

Original Article

# Predictive Modelling of High-Performance Recycled Aggregate Concrete using Artificial Neural Networks

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**Abstract** - The product of so many years of research that has now resulted in the incorporation of fibre reinforcement and other cementitious components to put Recycled Aggregate Concrete (RAC) to work is High-Performance Recycled Aggregate Concrete (HPRAC). Nevertheless, predicting the strength is complicated due to nonlinear relationships between the quantity of Recycled Aggregate, dosage of Calcined Kaolin Clay (CKC), the addition of Alkali-Resistant Glass Fibre (ARGF), and the age of curing. This paper creates an Artificial Neural Network (ANN) model using MATLAB®, which uses an experimental dataset of huge size ( $\approx 2,400$  data points) and 8 input parameters, trained to predict Compressive, Flexural, and Splitting Tensile Strengths. The accuracy of the prediction and generalization is validated by the ANN with Coefficients of Determination ( $R^2$ ) of more than 0.97 and Low Root Mean Square Error ( $RMSE < 2.0$  MPa) of all strength properties. Sensitivity analysis shows that the most important factor is curing age, followed by RCA content, CKC dosage, and ARGF addition. These findings indicate that through offering data-based decisions to implement recycled materials in high-performance uses, ANN-based modelling can significantly decrease experimental load, improve mix design to attain structural reliability, and promote sustainable concrete practices.

**Keywords** - Artificial Neural Network (ANN), High-Performance Recycled Aggregate Concrete (HPRAC), Mix Design Optimization, Strength Prediction, Sustainable Concrete.

## 1. Introduction

Concrete is the most common building material used in the world due to its strength in structure and versatility. However, for all its widespread use, it carries serious sustainability problems. Ordinary Portland Cement (OPC), which forms the bulk of the binder in concrete, uses huge reserves of natural aggregates and contributes to 5-8% of the yearly global CO<sub>2</sub> emissions. It hastens the expropriation of resources and environmental degradation [1, 2]. These factors have contributed to the growth of Recycled Aggregate Concrete (RAC), by which Construction and Demolition Waste (C&DW) is utilized to reduce landfill load and reduce the carbon emissions from commercial concrete production [3-5]. Despite these improvements in sustainability, RAC's structural applications are constrained by serious performance-based issues. Higher porosity, more water absorption, weaker interfacial transition zones (ITZ), and decreased mechanical strength in RAC mixtures are all frequently reported in studies [3, 6]. The causes of such inadequacies include old mortar stuck onto recycled aggregates, heterogeneities in the source material quality, which jeopardize the integrity and durability of the matrix. These disadvantages, which highlight how RAC's greater

porosity and weaker ITZ considerably lower compressive, tensile, and flexural strength when compared to standard concrete, have been extensively validated in recent research [7, 8]. Despite RAC's advantages for the environment, such performance drawbacks limit its employment in structural applications [9]. Due to the fact that RAC's mechanical properties are usually below a rigorous design specification, the usage of RAC for structural components is limited, and there are restrictions on environmental benefits [10].

Researchers explored ways to overcome these limitations, including Calcined Kaolin Clay (CKC) as a pozzolanic additive for improving pore structure and matrix densification, Alkali-Resistant Glass Fibers (ARGF) for crack bridging [11-19]. This has led to the new High-Performance Recycled Aggregate Concrete (HPRAC), which has become more rigid yet durable, and provides an additional degree of sustainability. Nonetheless, optimization of HPRAC mix designs is still a challenge caused by the robust nonlinear interplay of RCA content components, CKC dose, ARGF increase, and curing conditions, which makes standard empirical models inappropriate [20-24].



To overcome these issues, this study has created an Artificial Neural Network (ANN) structure that is trained on a large experimental dataset (over 2,000 data points) to make predictions regarding the compressive, flexural, and splitting tensile strengths of HPRAC. The proposed strategy aims to enhance optimization of mix designs, reduce the burden of experimentation, and promote sustainable building methods through accurate and data-based forecasts. Moreover, the experimental evaluation of each mix combination cannot be practiced as a technique because of the different types of recycled aggregates offered by the demolition suppliers, creating some levels of uncertainty. With no dependable predictive tool, optimizing mix designs for mechanical strength and durability in HPRAC is still challenging [20].

Despite progress in HPRAC experimental work, predictive modelling still has a significant gap [25]. Advanced modifiers (e.g., CKC and ARGF) are rarely used in contemporary ANN applications, as most of these applications focus on conventional RAC. In addition, most existing models face limitations for generalized approaches to diverse mix designs due to the fact that the datasets of many of the previous models are usually limited, and the input parameters are limited. This gap highlights the importance of a dependable data-driven method to foresee various HPRAC mechanical criteria and compound nonlinear interdependencies between RCA, CKC, ARGF, and the curing condition.

To close this gap, the present study develops ANN models that were trained using a vast experimental sample that can predict the compressive, tensile, and flexural strengths of HPRAC mixes. The structure and operation of the human brain, which is made up of layers of interconnected neurons that process inputs using weighted connections, served as the model for Artificial Neural Networks (ANNs). ANNs are also trained on an extensive amount of experimental data, and therefore, they are able to learn the underlying relationships between input parameters and the output responses; therefore, the accuracy in their prediction is high as opposed to many other models. They are specifically designed to forecast the mechanical and durability characteristics of the concrete system, with large datasets to be dealt with, the capability of adaptation to nonlinearities, and highly effective generalization skills.

The study is primarily aimed at evaluating the predictive ability of the ANN for the most significant HPRAC strength characteristics. Among the specific objectives are: (i) Building ANN architectures with suitable input and output parameters that represent mechanical properties and mix design variables; (ii) Training and validating the models using backpropagation algorithms optimized for convergence; (iii) Assessing the model performance using statistical sources (Root Mean Square Error (RMSE)) and coefficient of determination ( $R^2$ ); and (iv) Comparing the

ANN predictions with experimental results to determine accuracy and reliability.

The key area of the study is the mechanical strength properties of concrete, such as compressive strength, splitting tensile strength, and flexural strength, which are vital in the structural application of concrete. Even though they are significant, durability indices like permeability, chloride penetration, and sulphate resistance are not included in the main prediction framework developed here, while they are recognized as possible domains for further ANN-based modelling. Furthermore, the ANN models were built using controlled experiment datasets in a laboratory, and further validation will be needed to determine their generalization to field-scale variability. This study seeks to fill the open knowledge gaps that are evident in the literature review. First, while ANN has been used for the prediction of RAC, little research has been conducted for high-performance systems using fibre reinforcement and pozzolanic additives [26, 27].

In conclusion, this project at the interface of Artificial Intelligence (AI) uses in civil engineering and sustainable material development. It illustrates how ANN may be used as a prediction tool to optimize HPRAC's design and performance assessment, lowering experimental costs and promoting the wider use of sustainable building techniques. The results should offer useful advice for engineers looking to use recycled materials in high-performance structural applications as well as theoretical insights into data-driven modelling of complicated concrete systems [28].

Section 2 is a summary of prior research on RAC/HPRAC and AI-based prediction; Section 3 is the identification of the problem and research gap; Section 4 is methodology; Sections 5-7 are validation, results, and conclusion.

## **2. Literature Review**

### **2.1. RAC's Performance Challenges and Sustainability Drivers**

RAC is one of the circular methods of managing C&DW and reducing the embodied carbon. This is due to the fact that the manufacture of OPC and the extraction of virgin aggregates are the primary activities that contribute to the environmental footprint of the concrete. Nonetheless, due to the bonded aged mortar and source heterogeneity, RAC tends to exhibit higher porosity, higher water absorption, and reduced Interfacial Transition Zones (ITZ), leading to poorer mechanical performance than natural aggregate concrete. These new and hardened-state penalties are repeatedly confirmed by recent evaluations, which also highlight the necessity of materials/processing techniques that reduce ITZ flaws and heterogeneity while maintaining sustainability gains [29, 30].

## **2.2. The Contribution of Fibres and Other Cementitious Elements to High-Performance RAC**

Inherent constraints of RAC have been overcome by conducting experimental research on fibres and Supplementary Cementitious Materials (SCMs). Alkali-Resistant Glass Fibres (ARGF) have been proven to enhance crack-bridging and post-crack behaviour, leading to an increase in tensile and flexural performance due to distributions and dosing. Pozzolanic materials, such as Calcined Kaolin Clay (CKC), enhance the strength level and durability criteria by modifying pore structure and densifying the structure through secondary hydration. So, High-Performance RAC (HPRAC) is founded on the association of ARGF and CKC, where the performance loss caused by high recycled aggregate content is partially alleviated under the condition that mix design, curing, and fibre/matrix compatibility are optimized.

## **2.3. Empirical Regression to Artificial Intelligence in Concrete Predictive Modelling**

The inter-relationship between binders, aggregates, admixtures, fibers, and curing conditions is nonlinear and multivariate, and their representation is usually challenging for the conventional regression models, especially the modified or high-performance systems [31]. Thus, concrete family-specific AI methods are becoming a growing subject of interest in property prediction with a specific focus on Artificial Neural Networks (ANN), such as SVM, GP, CNN, and hybrid/meta-heuristic models. AI models are capable of reaching a high level of predictive accuracy with the right feature selection, normalization, regularization, and validation procedures, as shown by various studies. However, they warn against interpretability, limitations to extrapolation, and high-quality data curation and model management.

HPRAC experimentation has shown its viability, even though predicting its characteristics is a challenging problem. Due to the nonlinear nature of the interactions of multiple elements, e.g., RAC content, CKC dose, ARGF%, water-cement ratio, and curing age, conventional empirical models usually fail to account for this. Concrete's mechanical properties are highly nonlinear and alter a lot when the mix proportions change, especially when different pozzolans and fibres are added.

Therefore, deterministic models and empirical regression models generally find it tough to generalize across different datasets. Therefore, technologies, such as the ones that rely on AI, are increasingly popular in facilitating the modeling and prediction of the behaviour of complex material systems. ANNs have been of interest in civil engineering due to their ability to formidably predict with multivariate and nonlinear interactions without necessarily having a set of constitutive equations.

## **2.4. The Scope, Datasets, and Constraints of ANN And Related AI in Practice**

The application of ANN models to estimating concrete properties has grown significantly in the past decade. In order to ensure that the compressive strength of recycled aggregate concrete is predictable, Gao et al., Duan et al., and Zhou et al. [25-27] trained ANN models on more than 1000 datasets and found that training algorithms and network architecture greatly influence the accuracy of the prediction. A feedforward ANN model called a multi-layer perceptron is composed of neurons with many weighted connections that follow signals regularly along the output layer.

ANNs are computing systems inspired by research in neurology that mimic the neural network of the brain and determine correlations between inputs and outputs for data classification. There are three standard layers: the input layer, the hidden layer, and the output layer. The input layer provides the parameters to be used to either train or test the model. The output and input are connected by a hidden layer. The output layer contains the results of the model. A plurality of parallel neurons (nodes) within these layers is a part of the information processing system that is then interlinked with nodes above them in a weighted fashion. To obtain weighted connections, we compare the final values of ANN outputs with experimental values.

In the same vein, other researchers have predicted compressive, flexural, and tensile strength of various modified concretes through ANN, Convolutional Neural Networks (CNN), and hybrid AI models. These studies, in comparison to regression-based models, frequently reveal the extent of ANN in predicting the natural nonlinear behaviour of concrete. However, the predictive scope for high-performance mixes has been limited because a large portion of the prior work has concentrated on RAC without including sophisticated modifiers like CKC and ARGF [32]. The nonlinearity and intricacy of solutions to engineering problems have to be the actual force behind the popularity of ANNs, including bond strength prediction between concrete and FRP. However, the pre- and post-processing of the data involves a lot of work, including performance evaluation, output interpretation, and data selection. A further limitation of the ANN is that it does not extrapolate or yield new solutions for problems that fall outside the purview of the training data [33]. Also, practical implementations of trained neural networks in real-world scenarios might be difficult. In addition, it may overfit a training dataset, leading to a network with subpar performance [34].

Xi et al. [35] demonstrated high accuracy in modeling complicated geotechnical behavior by using a particle-swarm-optimized Artificial Neural Network (ANN) model to predict earthquake-induced landslide responses. Also, most of the previous research has used either simple input parameters or comparatively short datasets, making the

generalization capability of the models weak [36]. Many applications of AI are reported, including:

2.4.1. Predicting Strength in Modified Concrete

Artificial Neural Networks (ANN) or hybrid AI have been used to predict the compressive strength of high-performance mixes, including nano-silica/copper slag HPC, slag-based concretes, and geopolymer systems, often having very limited input space.

2.4.2. Learning Facilitated by Optimization

Although they have demonstrated improvements in accuracy for the RAC compressive strength, optimization-based networks (such as cascade forward or meta-heuristic adjusted models) usually have a limited scope (one attribute, few modifiers) [27].

2.4.3. Durability and Multiple Applications

Recent perspectives by RILEM TC 315-DCS and others

are focused on standardized procedures and more comprehensive data to boost the transferability as well as the opportunities and challenges of the generalization to durability predictions [20].

2.4.4. Methodological Direction

Limitations of prior work include: (i) Prediction of compressive properties only, not simultaneous multi-property prediction; (ii) Small industries or restricted mix variable combinations; and (iii) Scarcity of the fiber + SCM synergies (e.g., ARGF with CKC) necessary to HPRAC.

Similar challenges of overfitting, protocols under stress, cautious data splitting, early halting, and residual diagnostics motivate a more comprehensive, data-driven predictive approach with a specifically designed ANN architecture for HPRAC. Common AI-driven prediction research and their scope and limitations are presented in Table 1.

