear Parameters | 135 |
| Number of Nonlinear Parameters | 240 |
| Total Number of Parameters | 375 |
| Number of Fuzzy Rules | 15 |
| Number of Training Data Pairs | 246 |
| | |

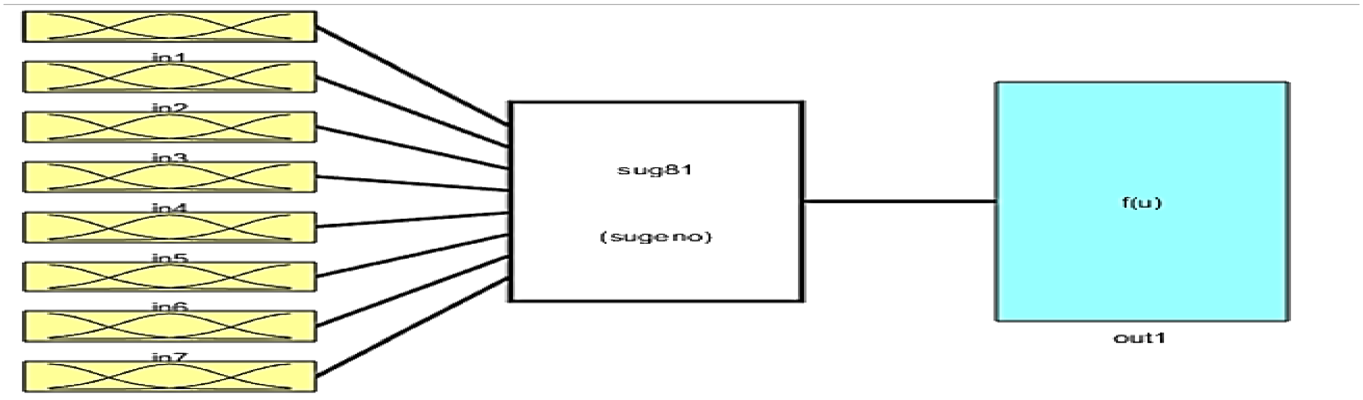


Figure 18 ANFIS Model Architecture

### *3.7.1 Comparative discussion of ANFIS performance*

Current ANFIS achieved $R^2$ = 0.9997 (training) and 0.9990 (validation/testing), aligning with Roy (2025) (97.1% accuracy). ANFIS effectively predicts PET-modified concrete strength with sufficient data.

### *3.7.2 ANFIS model membership functions*

Figure 19 shows membership functions for Sand, PET, Slump, Days. Optimized curves define fuzzy sets, with overlaps enabling smooth transitions. This granular representation supports the ANFIS model's non-linear predictive capability.

