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Predicting the Durability Properties of Concrete with Recycled Plastic Aggregate as a Partial Coarse Aggregate Replacement

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ABSTRACT

Disposal of plastic waste causes serious environmental problems, including landfills and water bodies degradation, greenhouse gas emission, soil contamination and so on. This study investigates the use of recycled plastic aggregate (RPA), as a partial replacement for conventional coarse aggregates by weight in lightweight concrete production. Concrete mixtures with different concentrations of RPA at (0, 15, 30, and 45%) were prepared and cured for 7, 14, 28, and 56 days. Including RPA into concrete reduced both density and compressive strength as the replacement level increased. Density decreased from 2,347 kg/m^3 at 0% RPA to 1,895 kg/m^3 at 45% replacement. Similarly, 28 days compressive strength decreased from 30.43 N/mm^2 (control) to 19.50 N/mm^2 at 45% replacement, reflecting the lower specific gravity and weaker bonding of RPA compared to traditional coarse aggregate. Additionally, the test results showed that RPA concrete has a low water absorption rate at 15% replacement, with 2.50% for water absorption and a 0.0235 $mm/s^{1/2}$ sorptivity value compared to control samples with 2.66% for water absorption and 0.024 $mm/s^{1/2}$ sorptivity value. However, concrete samples with up to 30% RPA replacement met the minimum requirements for structural lightweight concrete. This study also used machine learning models, including artificial neural networks (ANN), k-nearest neighbor (k-NN), and random forest (RF), to predict the durability properties of RPA concrete. Among these models, the k-NN model showed the best prediction accuracy with an R^2 value of 1.00, a mean absolute error (MAE) and a mean square error (MSE) of 0.001 for both the train and test data. These findings show that the use of treated RPA in concrete not only offers a sustainable alternative to natural aggregates but also improves the durability of the resulting structures.

Keywords: Artificial neural network, K-nearest neighbor, Random forest, Recycled plastic aggregate, Sorptivity, Water absorption.

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1. INTRODUCTION

The construction industry significantly impacts the environment through the use of large amounts of materials, waste generation, and greenhouse gas emissions. It consumes natural resources, produces large amounts of waste, and contributes to climate change by releasing carbon dioxide (CO_2) and other gases. Normal weight concrete (NWC) is commonly used in the construction of buildings, bridges, pavements, and other structures due to its strength and durability **(Wałach, 2021)**. However, the extraction and use of natural aggregates in construction have significant environmental concerns **(Agboola et al., 2021)**. This practice leads to land degradation, biodiversity loss, and soil erosion and leaching, which affects marine ecosystems **(Bosire et al., 2014).** According to (**Durán et al., 2018),** the extraction process alone emits between 0.005 and 0.01 kg of CO_2 per kilogram of material, depending on factors like aggregate type and machinery efficiency. Additionally, the processing stage, which involves crushing, screening, and washing, contributes an extra 0.002 to 0.004 kg of CO_2 per kilogram of material is released due to its energy efficiency. These environmental challenges highlight the need for more sustainable construction practices and materials **(Kibert, 2016; Galvez-Martos et al., 2018; Wu et al., 2019)**. These issues have led researchers to investigate the suitability of using industrial waste, such as waste plastic bottles (Polyethylene terephthalate), in concrete production.

The incorporation of recycled plastic aggregate (RPA) into concrete can reduce water absorption because the hydrophobic nature of the plastic reduces the penetration of water into the concrete matrix **(Muhammad and Agboola, 2025; Sathvik et al., 2024)**. This shows that the use of RPA can improve the durability and water resistance of concrete structures and provide a more sustainable way to design building materials. Also, due to the hydrophobic nature of the RPA, increasing the content of RPA in concrete reduces adsorption, increasing water resistance **(Al Fuqaha et al., 2023)**. In addition, superplasticizers help improve concrete durability by enhancing workability and flow without increasing water content. Concrete made with superplasticizer has low water absorption and sorptivity, improves resistance to moisture damage, and enhancing overall durability **(Du and Li, 2014)**. However, many studies report challenges with using RPA as a partial replacement for conventional coarse aggregates, such as inadequate strength and durability for structural purposes. To enhance the properties of lightweight concrete, several studies have concentrated on surface modification techniques. Altering the aggregate surface texture through methods such as roughening, coating, and applying surface modifiers increases the surface area and strengthens the bond between the aggregates and the cement matrix, thereby enhancing mechanical interlock and overall durability. According to **(Hilal, 2021)**, these modifications can improve strength and solve the problem of moisture penetration. Also**, (Zhang et al., 2025),** reported that including superplasticizers, particularly polycarboxylate ethers, significantly enhances workability and reduces water content, resulting in a denser, more uniform mix with improved mechanical properties. In addition, machine learning has been employed to address quality control challenges in production by analyzing process data to identify patterns and anomalies, facilitating predictive maintenance and optimization of material formulations **(Gamil, 2023)**.

Therefore, this study seeks to consolidate the effects of modified RPA as a coarse aggregate supplement in the production of lightweight concrete (LWC). The purpose of the study was to investigate the effects of modified RPA and polycarboxylate ether (PCE) based superplasticizers on concrete strength and durability.