Table 1. Summary of typical AI-based prediction studies in concrete, highlighting material systems, model types, input/output scope, and limitations compared to the present study

Study	Material System	Model Type	Typical Inputs	Outputs	Scope / Dataset Notes	Reported Limitations
Chithra et al. (2016)	HPC (nano-silica, Cu slag)	ANN vs. regression	Mix + SCMs	fc	HPC focus	No recycled aggregates/fibres
Amiri & Hatami (2022)	Slag & RAC blends	ANN	Mix + slag, RAC%	fc, durability	Multi-output; limited fiber use	Fiber effects are not modelled
Zhou et al. (2024)	RAC	Optimized ANN (cascade)	RAC%, w/c	fc	RAC-centric	Single output; no fibre/CKC
Duan (2024)	RAC	KNN + meta-heuristics	Mix + RAC	fc	RAC	Algorithmic focus; narrow output set
Kumar et al. (2025)	HPC & UHPC (review)	Soft computing review	—	—	Synthesis	Calls for larger, richer datasets
RILEM TC 315-DCS (2025)	Durability ML (position)	ML perspectives	—	—	Domain guidance	Stresses standardization & generalization
<b>Present study</b>	<b>HPRAC (RCA + CKC + ARGF)</b>	<b>ANN (MLP, LM)</b>	<b>8 inputs incl. CKC, ARGF, w/c (constant at 0.37 and retained for portability), age</b>	<b>fc, ft-split, ff</b>	<b>≈2,400 points (exp.), broad ranges</b>	<b>Targets fibre +SCM synergy; multi-output; generalization checks</b>

Abbreviations: **fc** = compressive strength; **ff** = flexural strength; **ft-split** = splitting tensile strength; RAC = recycled aggregate concrete; HPRAC = high-performance RAC; SCMs = supplementary cementitious materials.

2.5. The Current Study's Positioning

Continuing on the above, the present study develops an ANN to simultaneously forecast compressive, flexural strengths, and splitting tensile based on large, experimentally derived HPRAC data (≈2,400 data points) containing ten input features (cement, water, aggregates, CKC, ARGF, SP, w/c, and curing age). The model targets the coupled mechanisms (crack-bridging and matrix densification) that

control HPRAC performance by explicitly integrating ARGF and CKC [37]. To enhance the level of generality and interpretability, the framework follows the recommended modeling guidelines (normalization, stratified splitting, early stopping, residual analyses). This approach creates a comprehensive predictive tool for mix design optimization in HPRAC [38-43] and directly tackles recurring problems in the literature (Sections 2.3–2.4).

### 3. Research Gap and Problem Statement

Based on the synthesis in Section 2, there is a gap that remains persistent: existing AI models of RAC frequently predict one mechanical feature, use small datasets, and rarely take fibre-SCM synergies critical to HPRAC. As a result, we formulate the following issue. Alkali-Resistant Glass Fibre (ARGF), Calcined Kaolin Clay (CKC), and Recycled Coarse Aggregates (RCA) are combined to create high-performance recycled aggregate concrete (HPRAC), a sustainable substitute for traditional concrete [44]. While experimental studies showed that these developments can mitigate the intrinsic disadvantages of RAC, forecasting the mechanical properties of HPRAC is still challenging [45]. The RCA replacement level, CKC dosage, ARGF concentration, mix proportions, curing circumstances, and age are some of the factors that interact nonlinearly to influence the performance of such concrete [46].

Past studies of AI, summarized in Sections 2.3-2.4, are mostly compressive-only, with few modifiers, and tiny datasets. Consequently, none of the HPRAC-specific frameworks of predictions explicitly involves CKC and ARGF in different RCA contents and, at the same time, is capable of modelling fc, ff, and ft-split. Nevertheless, these models produce poor or erroneous predictions because they are unable to adequately represent the multivariable and nonlinear characteristics of HPRAC systems. For example, it is difficult to generalize the combined impact of CKC and ARGF on the interfacial transition zone using standard regression techniques, and predictive modeling becomes significantly more challenging due to the unpredictability of recycled aggregates.

Few studies have specifically used Artificial Neural Networks (ANNs) for HPRAC that includes both fibre reinforcement and pozzolanic additives, despite the fact that ANNs have shown good predictive capacity in other concrete applications [47-52]. The larger performance spectrum of high-performance mixes is often overlooked by existing ANN studies on recycled aggregate concrete, which usually depend on datasets restricted to compressive strength or a short range of mix variables [53]. Therefore, there is a glaring research need in creating ANN models that simultaneously predict several mechanical properties of HPRAC while taking into account a wide range of mix factors [54].

ANN models trained on a large experimental dataset of approximately 2400 test results produced from HPRAC mixes combining RCA, CKC, and ARGF are being built in this study in an effort to close that gap. Ten essential input factors were chosen, including cement, water, natural and recycled aggregates, CKC, ARGF, superplasticizer, water-cement ratio, and curing age. These outputs were compressive, tensile, and flexural strengths. Overfitting and interpretability are addressed in the modelling process by

using normalization approaches, structured data splitting into training, validation, and testing subsets, and rigorous error and regression analysis. The resultant ANN models provide valuable prediction data to evaluate the mechanical performance of HPRAC, minimising experimental test periods and helping in the formulation of more structurally sound and environmentally friendly concrete mixes.

### 4. Methodology

The prediction framework employed in this study was developed and validated in a systematic way, and the process was initiated by the collection of experimental data. The generated models were guaranteed to be statistically valid and data-driven by means of this approach.

#### 4.1. ANN Implementation using Simulink in MATLAB

A graphical environment for creating and Training Multi-Layer Perceptron (MLP) architectures is provided by MATLAB R2023a Simulink Neural Network Toolbox, which was the basis of the predictive modelling. The procedure entailed:

##### 4.1.1. Model Architecture Setup

Using the Neural Network block set, a feedforward ANN with an L8-10-10-10 topology was set up in Simulink. In line with high-accuracy regression tasks, the Levenberg-Marquardt backpropagation algorithm and activation functions (purelin for output and tansig for hidden layers) were chosen for training.

##### 4.1.2. Data Preparation and Upload

Microsoft Excel was used to compile the 2,400 entries that made up the experimental dataset, which covered aggregate characteristics, target strengths, cement, water, superplasticizer, RCA%, CKC%, and ARGF%. The CSV file was then exported. To import this file into MATLAB, we took the readable functionality. We then normalised it and divided it into three sets: training (70%), validation (15%), and testing (15%). Processed data were connected to the Simulink ANN block in From Workspace and To Workspace blocks for efficient simulation and performance tracking.

##### 4.1.3. Training and Validation

An early halting was performed based on the performance of validation, and the model was trained iteratively. Mean Squared Error (MSE) and regression plots were observed to converge in the training process through real-time visualisation tools with the aid of Simulink. The major reason why we selected MATLAB(r)/Simulink(r) is that it supports the most sophisticated Levenberg-Marquardt (LM) algorithm and integrated dataflow visualization capabilities, and unifies training diagnostics (MSE traces, regression plots, and error histograms) that help to choose models and control overfitting. Moreover, the environment simplifies repeatability and auditability, which are needed to ensure reliable engineering prediction tools (saved sessions, block parameters).

## 4.2. Data Source

An extended experimental program on High-Performance Recycled Aggregate Concrete (HPRAC) provided the dataset utilized for ANN modelling. The program involved inclusion of Alkali-Resistant Glass Fibre (ARGF) of 0-1.5% of cement weight, the use of Calcined Kaolin Clay (CKC) in place of regular Portland cement of up to 15 percent, and the use of coarse aggregates such as RCA in place of natural coarse aggregates at a ratio between 0 and 100 percent. The admixture was high-range water-reducing and was used to control the workability, and the water-cement ratio was maintained at 0.37. Considering various curing ages allowed us to obtain nearly 2400 valid data points in compressive, flexural, and tensile strength testing. The dataset used in ANN modelling was a comprehensive experimental program on HPRAC. The program adopted a full-factorial format that used three important factors keeping the water-binder ratio constant ( $w/b = 0.37$ ): the dosage of Alkali-Resistant Glass Fiber (ARGF) (0–1.5%), the substitution of Calcined Kaolin Clay (CKC) (0–15%), and the replacement of Recycled Coarse Aggregate (RCA) (0–100%). This produced 80 distinct mix combinations tested at multiple curing ages. Mechanical properties were determined in standard specimens: compressive strength (7, 28, 56, 91 days) using 150 mm cubes, splitting tensile strength (28, 56, 91 days) using 100 x 200 mm cylinders, and flexural strength (28, 56, 91 days) using 100 x 100 x 500 mm prisms. Each age and property was measured in three duplicates. After being demolded after a day, the specimens were water-cured at  $20 \pm 2$  °C. Every test met the requirements of BS 1881-121 and the BS EN 12390 series. The final dataset consisted of about 2,400 observations that maintained the variability by not averaging the values but by an individual replicate. Ten outputs that indicate multi-age (Compressive strength (fc): 4 ages at 7, 28, 56, 91 days; Flexural strength (ff): 3 ages at 28, 56, 91 days; Splitting tensile strength (ft, split): 3 ages at 28, 56, 91 days) strength prediction and eight input descriptors (cement, water, NCA, RCA, NFA, CKC, ARGF, SP) are included in each record. Water-to-cement ratio was maintained as an input parameter to portability of future datasets, but it was maintained at the same level, whereby it was 0.37. To maintain the range of prediction of mechanical strength, durability indicators (sorptivity, chloride ingress, and sulphate resistance) were measured in the experimental campaign but excluded from the ANN framework.

### 4.2.1. QA/QC and Standards Compliance

For specimen shape, stress, and age, all strength tests adhered to BS EN 12390-3, -5, -6, and BS 1881-121 [55, 56]. Aggregates were conditioned to SSD; a predetermined mix was made (dry blend  $\rightarrow$  ~80% water  $\rightarrow$  binders  $\rightarrow$  remaining water + SP  $\rightarrow$  ARGF). Then they were allowed to cure in water at  $20 \pm 2$  °C. To guarantee consistency throughout approximately 2,400 observations, outlier tests came before ANN preprocessing.

## 4.3. Input and Output Parameters

Ten input variables were shown to be crucial for predictive modelling:

- Cement content ( $\text{kg}/\text{m}^3$ )
- Water content ( $\text{kg}/\text{m}^3$ )
- Natural coarse aggregate ( $\text{kg}/\text{m}^3$ )
- Recycled coarse aggregate ( $\text{kg}/\text{m}^3$ )
- Fine aggregate ( $\text{kg}/\text{m}^3$ )
- CKC replacement level of cement (%)
- ARGF dosage (% of cement weight)
- Superplasticiser dosage (%)
- Water-cement ratio (remained constant at 0.37 in this dataset; kept to make it portable to other datasets in the future)
- Curing age (days)

### 4.3.1. Rationale for the Chosen Input Features

The ten input variables were chosen to ensure that transferability to close mix spaces was possible and to capture the regulating processes of strength development in HPRAC at low  $w/b$  conditions:

- The main binder that regulates paste volume and clinker hydration products is cement ( $\text{kg}/\text{m}^3$ ), which has a high correlation with both early and later age strengths.
- Water ( $\text{kg}/\text{m}^3$ ), a major factor influencing strength and variability, regulates effective  $w/b$ , capillary porosity, and degree of hydration when combined with binder content.
- Natural coarse aggregate, or NCA ( $\text{kg}/\text{m}^3$ ), affects elastic response, crack path tortuosity, and skeletal stiffness.
- Recycled coarse aggregate, or RCA ( $\text{kg}/\text{m}^3$ ), is a crucial sustainability lever that influences ITZ quality, porosity, and water demand because of adherent mortar and increased absorption; if left unchecked, it is known to reduce strength.
- Natural fine aggregate, or NFA ( $\text{kg}/\text{m}^3$ ), influences rheology, packing density, and paste demand, which in turn affects dispersion and microcracking.
- CKC (% of cement): shown in the experimental program to reduce RCA penalties, this highly reactive Class F pozzolan (metakaolin) consumes portlandite and densifies the matrix/ITZ via secondary C (A) S H, enhancing later age strength and stiffness.
- ARGF (% of cement mass) is a discrete fibre reinforcement that interacts with matrix density and fibre dispersion at low  $w/b$ , bridges cracks, and improves tensile/flexural performance and post-peak behaviour.
- Superplasticizer, SP (%): PCE-based HRWR is necessary to attain a practical rheology at  $w/b = 0.37$ , allowing for uniform aggregate and fibre dispersion and lowering scatter caused by defects.
- Water-to-cement ratio ( $w/c$ ), a conventional predictor of capillary porosity and strength, is added to improve the

portability of the model to those datasets with varying w/c. Since w/c is kept constant at 0.37, it mostly contributes to intercept calibration rather than variance.

- Curing age (days) is a key component that captures hydration/maturity effects; age is consistently found to be the most significant predictor across outputs in both the experimental and ANN sensitivity analyses.

These choices represent both practical design variables employed by engineers and mechanistic importance (skeleton effects via aggregates, matrix densification via CKC, crack kinematics by ARGF). Particularly for tensile and flexural responses, the companion experimental investigation reveals that CKC (10–15%) and ARGF ( $\approx 0.5$ –1.0%) partially balance strength losses at greater RCA contents—relationships the ANN learns and reproduces in predictive mode. Compressive strength, splitting tensile strength, and flexural strength are the three key mechanical strength indices that allow predicting strength in multi-age (Compressive strength (fc): 4 ages at 7, 28, 56, 91 days; Flexural strength (ff): 3 ages at 28, 56, 91 days; Splitting tensile strength (ft, split): 3 ages at 28, 56, 91 days)—were the results of the ANN models. Table 2 displays this thorough architecture of inputs and outputs.

**4.4. ANN Architecture**

The compressive strength (fc) at 7, 28, 56, and 91 days, flexural strength (ff) at 28, 56, and 91 days, and the splitting tensile strength (ft split) were predicted using the ANN at 28, 56, and 91 days. The initialisation of the ANN occurred as a feedforward multi-layer perceptron with 8 input neurons, 10 neurons in the two hidden layers, and 10 neurons in the output layer to estimate multi-age strength. The Artificial Neural Network’s structural data flow for this arrangement is (L8 10 10) as illustrated in Figure 1. The output layer applies a linear (purelin) function for real-valued predictions, whereas hidden layers employ the tangent sigmoid (tansig) activation function. After inference, inputs and outputs were inverted, mapped, and normalized to [0,1]. Levenberg-Marquardt [57] backpropagation with early stopping was used for training on a 70/15/15 train/validation/test split, which was chosen for quick convergence and low RMSE.