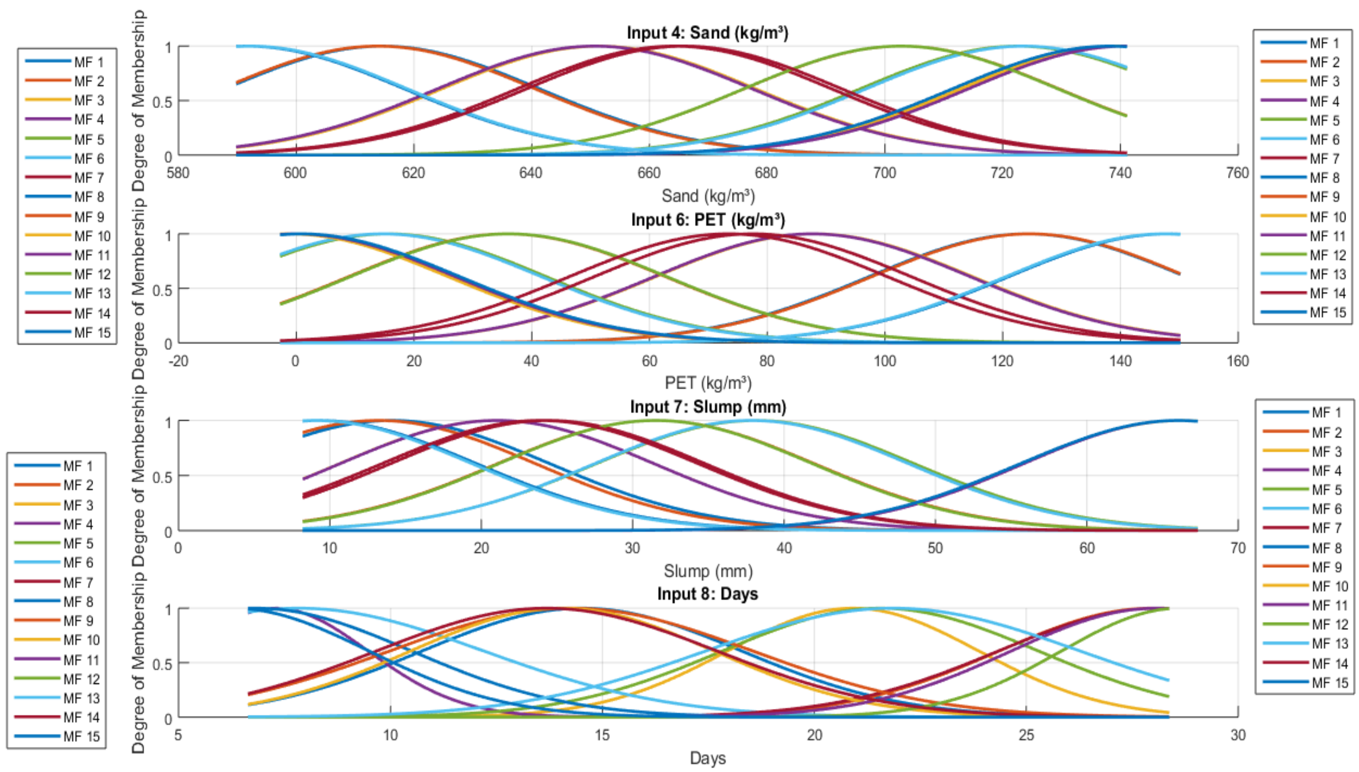


Figure 19 ANFIS membership functions with custom legend

### *3.7.3 ANFIS error distribution*

Figure 20 shows bell-shaped error distributions centered at zero for ANFIS training and testing data, indicating accurate, unbiased predictions. Training errors cluster more tightly; testing errors show slightly wider spread. Close alignment with normal distribution (red curve) confirms random, well-behaved errors and effective generalization.

### *3.7.4 ANFIS regression plots*

Figure 21 shows ANFIS model outputs closely match targets (Y=T line). High $R^2$ values near 1 across all datasets confirm good generalization without overfitting.

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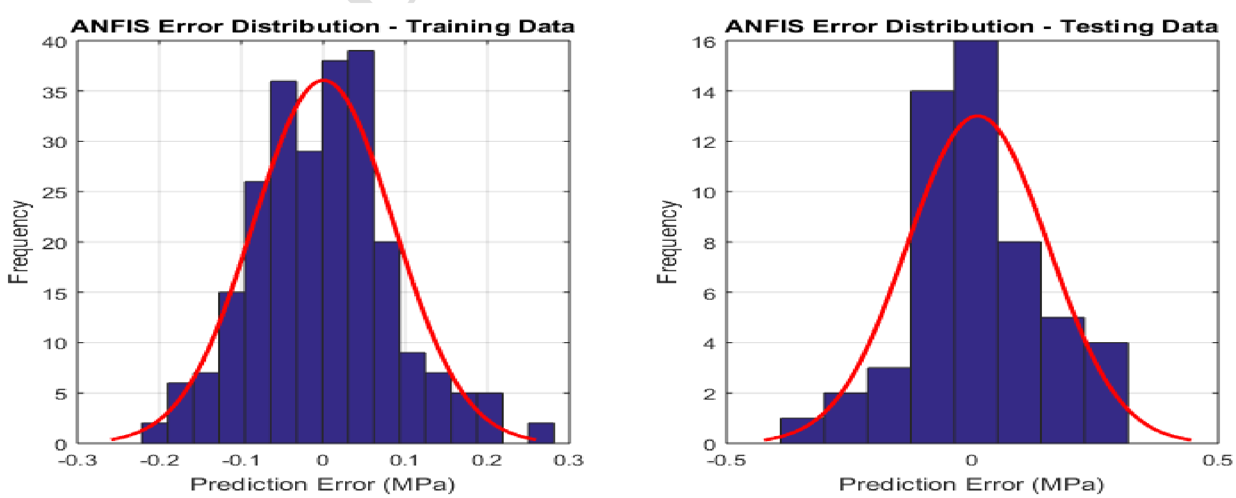