2. MATERIALS AND METHODS

2.1 Materials

Materials that were used in this work are: cement, fine aggregate, coarse aggregate, recycled plastic bottles aggregate (RPA), polycarboxylic acid (superplasticizer), and water, see the images in **Fig. 1.**

Figure 1. Concrete Materials (a) Recycled Plastic Aggregate (b) Fine Aggregate (c) Coarse Aggregate (d) Polycarboxylic Acid

2.2 Methods

2.2.1 Experimental Design

This study investigates the capillary absorption properties of concrete produced with RPA as a partial coarse aggregate replacement in lightweight concrete. First, the RPA was produced by crushing the waste plastic bottles into sizes ranging from 10 to 20 mm. Before including it in concrete mixtures, RPA was treated for 24 hours by soaking in an oxidizing solution. This solution was made by dissolving 500 grams of calcium hypochlorite ($Ca(ClO)_2$) in 5 liters of water. **Fig. 2** shows the process of treating the used recycled plastic aggregate in this work. Applying this treatment changed the plastic surface texture, which consequently enhanced its bonding power with the cement paste when used as a partial replacement for traditional coarse aggregate in concrete. The treated RPA was then air dried to ensure no residual chemical remained on the surface. A superplasticizer at 1.0 % of the weight of cement in kg/m^3 was added to the mix as a chemical admixture to slow the hydration process and improve the workability of the RPA fresh concrete mix. Cube sizes of 100 x 100 x 100 mm were produced to study the physical, mechanical, and durability properties of the samples.

Figure 2. Process of Treating Recycled Plastic Aggregate (a) Recycled Plastic Aggregate Sample (b) Dissolving $Ca(ClO)_2$ in Water (c) Soaking RPA in Solution

All samples were cured for a period of (7, 14, 28 and 56 days). Four mixes were prepared: the control (0%), the remaining three mixes included RPA replacing 15, 30 and 45% of the volume of conventional coarse aggregate with an equivalent volume of RPA. The concrete curing process was carried out following **(BS EN 1992-1-1, 2004)**.

2.2.2 Mixing Procedure and Sample Preparation

The mixing process consisted of mixing the cement and sand by hand for three minutes, followed by the addition of crushed granite and RPA for another three minutes following the guidelines for hand mixing provided in (**BS 5328-3, 1990)**. After dry mixing, the water and superplasticizer were added and the mixture was further mixed for three minutes before casting the fresh RPA concrete into 100 x 100 x 100mm plastic molds in three layers, with eachlayer manually compacted using a tamping rod with 25 strokes per layer following the guidelines for hand compaction provided in (**BS EN 12390-2, 2019)**. The samples were covered with plastic bags and placed in the laboratory 24 hours before curing. Post remolding, specimens were cured in a curing tank according to **(BS 8110-1, 1997)** before being subjected to physical, mechanical and durability tests. In total, four concrete mixes containing various percentages of RPA and a control sample with conventional materials were examined in this study. The mix design of normal weight and lightweight concrete was carried out according to **(ACI 211. 2, 1998)** to design a 30 N/mm^2 concrete grade at 28 days. The compositions of the concrete mixtures are detailed in **Table 1**. The mix design procedure adhered to (**ACI 211.2, 1998)** standard.

Table 1. Mix Proportion of RPA Concrete

Parameters	0% RPA	15% RPA	30% RPA	45% RPA
W/C ratio	0.52	0.40	0.40	0.40
Water content (kg/m^3	181	139	139	139
Cement content (kg/m^3)	348	348	348	348
Sand content (kg/m^3)	627	627	627	627
Coarse agg. (kg/m^3)	1226	1042	858	674
RPA (kg/m^3)	0	36	72	108
SP at 1% of cement (kg/m^3)	0	3.48	3.48	3.48
Target Density (kg/m^3)	2382	2195	2047	1899

3. Experimental Work

3.1 Slump Test

The slump test is an empirical test that measures the workability of fresh concrete and was done in accordance with **(BS EN 12350- 2, 2009)**. The test was carried out using a metal cone filled up with concrete in three different layers, with each layer tamped with a metal rod 25 times. The cone was then lifted, and the slump was measured as the distance from the top of the slump concrete to the top of the inverted cone. **Fig. 3** shows the slump test.

Figure 3. Slump test.

3.2 Density Test

The density test is of interest to the study because of numerous reasons, including its effect on durability, strength, and resistance to permeability. The test was carried out according to (**BS EN 12390-7, 2019)**. The concrete density test was carried out on 7, 14, 28 and 56 days. The densities of the concrete are expected to reduce over time because the specimens were subjected to air drying at room temperature after curing until the day of testing.

3.3 Mechanical Property

Mechanical property tests are usually conducted to determine the hardened properties of the concrete samples. In this study, a compressive strength test was conducted.

3.3.1 Compressive Strength Test

The compressive strength test was carried out using universal crushing machines that conform to **(BS EN 12390-3, 2009).** The compressive strength test was carried out on 7, 14, 28 and 56 days, respectively. The average value of three samples was used as the compressive strength result. **Fig. 4** shows the compressive strength test.