Neuron count sweeps were used to define the final topology in order to balance generalization and precision. Using a block diagram approach with real-time training monitors and regression plots to guarantee reproducibility and adherence to suggested ANN protocols, the model was created in MATLAB® Neural Network Toolbox within Simulink®. The network takes input to the network and sums them with weighting, and it occurs in a nonlinear manner within the hidden layers and projects in a linear manner to the output layer. Single hidden neuron j net input is:

$$net_j = \sum_{i=1}^n w_{ji} x_i + b_j, \tag{1}$$

Where  $x_i$  are the (possibly normalized) inputs,  $w_{ji}$  are the weights of input  $i$  to neuron  $j$ , and  $b_j$  is the bias term. The hidden neurons employ the tangent-sigmoid (tansig) activation, which can be written equivalently as the hyperbolic tangent or in the logistic form:

$$\phi(net) = \tanh(net) = \frac{e^{net} - e^{-net}}{e^{net} + e^{-net}} = \frac{2}{1 + e^{-2net}} - 1 \tag{2}$$

The derivative that backpropagation requires is:

$$\phi'(net) = 1 - (\phi(net))^2 \tag{3}$$

The linear (purelin) activation used by the output neurons is:

$$\psi(net) = (net) \tag{4}$$

With derivate

$$\psi'(net) = 1 \tag{5}$$

Thus, without range clipping, the network generates continuous real-valued predictions (strength in N/mm<sup>2</sup>). For a single hidden layer, the forward pass in compact vector form is:

$$h = \phi(W^{(1)}x + b^{(1)}) \tag{6}$$

$$y = W^{(2)}h + b^{(2)} \tag{7}$$

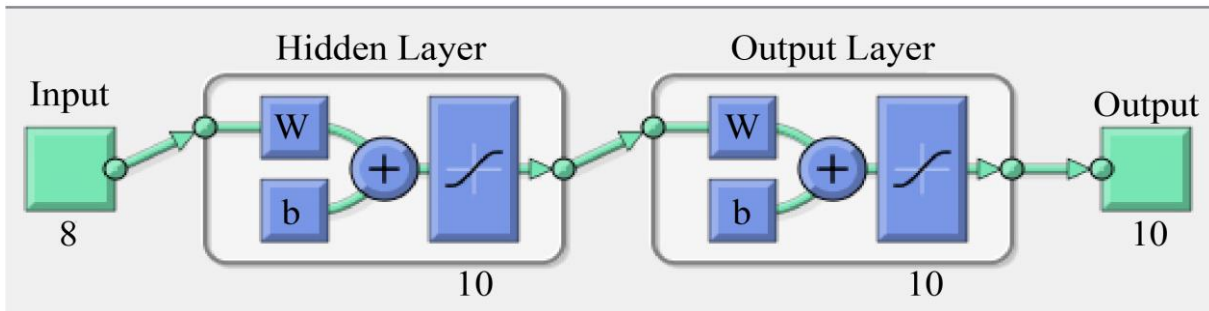
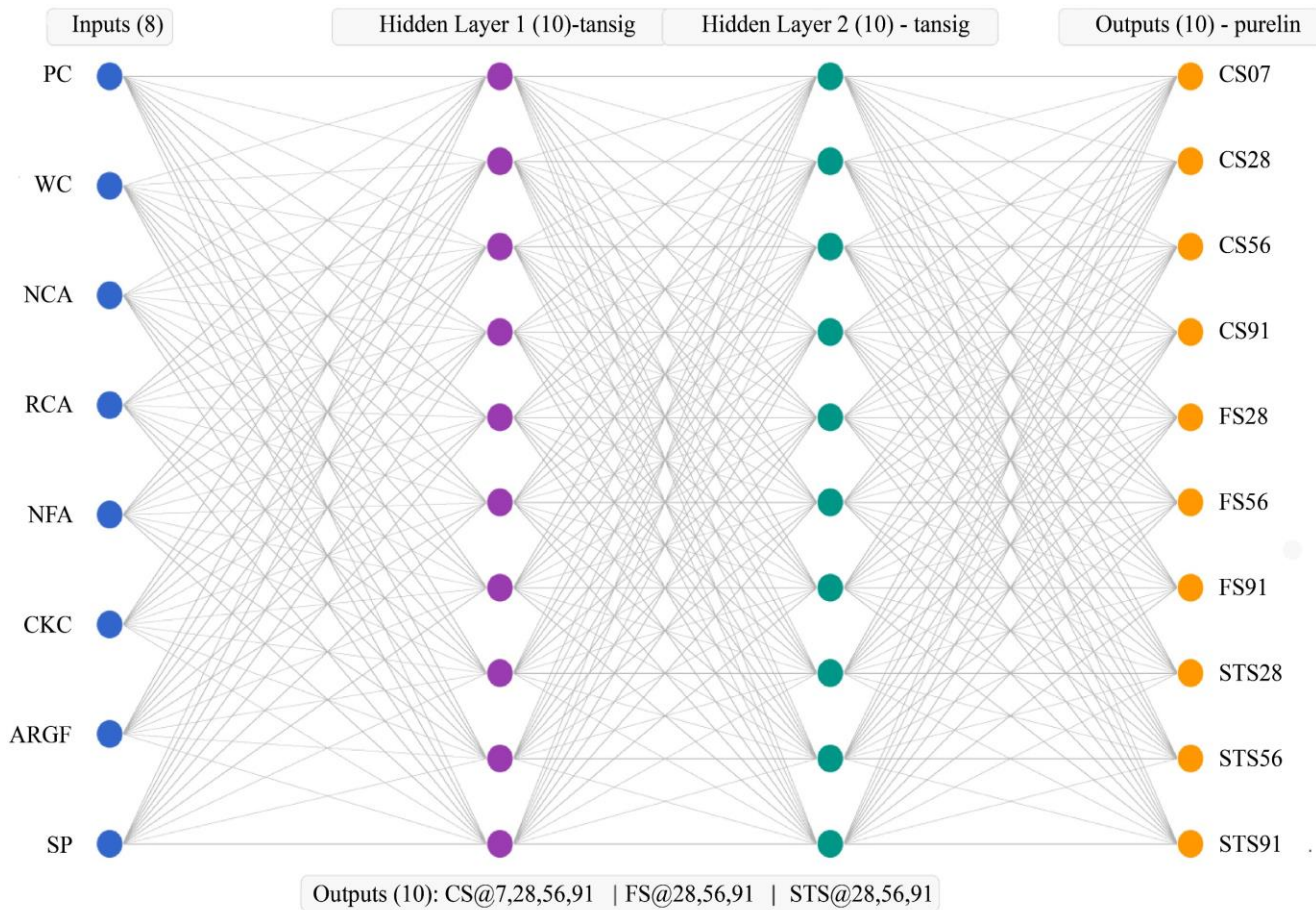


Fig. 1 ANN model structural data flow (L8-10-10 topology) with eight input neurons, two sets of 10 hidden layers, and ten output neurons in multiple age strength prediction

**Table 2.** ANN input and output parameter statistical descriptors, such as ranges, averages, and variability, are used to normalize the data set

Category	Parameter	Description	Minimum	Maximum	Average	Std. Deviation	Variance
Inputs	WC	Water content (kg/m <sup>3</sup> )	160	210	185.0	14.43	208.33
	PC	Cement (kg/m <sup>3</sup> )	350	450	400.0	28.87	833.33
	NFA	Natural fine aggregate (kg/m <sup>3</sup> )	650	820	735.0	49.07	2408.33
	NCA	Natural coarse aggregate (kg/m <sup>3</sup> )	400	1000	700.0	173.21	30000.00
	RAC	Recycled coarse aggregate (kg/m <sup>3</sup> )	0	1000	500.0	288.68	83333.33
	ARGF	Alkali-resistant glass fibre (% of cement weight)	0	1.5	0.75	0.43	0.19
	CKC	Calcined kaolin clay (% replacement of cement)	0	15	7.5	4.33	18.75
	SP	Superplasticiser dosage (%)	0.5	2.0	1.25	0.43	0.19
Outputs	CS	Compressive strength (N/mm <sup>2</sup> ) at 7, 28, 56, 91 days	20	80	50.0	17.32	300.00
	FS	Flexural strength (N/mm <sup>2</sup> ) at 28, 56, 91 days	3	9	6.0	1.73	3.00
	STS	Splitting tensile strength (N/mm <sup>2</sup> ) at 28, 56, 91 days	2	6	4.0	1.15	1.33



Activations: tansig (hidden), purelin (output) • Normalization: min-max [0,1] • Training: LM (70/15/15, early stopping)

**Fig. 2** Detailed ANN architecture of the input layer, hidden layers, and output layer to predict compressive, flexural, and splitting tensile strengths

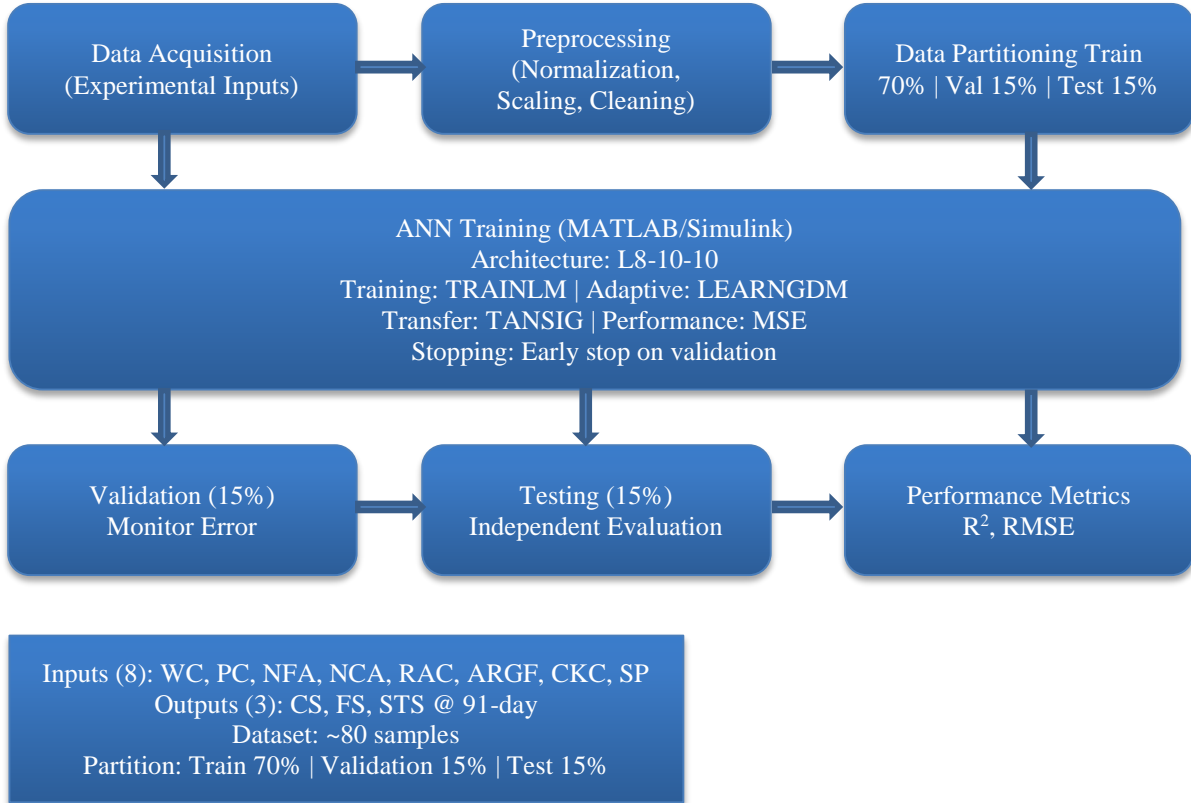


Fig. 3 ANN model development workflow, such as data preprocessing, training, data collection, validation, and performance analysis.

$W^{(1)}$  and  $W^{(2)}$  are the weight matrices of the input-hidden and hidden- output layers, respectively. These bias vectors are  $b^{(1)}$  and  $b^{(2)}$ , and elementwise tansig is  $\phi(\cdot)$ . The output vector that is predicted is  $y = [CS, FS, STS]^T$ . Since the training normalized inputs and outputs, the preprocessing min-max scaling is:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (8)$$

Moreover, the reverse mapping, which is used to retrieve engineering units following a prediction, is:

$$y^{\wedge} = y'(y_{max} - y_{min}) + y_{min}. \quad (9)$$

The network can learn the intricate relationships between RCA, CKC, ARGF, mix proportions, and curing age while generating physically relevant strength values thanks to this combination of purelin in the output for real-valued predictions and tansig in the hidden layers for nonlinear mapping. During training, the Levenberg-Marquardt backpropagation updates make use of the aforementioned basic closed-form derivatives.

#### 4.5. Training Algorithm and Data Partitioning

To train the model, we used the Levenberg-Marquardt (LM) backpropagation algorithm, which is known to

converge quickly and is used in nonlinear regression. To deal with the scale effects and speed up the learning, we scaled down the dataset to the range 0 to 1.

The dataset was divided into three random groups; 70% of them were used as a training set, 15% were used as a validation set, and the 15% as a test set to enhance the generalization process and reduce overfitting. For this, Figure 3 summarizes the steps throughout ANN model development from data collection, preprocessing, model training, to validation and performance assessment.

#### 4.6. Model Performance Evaluation

ANN models were assessed both through statistical indices and graphical analysis. The key measure was the coefficient of determination ( $R^2$ ), which is a measure of the relationship between the anticipated and actual value. The extent of error was measured in terms of Root Mean Square Error (RMSE). The Mean Absolute Error (MAE) was also used to determine the average deviation.

Furthermore, alignment of predictions with experimental results was examined using regression plots (Figures 4-6), and the residual distribution was elucidated using error histograms (Figure 7). The LM algorithm's smooth convergence was further validated by training state graphs [58].