Figure 20 ANFIS error distribution

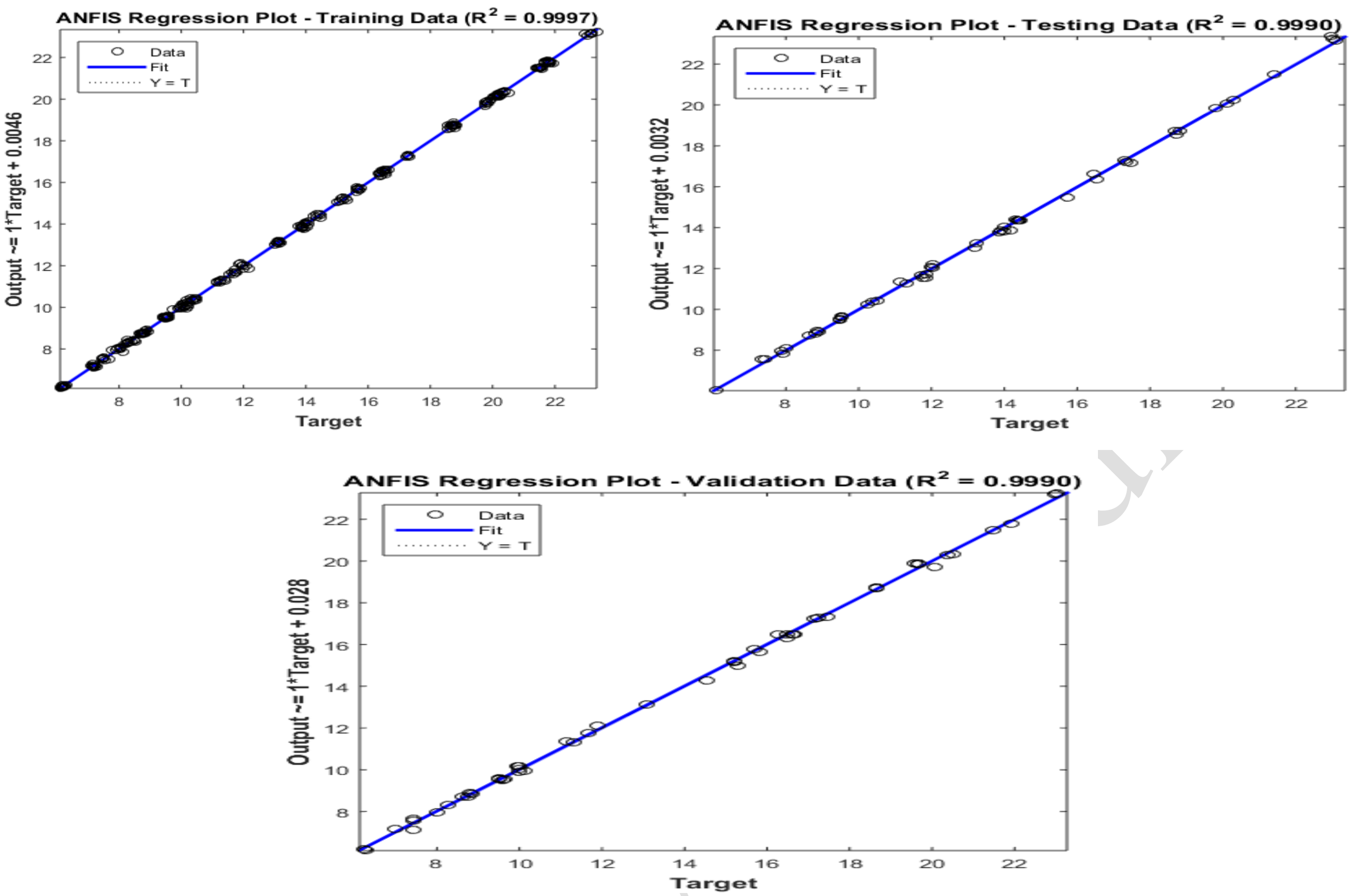


Figure 21 ANFIS regression plots showing the $R^2$ values

### *3.7.5 ANFIS 3D surface plot*

Figure 22 shows ANFIS-predicted compressive strength vs. days and PET. Strength increases with curing time. PET shows a non-linear effect: strength rises to an optimal PET level, then declines. Strength ranges from ~10 to 22 MPa.