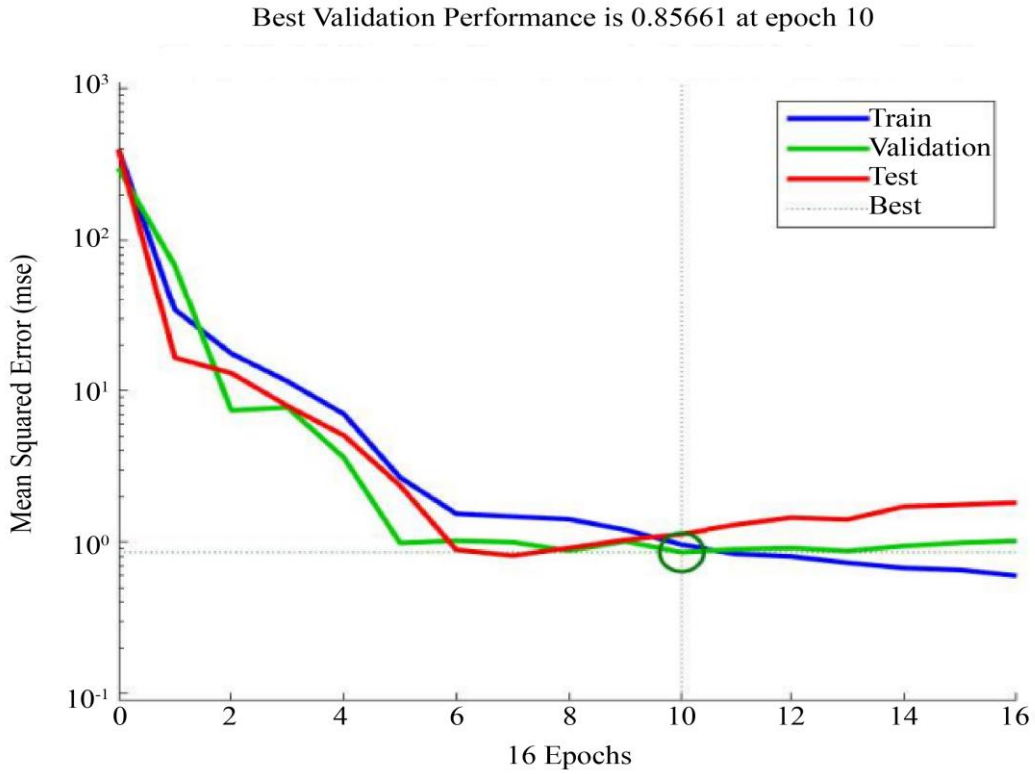


Fig. 4 Regression plots of ANN prediction accuracy of training and test datasets, which indicate the existence of a strong correlation between experimental and predicted values ( $R^2 > 0.97$ )

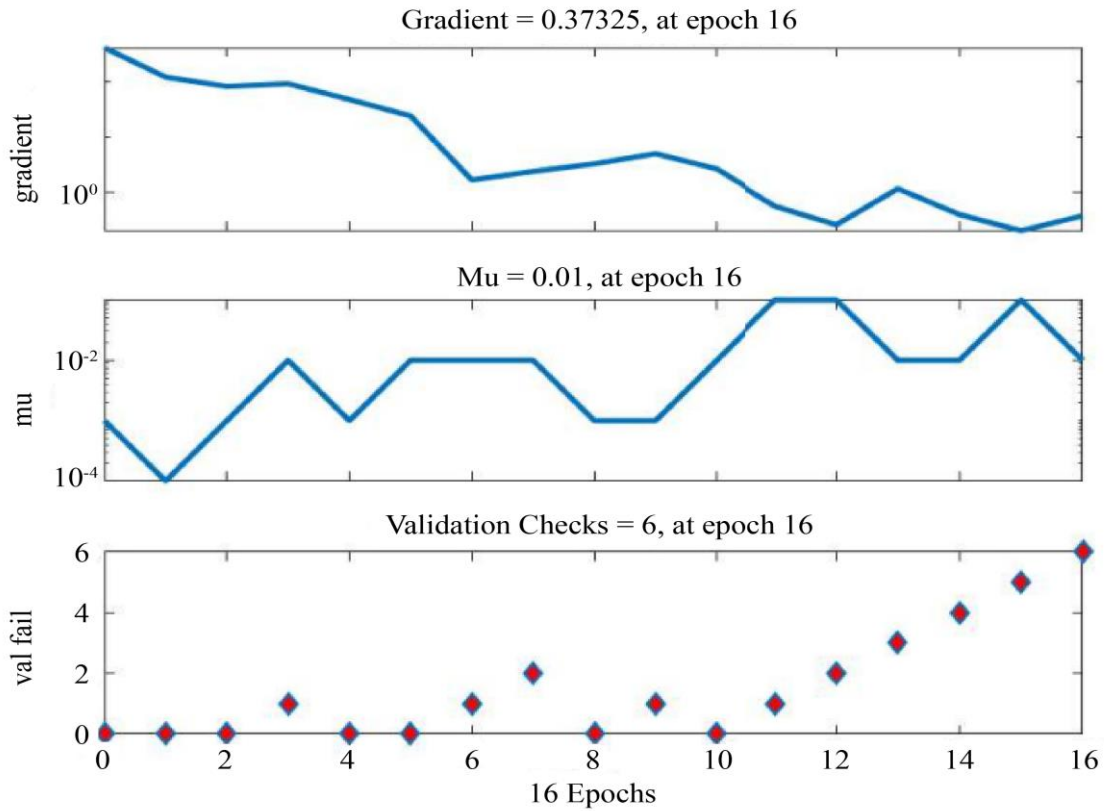


Fig. 5. Training state graph that represents Mean Square Error (MSE) convergence in ANN training based on the Levenberg-Marquardt algorithm

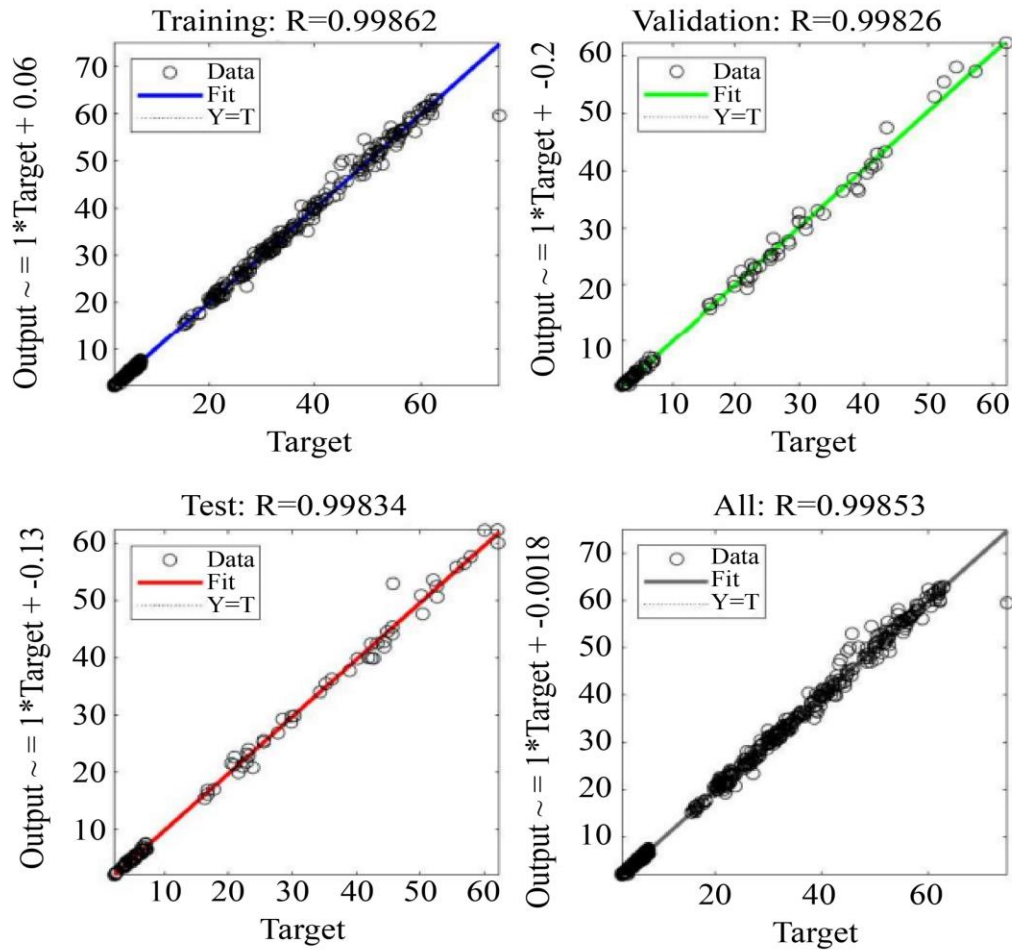


Fig. 6. Comparison of experimental and predicted values of training, validation, and testing subsets that show high generalization capability

The methodology ensured that the models were correct and generalizable by integrating a large experimental dataset with strong ANN modelling procedures [59]. A solid foundation for employing ANN as a predictive tool for HPRAC mechanical performance is established by the integration of numerous input factors and thorough validation checks.

### 5. Validation of the ANN model

The constructed ANN models were tested and evaluated through a set of graphical evaluation tools and numerical performance indices to check the models' accuracy, generalization, and robustness. The predictive power of ANN was measured by  $R^2$ , MAE, and RMSE. In the models, all three mechanical properties, including compressive, splitting tensile, and flexural strengths, had  $R^2$  values exceeding 0.97. Low corresponding MAE and RMSE values showed minimal variation and a great connection between the observed and anticipated values. The ANN framework's dependability in simulating the nonlinear interactions present in High-Performance Recycled Aggregate Concrete (HPRAC) is thus

confirmed. Figures 4–7 display representative regression plots. For training, validation, and test data, the expected values are presented by these graphs along with the corresponding experimental measurements. The ANN models generalized well beyond the training data, as we observed the regression lines sticking closely to the line of equality and slopes near unity. Predictive performance on unknown data was preserved, and overfitting was prevented by using the same models among the subsets [60]. Figure 8 shows the Correlation of data validation of experimental and predicted values. The error histogram shows the residual distribution (Figure 7). The number of errors is close to zero, with only a few outliers representing it, indicating that the prediction mistakes have been symmetrically distributed and on a smaller scale [61]. Such clustering further supports the ANN models' prediction power and shows how stable they are. Performance curves, which showed how Mean Squared Error (MSE) changed throughout training epochs, were used to evaluate training convergence. The validation curves did not deviate from the training curves, and the charts display a smooth, oscillation-free fall in MSE. This indicates that an effective learning technique (Levenberg–Marquardt) was

selected and that overfitting was averted efficiently by the data segmentation technique [62]. Summarily, the validation procedure attests to the accuracy, resilience, and dependability of the ANN models created in this investigation. ANN framework offers an appropriate fit in

predicting compressive, flexural, and tensile strengths of HPRAC as indicated by the high  $R^2$ , low error magnitudes, positive regression trends, and consistent convergence in training. This is a great starting point for further discussions of results and implications.

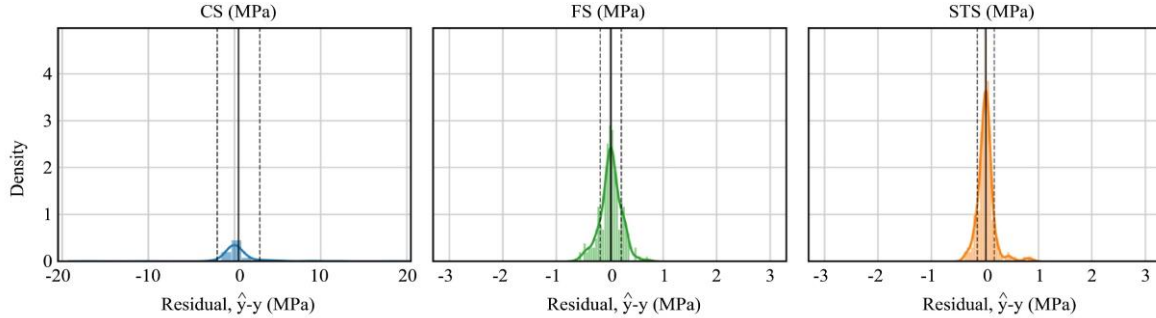


Fig. 7 Error histogram indicating residual distribution clustered around zero, indicating minimal prediction bias and strong model accuracy

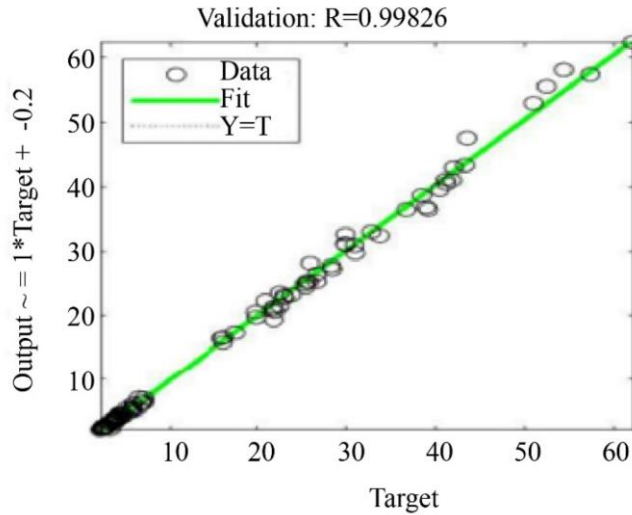


Fig. 8. Correlation of predicted and experimental values of the validation dataset, to validate ANN reliability on unseen data

## 6. Results and Discussion

Mechanical strength parameter of HPRAC was guessed using the ANN models that were developed in this work. This was compared to the outcomes of the lab program. The discussion largely revolves around the three categories of strength: compressive, flexural, and splitting tensile. It continues to demonstrate the impacts of the significant input factors on the anticipated outcomes.

### 6.1. Mechanical Strength Predictions

Values of compressive strength of different combinations of RCA, CKC, and ARGF match the expected results. Across all curing ages and mix proportions, the ANN predictions and the experimental results showed excellent agreement. Figure 9 shows representative comparisons, where projected values closely match experimental patterns. This excellent performance was validated by statistical analysis, which showed that the ANN's coefficients of

determination ( $R^2$ ) for compressive strength were more than 0.98 and that the RMSE values showed very little variation from the measured values. These findings confirm that the model can accurately represent the nonlinear relationships among RCA content, fibre reinforcement, pozzolanic substitution, and curing age. The predictions on the splitting tensile strength of the ANNs were once again confirmed, as shown in Figure 10, along with the testing results. The ANN-based models consistently gave  $R^2 > 0.96$ , while tensile strength typically is more variable due to microcracking and heterogeneity of the interfacial transition zone. This high level of predicted performance also demonstrates that the ANN can endure an intrinsic scatter of tensile strength data. This model appropriately considered how ARGF enhances the crack-bridging performance and how CKC fine-tunes the matrix. Similarly, in Figure 11, the prediction of the flexural strength, with more than 0.95 correlation values, was observed with high accuracy. Flexural strength also has

excellent correlation strength to fibre dose, and such a nonlinear relationship is captured well by ANN. As observed, the CKC-induced densification and ARGF-induced crack management combined reinforcement mechanisms were learned successfully by the network.

**6.2. Comparison with Existing Literature**

Compared to the above models of ANN-based models of RAC and HPC, which generally show  $R^2$  values between 0.85 and 0.95 to predict compressive strength (Gao et al., and Chithra et al.), the estimated accuracy obtained in this paper ( $R^2 > 0.97$ ,  $RMSE < 2$  MPa) is beneficial. Unlike previous works, the present work relies on roughly 2,400 points of data to compute compressive, splitting tensile, and flexural strengths at the same time and includes CKC and ARGF modifiers that were rarely taken into account in prior models. The more comprehensive domain in sustainable mix design optimization allows for greater generalization and applicability (see Table 4).

There are a number of reasons why the suggested ANN model performs better than state-of-the-art methods ( $R^2 > 0.97$ ,  $RMSE < 2$  MPa). First, despite the fact that previous studies often used smaller datasets (<1,000 points) with low variable diversity, the application of a large, internally generated dataset ( $\approx 2,400$  points) with large ranges of RCA, CKC, and ARGF gave greater learning and reduced bias. Second, the model allowed consideration of the synergistic effects that have a significant influence on mechanical properties by adding CKC and ARGF as input factors, which were not considered in the earlier ANN frameworks. Third, a multi-output model offers an advantage over single-output

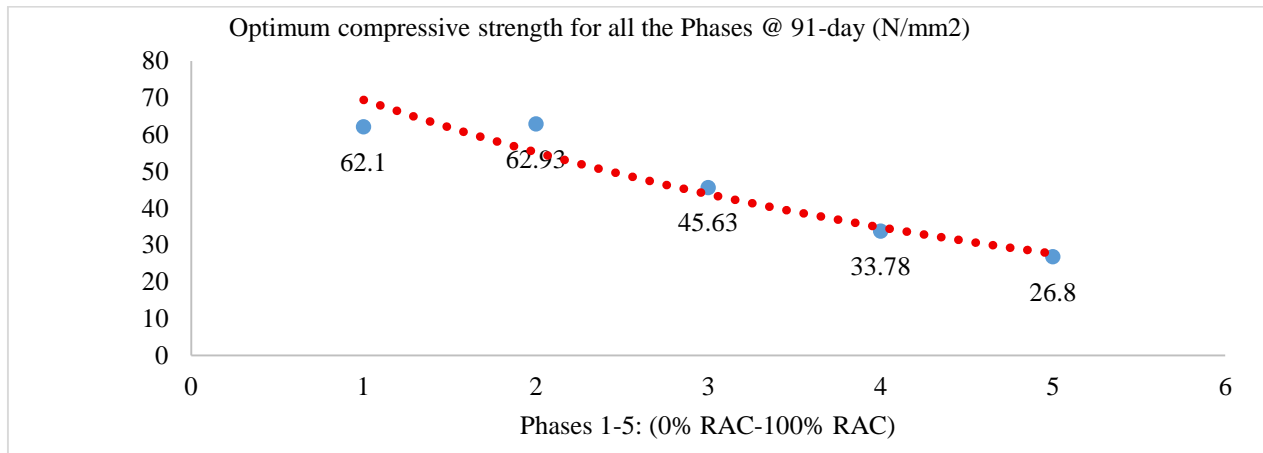
approaches when it comes to efficiency and consistency, because the compressive, flexural, and splitting tensile strengths can be predicted concurrently. Finally, the Levenberg-Marquardt algorithm with strong training guidelines (normalization, stratified data splitting, and early stopping) assisted in providing fast convergence and reduced error. The improved prediction accuracy and generalization observed in this investigation can clearly be accounted for by these methodological improvements when taken together.

**6.3. Error and Performance Trends**

The ANN-predicted and experimental values consistently agree throughout training, validation, and testing subsets, as shown by the regression plot (Figure 12). The trustworthiness of the forecasts is further supported by error histograms (Figure 13), which show that residuals were symmetrically distributed about zero with the majority of errors confined within small bands. This suggests little bias and reliable results across samples.

**6.4. The Impact of Significant Variables**

The ANN-generated response surfaces (Figures 14-15) were used to see the impact of vital input parameters upon mechanical performance. In line with experimental results, it was commonly noted that increasing RCA content was frequently linked to a decrease in strength, although CKC and ARGF moderated this effect. ARGF achieved better tensile and flexural properties through fibre bridging, and CKC enhanced the cement matrix by secondary hydration processes. The ANN modelled these compensating effects successfully, and the ANN is thus demonstrated to be effective as a design tool for HPRAC mixture optimization.



**Fig. 9** Experimental compressive strength results for HPRAC mixes across different phases and curing ages.

The RMSE trends for training and testing datasets with different hidden layer sizes are shown in Figure 16. In order to balance model complexity with generalization, the ideal number of neurons was determined at the point of minimum testing RMSE. The input weights and hidden biases were shown in Table 3(a) and Table 3(b). These numbers show how each input parameter affects the buried neurons. Strong

linkage between cement and RCA was noteworthy, suggesting that they play a vital role in strength development. Normalised input variables are presented in Table 3(a), and they are cement, Fine Aggregate (F.A.), natural Coarse Aggregate (C.A.), Recycled Coarse Aggregate (RCA), free water, ARGF dosage, Nano-Powder (NP) content, superplasticizer (SP), water-to-cement ratio

(w/c), and curing age. Table 3(b) presents the estimates of the output variables that are Compressive Strength (CS), Flexural Strength (FS), and Splitting Tensile Strength (STS) at various values of curing age (7, 28, 56, and 91 days).

All inputs were scaled for ANN training, and outputs were modelled across multiple age intervals to capture strength development trends. Inputs are color-coded in red and outputs in black throughout the figures and tables for clarity.

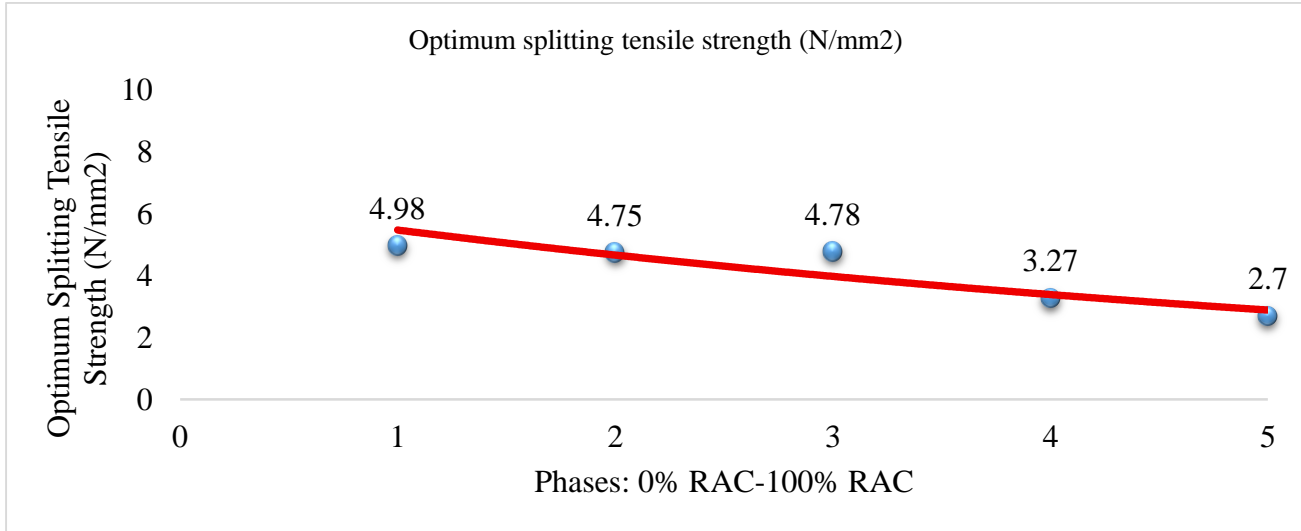


Fig. 10 Experimental tensile strength splitting results at 91-day curing age of HPRAC mixes.

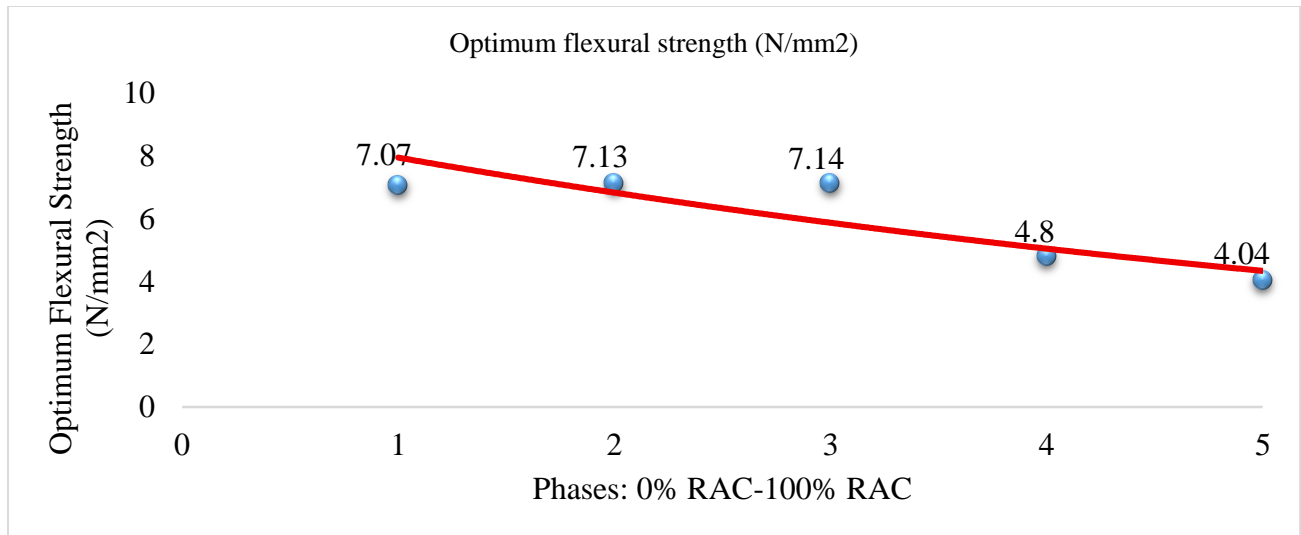


Fig. 11 Experimental flexural strength outputs for HPRAC mixes at 91-day curing age

Output weights and biases were shown in Table 4(a) and Table 4(b) using abbreviated acronyms (CS91 for 91-day compressive strength, for example). The weight distribution indicated the network had specific learning paths, as there were some hidden neurons that provided more weight to specific outputs. An ideal prediction was then indicated by the diagonal reference line ( $y = x$ ) in Figure 17, which shows how the ANN performed on testing data.

The model was shown to be accurate in its predictions by data clustering on the cluster of points around this line.

The experimentally determined values of STS, FS, and CS at 7, 28, 56, and 91 days are shown in Table 4(a), while the comparable ANN-predicted values for the same attributes and age ranges are displayed in Table 3(b). The tables allow you to compare experimental data and predicted output directly, and the model's ability to accurately approximate the performance can be easily evaluated. Cement, aggregates, water, ARGF, nano-powder, superplasticizer, age, and w/c ratio are some of the inputs taken into the prediction. Inputs are expressed in red across all parts of the article, and outputs are given in black, representing the uniformity of inputs.

Figure 18a-c showed plots of the training, testing, and total test plot and the correlation equations of trained/ test data, in which the great Correlation of the prediction with the experimental data, which is strong and positive with all samples, supported the strength of the model. The generalization capabilities of the model were confirmed by

validation data shown in Figure 19. The Correlation remained high for unknown data, a testimony to ANN reliability. For the ANN, a regression model was depicted in Figure 20, and the corresponding predicted and realistic values displayed a strong linear pattern. That offered us more proof that the model is effective.

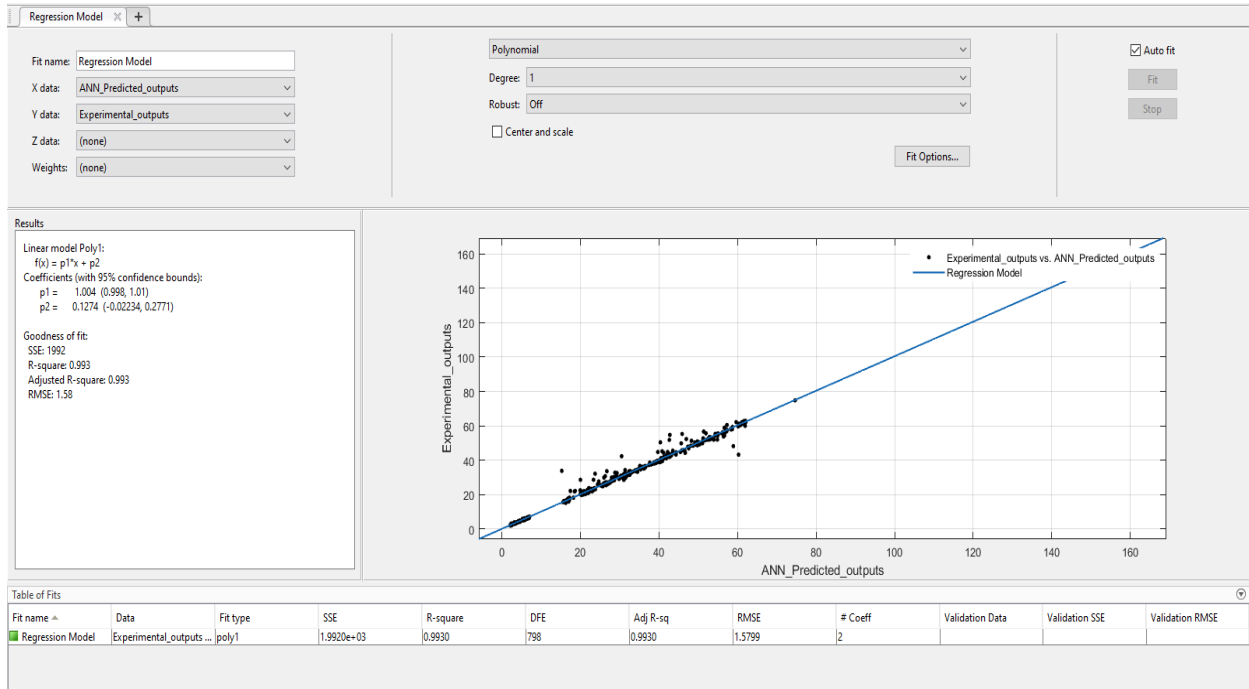


Fig. 12 Regression model of ANN predictions on all datasets, with a high level of linear Correlation with experimental results