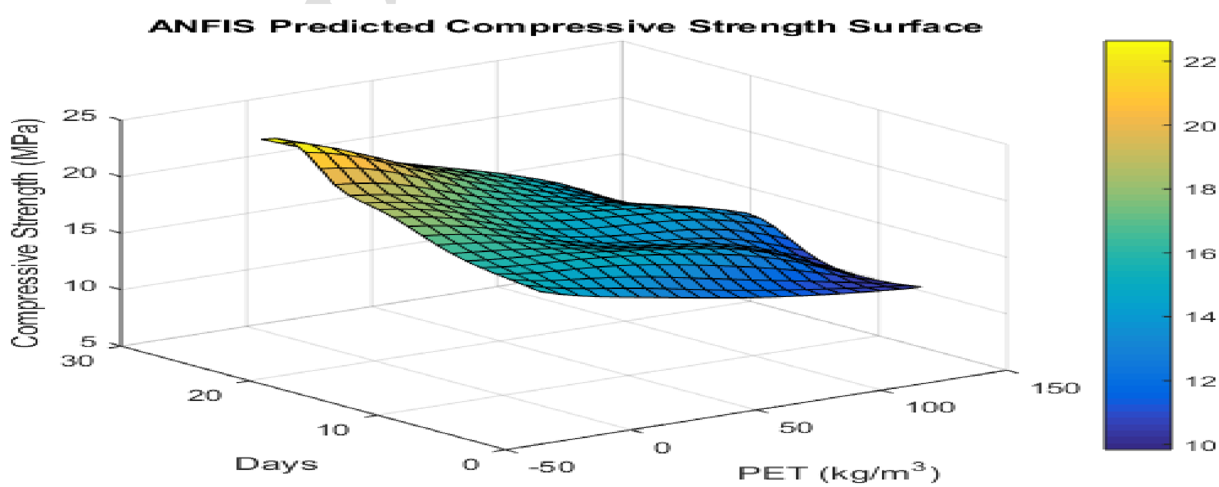


Figure 22 ANFIS predicted compressive strength surface

## 3.8 Performance comparison of the two models

Figure 23 and Table 7: Both ANFIS and ANN achieved near-identical high performance ($R^2 > 0.998$) with very low errors. Testing $R^2$: ANFIS 0.9990, ANN 0.9988. Both models generalize well for PET-modified concrete.

Table 7 Comparison of ANN and ANFIS Model Performance Metrics

| Metric | Dataset | ANN Value | ANFIS Value |
|---|---|---|---|
| R2 | Training | 0.9993 | 0.9997 |
| | Validation | 0.9992 | 0.9990 |
| | Testing | 0.9988 | 0.9990 |
| RMSE | Training | 0.1254 | 0.0853 |
| | Validation | 0.1442 | 0.1605 |
| | Testing | 0.1554 | 0.1423 |
| MSE | Training | 0.0157 | 0.0073 |
| | Validation | 0.0208 | 0.0258 |
| | Testing | 0.0242 | 0.0202 |
| MAE | Training | 0.0993 | 0.0667 |
| | Validation | 0.1130 | 0.1313 |
| | Testing | 0.1249 | 0.1083 |



### 3.8.1 Architectural and training comparison

ANN: feedforward, 10 neurons, trained 30 epochs, stopped by validation. ANFIS: Sugeno-type, 15 rules, 375 parameters, trained 100 epochs (parameters > training pairs).