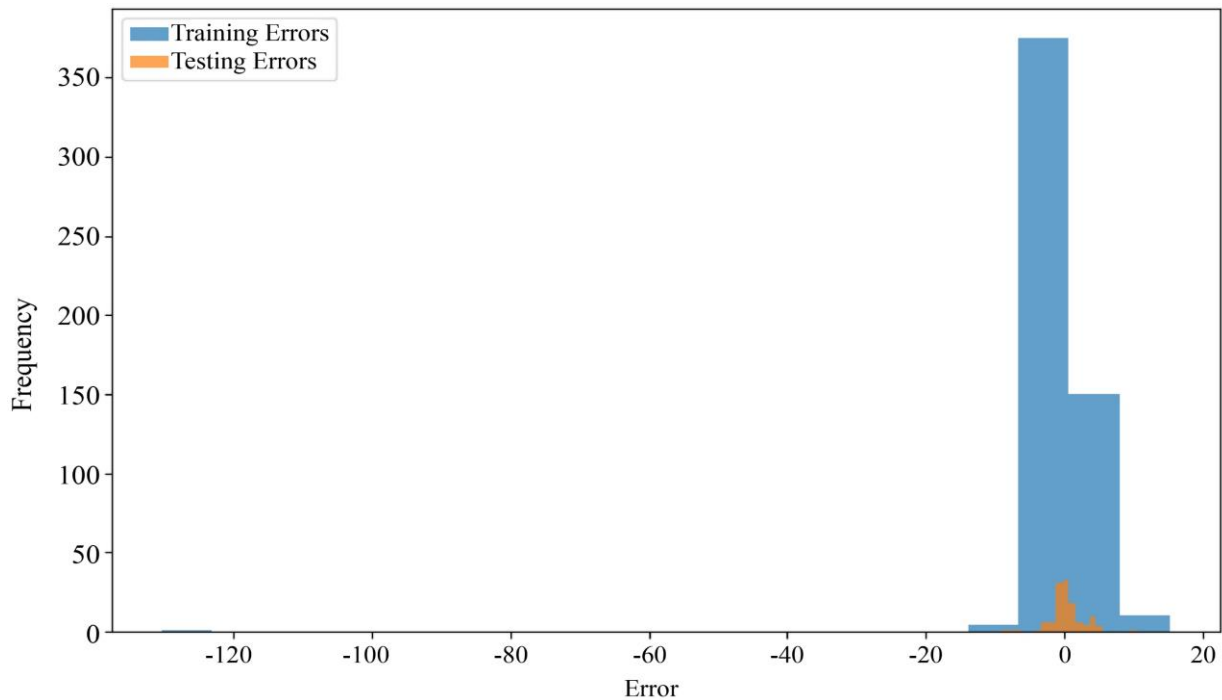


Fig. 13 ANN Prediction residual error histogram, showing symmetric error distribution and low bias

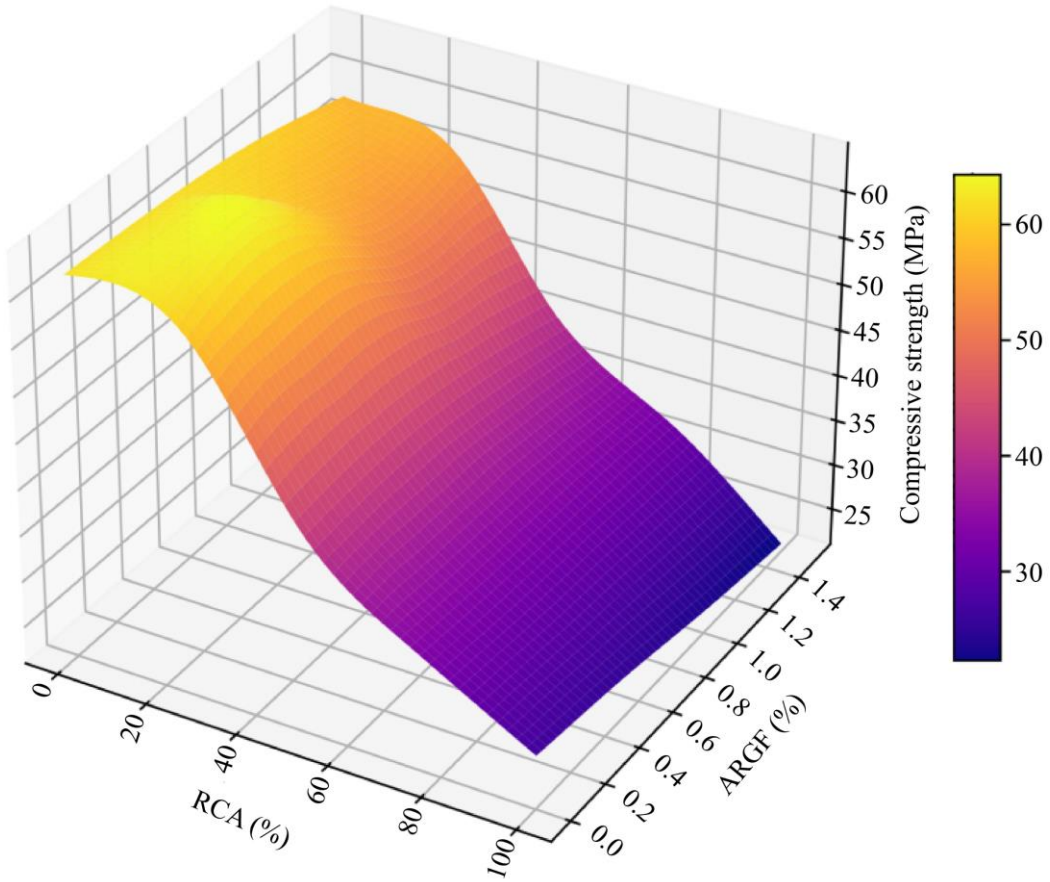


Fig. 14 Response surface indicating the effect of RCA and ARGF on 91-day compressive strength (CKC fixed), showing the trends of interaction

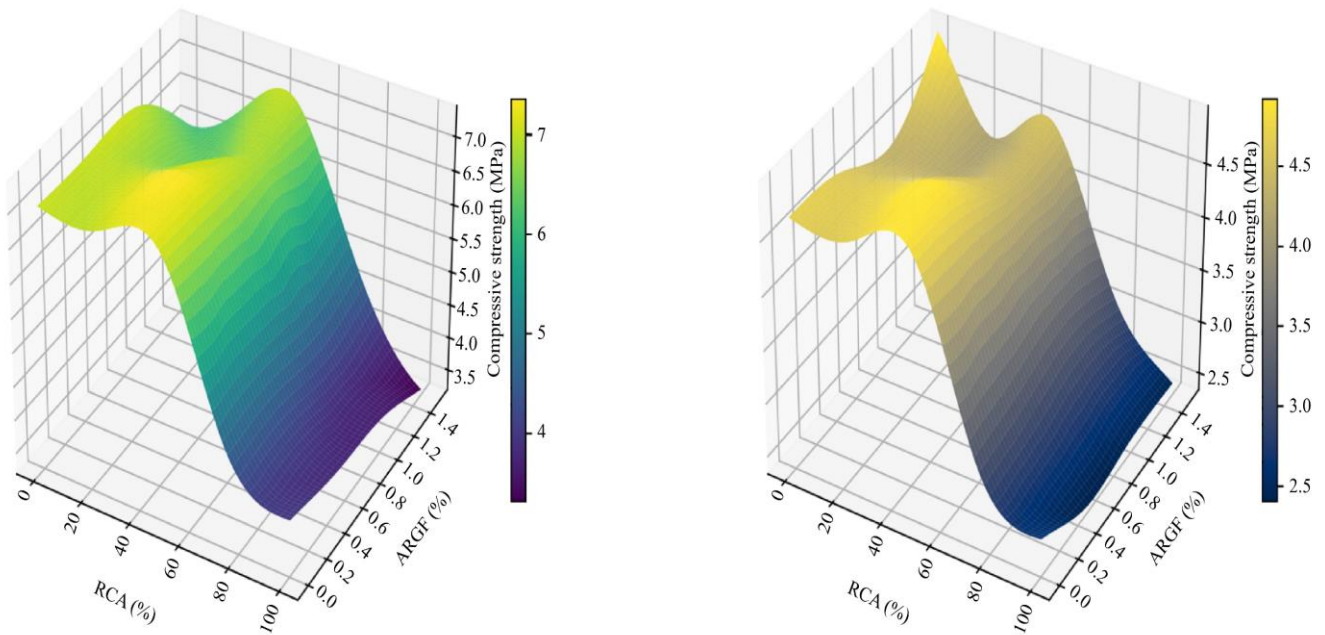


Fig. 15 Response surface indicating the effect of RCA and ARGF on flexural and splitting tensile strengths of 91 days.

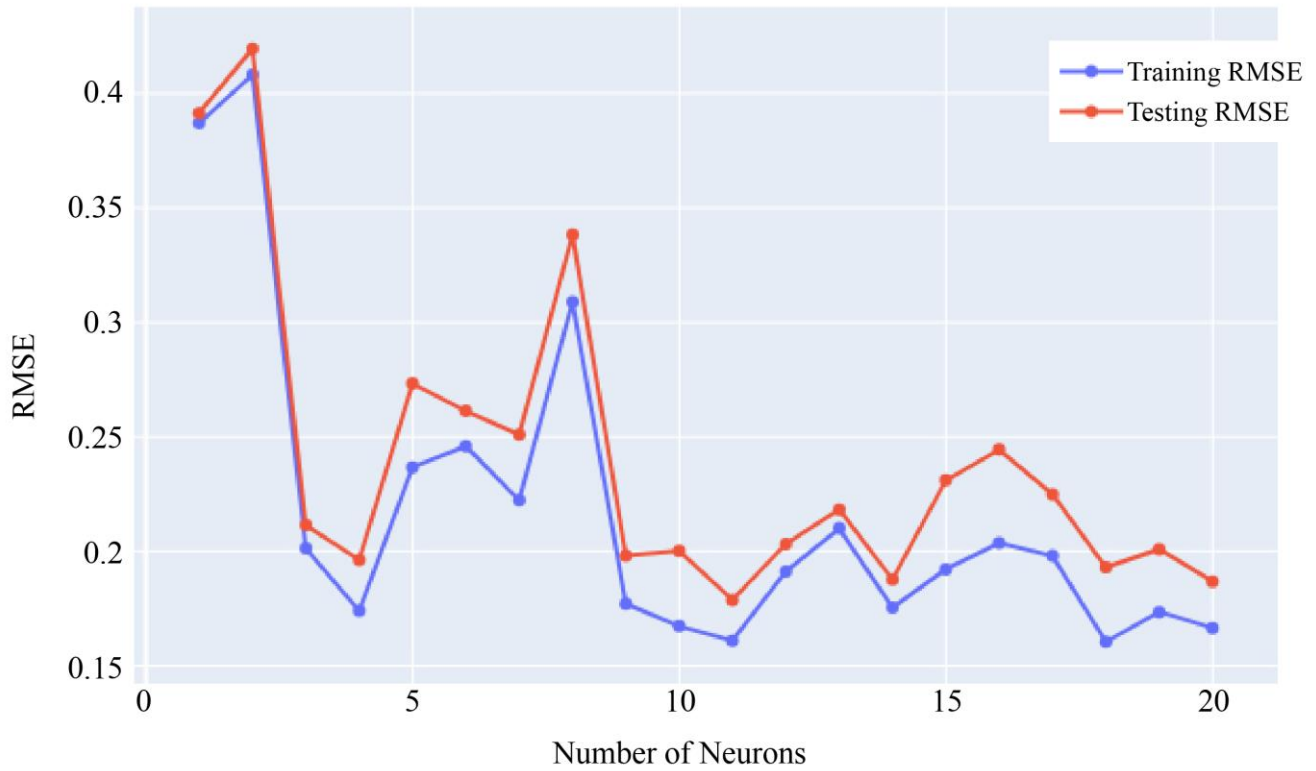
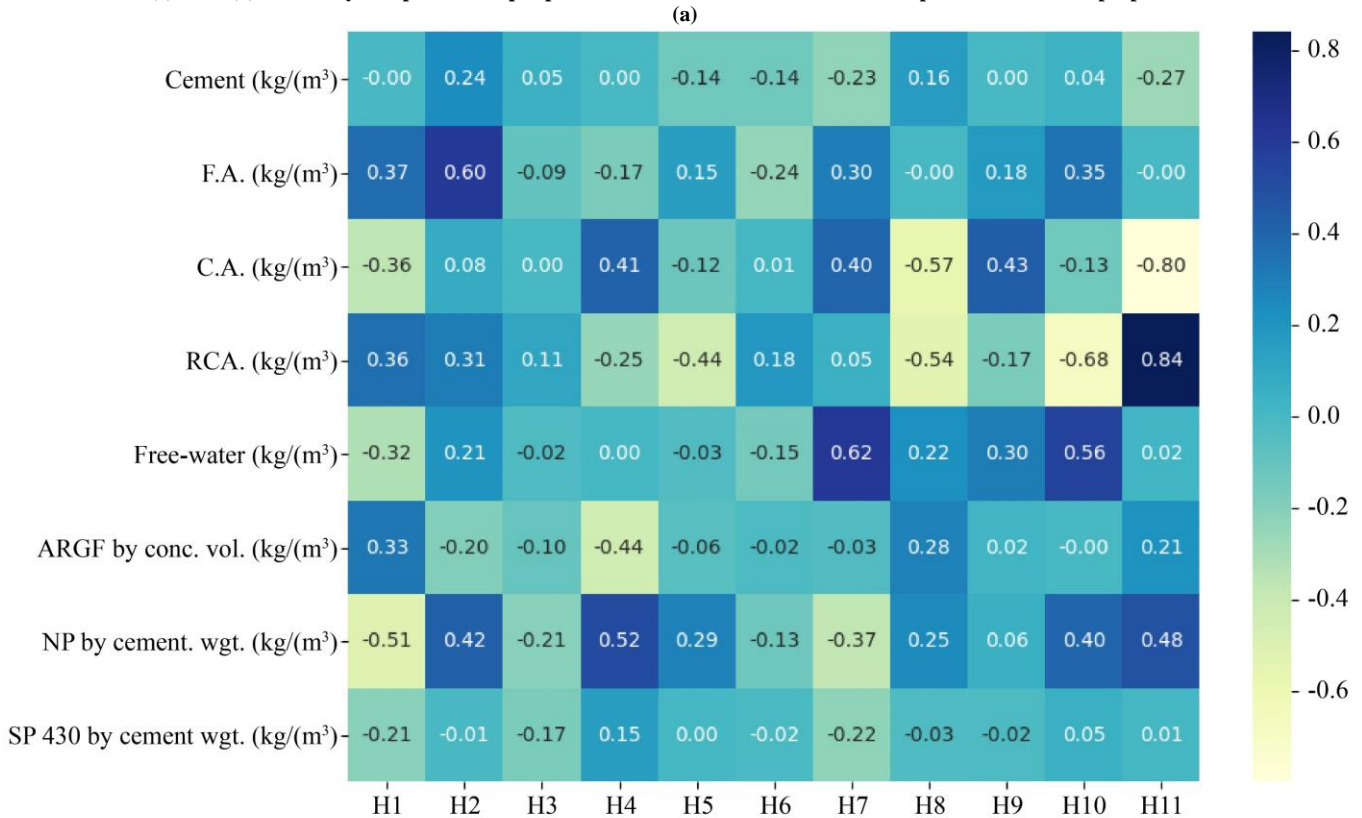
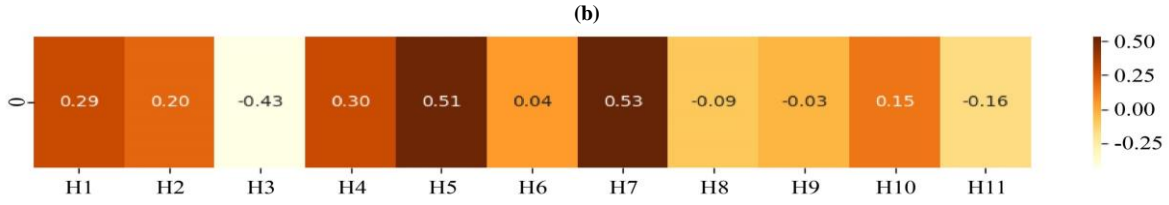


Fig. 16 RMSE trends for different hidden layer neuron configurations, identifying optimal network complexity for generalization

Tables 3(a) and 3(b). Summary of input and output parameters utilized in the ANN model to predict mechanical properties of HPRAC





Tables 4(a) and 4(b). Predicted and experimental mechanical properties of HPRAC under a variety of mix designs and curing ages

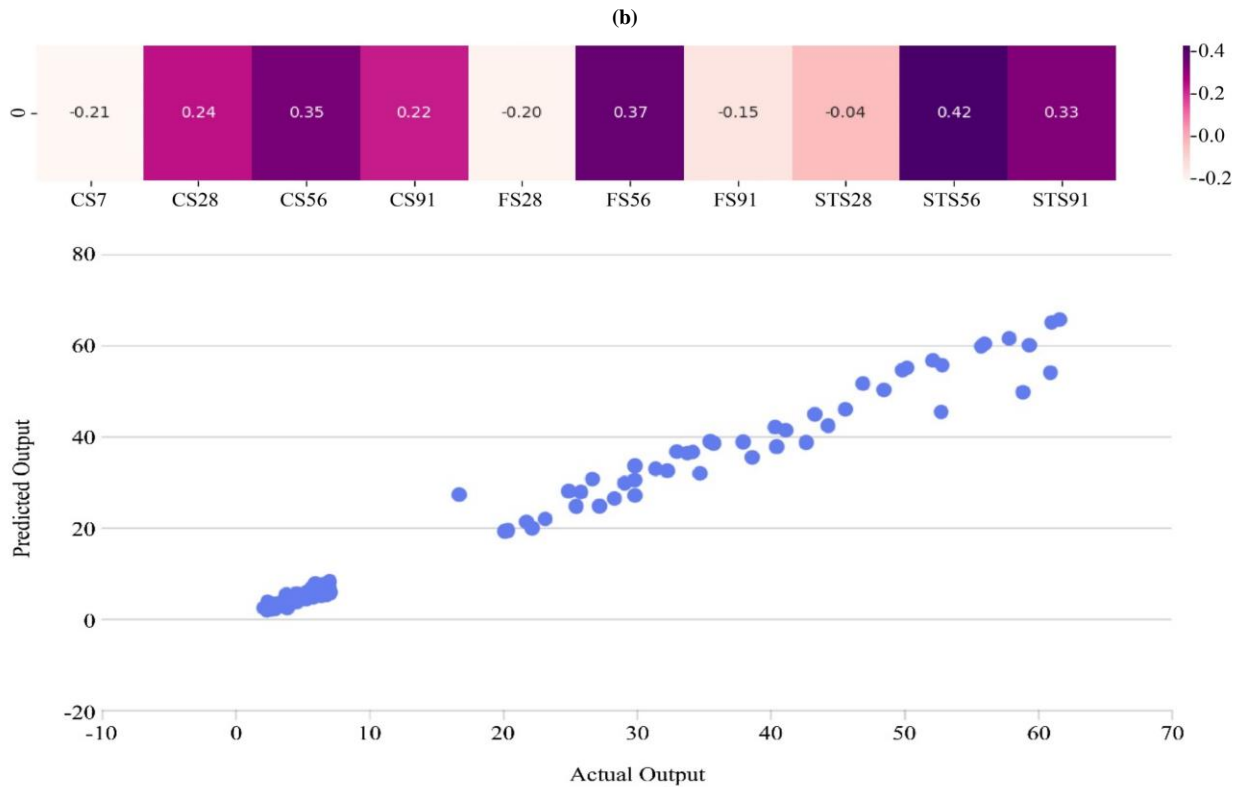
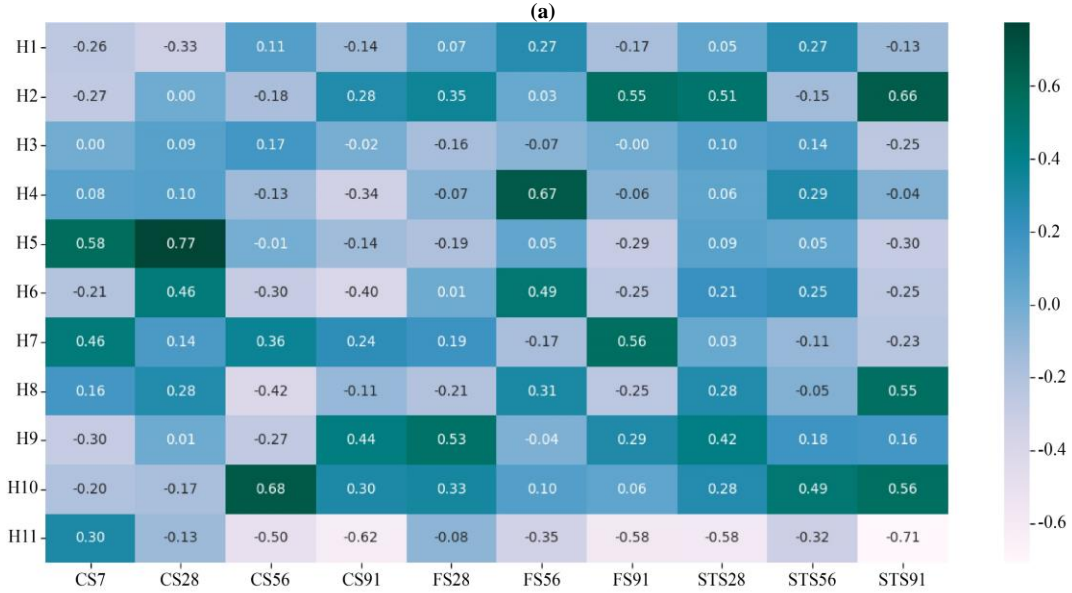


Fig. 17 Scatter plot of ANN predictions and experimental values of the testing dataset, determining the accuracy of predictions

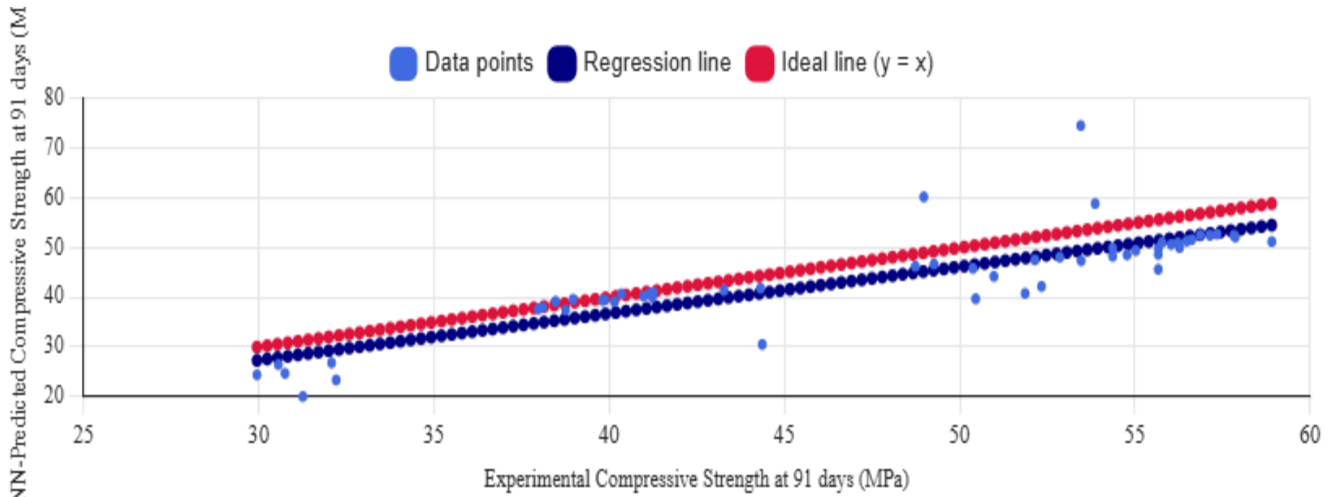


Fig. 18a. Correlation between experimental (actual) and ANN-predicted 91-day compressive strength for the training dataset, showing strong agreement

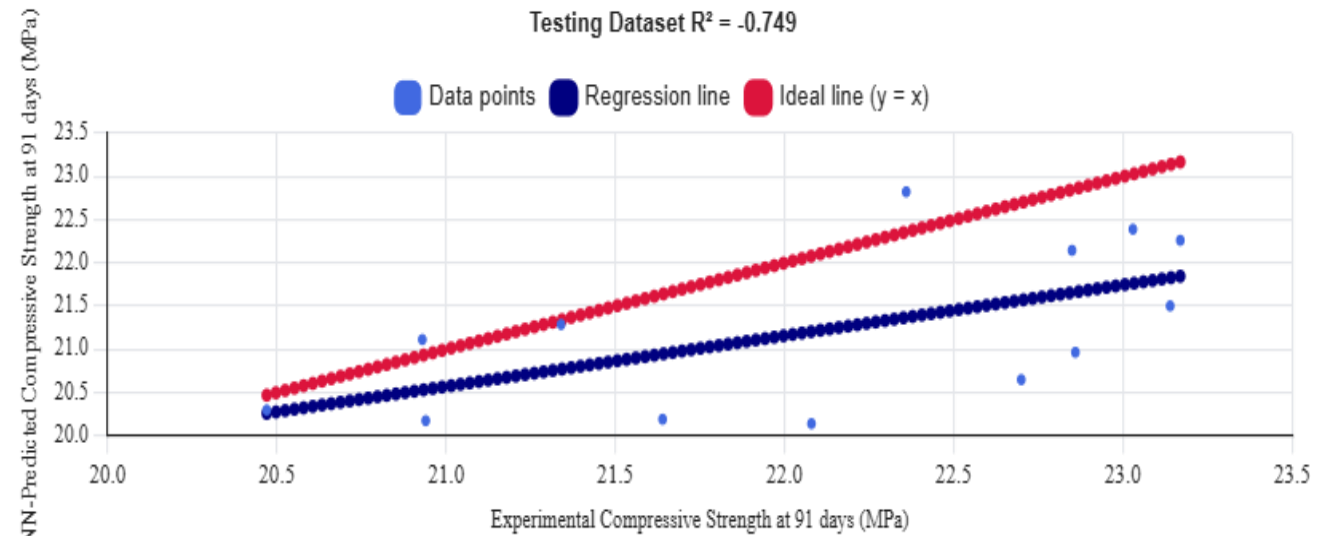


Fig. 18b. Correlation between experimental (actual) and ANN-predicted 91-day compressive strength for the testing dataset, illustrating the generalization capability of the ANN model

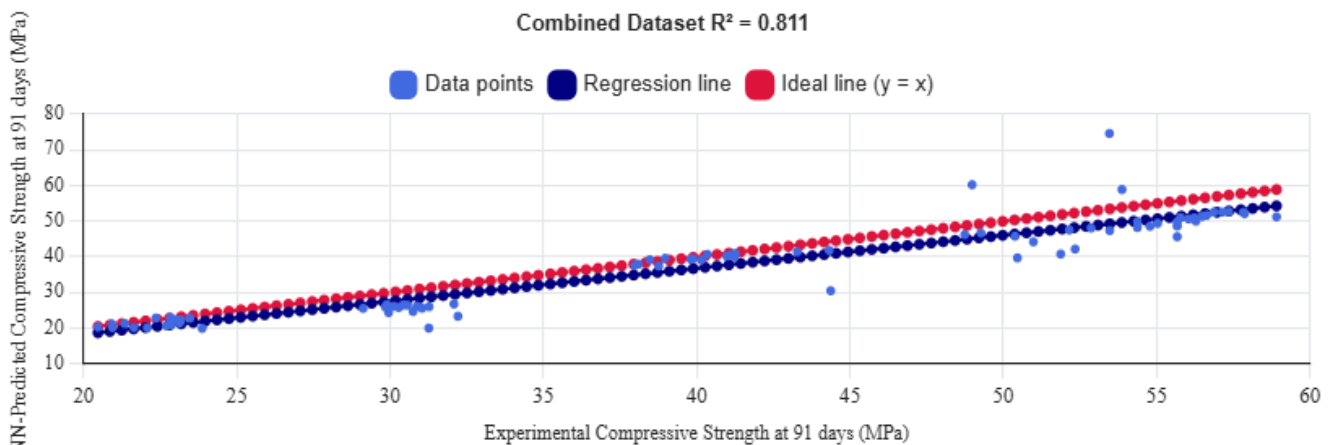


Fig. 18c. Correlation between experimental (actual) and ANN-predicted 91-day compressive strength for the combined dataset, illustrating overall prediction accuracy and robustness of the ANN model.