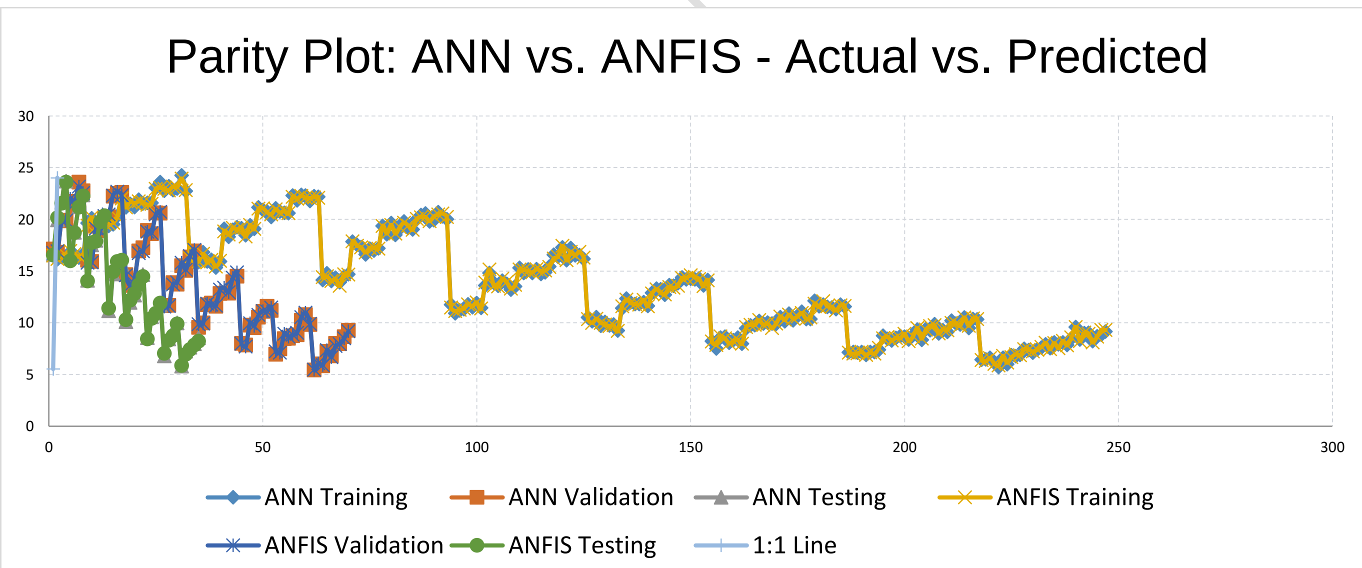


Figure 23 ANN and ANFIS model comparison

### *3.8.2 Model behavior and insights*

ANN shows consistent negative PET-strength correlation. ANFIS reveals non-linear relationship: strength initially increases with PET to an optimum, then declines, capturing more complex material behavior.

## 3.9 Real-world implementation and broader implications of the research

This study produced permeable concrete using PET waste as partial coarse aggregate replacement (0–20%). Higher PET content reduced compressive strength and permeability coefficient, but concrete remained suitable for pavements, sidewalks, parking lots, and stormwater management. A data augmentation technique using random noise in MATLAB expanded the limited dataset. This method benefits small-dataset fields like seismic analysis, audio processing, and medical imaging. Thus, PET-based permeable concrete is technically feasible and sustainable, supporting both construction and data science.

## 4.0 Conclusion

This study successfully demonstrated the technical and environmental viability of utilizing PET waste as a partial replacement for coarse aggregate in permeable concrete. A comprehensive analysis of the constituent materials confirmed their suitability, with tests conducted on Ordinary Portland Cement (OPC), coarse aggregate, fine aggregate, and PET waste. The experimental results quantitatively confirmed the influence of PET content on the mechanical and hydraulic properties of the concrete. As the volumetric replacement of PET waste increased from 0% to 20%, a clear inverse correlation with compressive strength was observed, with a maximum reduction of 62.3% at the highest replacement level, dropping from 23.1 N/mm² to 8.7 N/mm² at 28 days. Other key properties, such as the permeability coefficient and water absorption, also decreased with the addition of PET. For instance, the permeability coefficient decreased from 0.87 cm/s to 0.54 cm/s. These findings suggest that incorporating PET particles fills the internal voids and pores, making the concrete less porous but also weakening the interfacial transition zone. However, the mixes containing up to 10% PET waste maintained a satisfactory balance, exhibiting adequate compressive strength and permeability suitable for applications in pedestrian walkways, bicycle lanes, and other light-duty stormwater management infrastructure. The successful application of a data augmentation technique using MATLAB R2015a also proved to be an effective method for expanding the limited dataset from 32 to 352 points, thus providing a more comprehensive basis for analysis. The development and comparison of two predictive models, ANN and ANFIS, further reinforced the experimental findings, with both models demonstrating high accuracy ($R^2 > 0.9988$). Both models effectively captured the complex, non-linear relationship between PET content and compressive strength, confirming their utility in identifying the performance trends and optimal inclusion points for PET waste.

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## CRediT authorship contribution statement

EEE participated in carrying out the entire laboratory work. He wrote the introduction, results and discussions of compressive strength, statistical analysis, AI modeling and discussions while HOO supervised the entire laboratory work. He also wrote the abstract, methods, conclusion and reviewed past related works. All authors read and approved the final manuscript.

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## Conflicts of interest

The authors declare no conflict of interest.

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