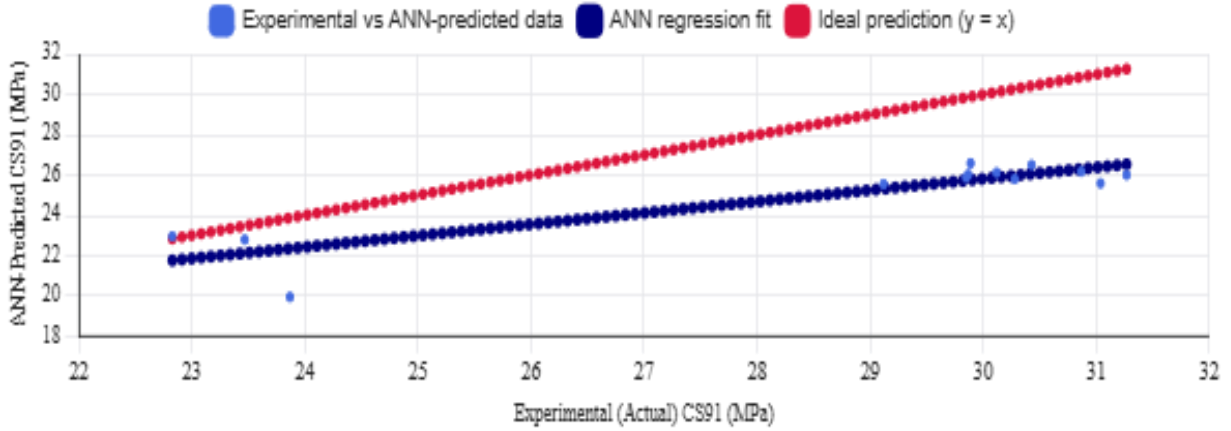


Fig. 19. Validation correlation between ANN-predicted and experimental (actual) outputs of the validation dataset, demonstrating the generalization capability of the model

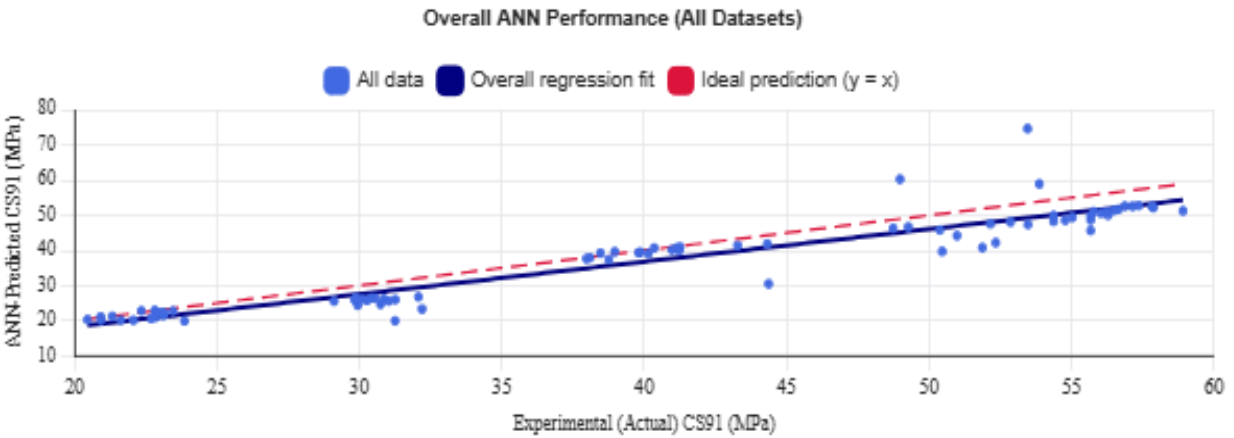


Fig. 20. Overall regression fit across all data subsets, showing high predictive accuracy of the ANN model

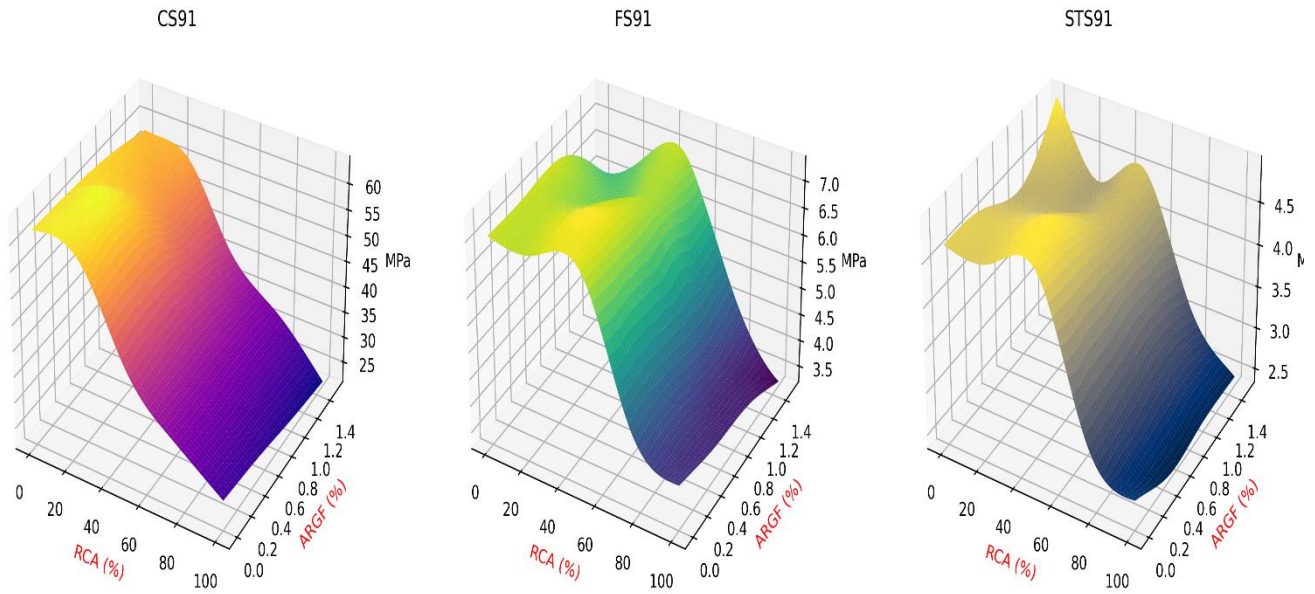


Figure 21 shows ANN-generated response surfaces that emphasize synergistic optimization behavior by showing the combined impact of RCA and ARGF on 91-day compressive, flexural, and splitting tensile strengths, with CKC remaining constant.

### 6.5. Mix Optimization Implications

By predicting many mechanical properties accurately in mix design parameters, the results of these algorithms highlight the feasibility of ANN modelling in decreasing experimental workload. By integrating RCA for sustainability with CKC/ARGF for performance enhancement, the ANN framework is a useful mechanism to achieve the trade-off between structural reliability and ecological benefits. This predictive power can help engineers to optimize HPRAC mix designs for different structural applications through reduced trial-and-error experimentation. To sum up, ANN models constructed in the present study demonstrated excellent capability in forecasting flexural, splitting tensile, and compressive strengths of HPRAC.

The results show that artificial neural networks can capture complex material systems, especially where nonlinear behaviour of fibre reinforcement, pozzolanic additives, and recycled aggregates is important.

While keeping CKC constant, Figure 21 shows a combined response surface analysis of the impacts of RCA and ARGF on 91-day compressive, flexural, and splitting tensile strengths. Because it unifies the parametric interactions that were previously shown separately in Figures 14 and 15 into a single multi-output framework, its inclusion is crucial. The synergistic balance between performance improvement, achieved through the addition of ARGF, and sustainability, represented by the introduction of RCA, is further illustrated in the figure. Furthermore, it clearly validates the main hypothesis of this research, which is that the intricate nonlinear coupled mechanisms regulating HPRAC behavior may be captured by the ANN model. From an engineering standpoint, the picture further improves the model's actual usability by clearly showing the ideal areas for mix design optimization.

### 6.6. Model Limitations and Future Work

Despite the ANN's excellent prediction accuracy, there are also possible drawbacks. Normalization, stratified data splitting (70/15/15), and early halting reduced the risk of overfitting; however, ANN models are vulnerable to dataset bias by nature. The generalization of the current framework to field circumstances with varied RCA quality needs additional confirmation because it is based on controlled laboratory data. To increase robustness and generalization, future research should investigate hybrid AI models, include durability indices (such as sorptivity and chloride intrusion), and enlarge datasets.

### 6.7. Experimental Context and Validation

The authors assessed HPRAC mixes under identical factorial changes of RCA, CKC, and ARGF in companion experimental research. The findings demonstrated that while

ARGF improved tensile and flexural performance without sacrificing permeability, CKC greatly increased durability (reduced sorptivity and chloride ingress). These results underline the need to use durability indicators in the next AI frameworks and validate the prediction trends of the ANN model.

### 6.8. Key findings and Novelty of the work Key findings

Using a solid dataset of approximately 2400 experimental data points, the ANN model showed excellent predicted accuracy across all strength parameters—compressive, flexural, and splitting tensile. The inclusion of alkali-resistant glass fibre (ARGF), dose of calcined kaolin clay (CKC), and recycled aggregate concrete (RAC) were proven to be less significant than curing age. The low values of RMSE and  $R^2$  over 0.97 proved the model to have high dependability. Correlation study showed that CKC and ARGF contributed favourably, particularly to tensile and flexural performance, while RAC had a negative effect on strength. These results confirm the ANN's capacity to capture intricate nonlinear correlations in HPRAC behaviour and are consistent with experimental data.

### 6.9. Novelty

This study presents a complete ANN-based model to predict both the mechanical behaviour predictors and the mechanical behaviour of HPRAC. As opposed to the past models, it provides a single prediction system using ten input features, such as material proportions and curing age. The high empirically validated data set increased the stability and applicability of the model.

A recent design approach for ANN as an enhancement of previous design steps demonstrated the ability of ANN to effectively replicate compensating functions of CKC and ARGF on RAC-induced strength loss. The sensitivity analysis and regression diagnostics confirm its effectiveness as a data-driven approach for optimizing HPRAC mix formulations with reduced need for intensive laboratory testing. Table 4 compares the current study with comparable previous research on recycled aggregate concrete prediction using ANN and similar AI models to demonstrate the novelty of this work. The comparison takes into account input variables, dataset size, expected results, and the addition of modifiers that improve performance. This methodical examination shows how the suggested paradigm offers a wider prediction scope and resolves issues in earlier research.

The study introduces a solid ANN model that is trained on over 2,000 experimental data items, as compared to previous studies that just analyzed compressive strength and had small datasets analyzed. It simultaneously forecasts three important mechanical properties on a ten-factor input basis. Additionally, it takes into account sophisticated modifiers like Alkali-Resistant Glass Fibre (ARGF) and Calcined

Kaolin Clay (CKC), which are rarely taken into account in earlier ANN-based models. This comprehensive approach highly enhances prediction accuracy and generalization, which is a valuable platform for high-performance sustainable concrete optimization.

## 7. Summary

The ANN model for forecasting the mechanical characteristics of RAC was effectively created and validated in this work. The model demonstrated great generalization, small error margins, and high accuracy across training, testing, and validation data. Reaction surface analysis explained how the critical mix design elements, i.e., RCA and cement, affected them.

## 8. Conclusion

An effective prediction tool for RAC mix design optimization is provided by the ANN model. It is suitable in practice in the context of sustainable concrete engineering since it is able to comprehend intricate nonlinear relations among input variables and mechanical characteristics. Future studies might look into the hybrid modelling approaches and expand the framework to include the environmental effect evaluation as well as the durability indicators. From the discussion above, we can come to the following conclusions:

- i. Prediction framework using ANN: The multi-layer perceptron models were effectively created to forecast the compressive, splitting tensile, and flexural strengths of HPRAC mixes with RCA, CKC, and ARGF.
- ii. Strong dataset and inputs: The models had been trained and tested on a huge experimental dataset ( $\approx 2,400$  results) with 10 major features of inputs, such as mix proportions and curing age.
- iii. High predictive accuracy: ANN achieved  $R^2 > 0.95$  with low RMSE and MAE across all strength properties, confirmed by regression plots and error histograms, and demonstrated strong generalization without overfitting.
- iv. Key material interactions: RCA content showed a negative effect on strength, while CKC and ARGF mitigated this impact through matrix densification and crack-bridging, respectively—relationships effectively captured by the ANN.
- v. Practical significance: The developed ANN tool offers a reliable, data-driven approach for optimizing HPRAC mix designs, reducing experimental

workload, and promoting sustainable concrete technologies.

A useful tool for optimizing High-Performance Recycled Aggregate Concrete (HPRAC) mix designs is provided by the proposed ANN framework. The model can greatly decrease trial-and-error testing and save time and resources in structural concrete design by properly predicting compressive, flexural, and splitting tensile strengths from important mix factors. This predictive capability encourages sustainable building because it has made it possible to use recycled aggregates, fibre, and pozzolanic additives to good effect without compromising performance.

Future studies must concentrate on the extension of the model to include the aspects of durability that are critical in predicting service life, including sorptivity, chloride ingress, and sulphate resistance. The ANN framework will also be enhanced with robustness and generalization by testing it with the field-scale variability and exploring the hybrid AI strategies (e.g., ANN coupled with fuzzy logic or optimization algorithms). The idea of real-time mix design integration with decision-support systems may encourage its practical use in industry.

## CRedit Author Statement

- Dr. Olutosin Peter Akintunde: Original Draft, Conceptualization, Methodology, Investigation, and Writing.
- Prof. Jacques Snyman: Editing, Review, Supervision, and Funding acquisition.
- Dr. Chris Ackerman: Review and Editing.
- Prof. W.K. Kupolati: Resources, Validation, Review, and Editing.

## Declaration of Competing Interest

The authors declare that they possess no identifiable conflicting financial interests or personal ties that would have seemed to affect the work presented in this research paper.

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