Figure 4. Compressive strength test.

3.4 Durability Properties

The durability test was conducted on 28, and 56 days for the water absorption test, while sorptivity tests were carried out after 5, 10, 15, 30, 45 and 60 minutes, respectively after 28 days of curing.

3.4.1 Water Absorption Test

The water absorption test was carried out in accordance with **(BS EN 13755, 2008)**. The amount of water absorbed by concrete is termed as concrete water absorption, which is the weight of the absorbed water by the concrete to the dry weight of the concrete. The water absorption test was conducted using concrete cube samples of 100x100x100mm. **Fig. 5** shows the water absorption test conducted.

(a) (b) (c)

Figure 5. Water Absorption Test (a) Immersion in Water (b) Removal from Water (c) Weighing air dried Samples

3.4.2 Sorptivity Test

The sorptivity test was conducted according to (**BS EN 480-5, 2005)**. The cylinder dimensions are 100 mmØ x 50 mm long. After a 24 hour casting period, the samples were placed in water and cured for 28 days, then air-dried for a week till they reached a constant mass after completing the curing process. The specimens were immersed in water with a water level not more than 5 mm above the base of the samples. Then the samples were removed at the end of 5, 10, 15, 30, 45, and 60 minutes of the test mechanism and weighed at an accuracy of 0.01 g. The surface water on the sample was wiped off with a dampened tissue to remove excess water and each weighting operation was completed within 30 seconds. This test was used to determine the rate of absorption (Sorptivity) of water by measuring the increase in the mass of a sample resulting from absorption of water as a function of time when only one surface of the sample is exposed to water ingress of unsaturated concrete by capillary suction during initial contact with water. **Fig. 6** shows the Sorptivity test.

(a) (b) (c)

Figure 6. Sorptivity Test Process (a) Weighing Air-dried Sample (b)Sorptivity Test (c) Rate of Water Rise

3.3 Machine Learning Method

3.3.1 Artificial Neural Networks (ANN)

An Artificial Neural Network (ANN) is a computational model designed to mimic how the human brain processes information. ANNs are made up of interconnected units called neurons, which are arranged in layers: an input layer, one or more hidden layers, and an output layer. Each connection between neurons has a weight that is adjusted during training to reduce the difference between the predicted output and the actual output. In concrete technology, ANNs are used to predict the properties and performance of concrete mixtures, optimize mix proportions, and model complex relationships between concrete ingredients and their resulting properties **(Develi and Kabalci, 2016)**. For example, ANNs can predict the compressive strength, workability, and durability of concrete based on input factors such as cement content, water-cement ratio, and aggregate properties **(Netam and Palanisamy, 2022; Li et al., 2010).** These predictive abilities assist in enhancing concrete mix designs and ensuring consistent quality in concrete production.

3.3.2 K-Nearest Neighbors (k-NN)

The k-nearest neighbors (k-NN) algorithm is a straightforward, non-parametric method used in machine learning for classification and regression. It sorts data by considering the class of its nearest neighbors. The algorithm works by finding the k nearest neighbors to the problem using a distance measure such as Euclidean distance and assigning the problem to a general class of these neighbors. In concrete technology, k-NN is used to predict properties such as compressive strength, workability, and durability based on historical data. Researchers have used k-NN to predict concrete mix properties by analyzing past experimental results, optimizing mix design, and improving material performance **(Migallón et al., 2023)**. This application helps reduce material costs and increase the efficiency of construction processes.

3.3.3 Random Forests

The Random Forest algorithm, developed by Breiman in 2001, is a machine learning method that creates multiple decision trees during training. For classification tasks, it uses the majority vote from these trees, while for regression tasks, it calculates the average of their predictions. The algorithm increases the accuracy and reliability by selecting different types of features and models to build an unrelated tree **(Liaw and Wiener, 2018)**. In concrete technology, Random Forest is used to predict concrete properties like compressive strength and durability by analyzing various factors such as mix proportions, curing conditions, and material properties. Research has shown that it effectively optimizes concrete mix designs for better performance and sustainability by evaluating data from numerous experiments to find the best ingredient combinations and conditions **(Huang et al., 2025)**. As a result, Random Forest is a valuable tool for advancing concrete technology through data driven insights and innovation.

3.3.4 Predictive Models Evaluation

To evaluate the effectiveness of the prediction model, three indicators were used: coefficient of determination (R^2), mean absolute error (MAE), and mean squared error (MSE).

3.3.4.1 Coefficient of Determination (R^2)

The R^2 measures the proportion of the variance of the dependent variable predicted by the independent variables, ranging from 0 to 1, where 1 indicates perfect prediction as shown in Eq. (1).

$$R^2 = 1 - \frac{RSS}{TSS} \tag{1}$$

3.3.4.2 Mean Absolute Error (MAE)

MAE evaluates the average magnitude of errors in predictions without considering their direction, providing insight into how far predictions are from actual outcomes on average as shown in Eq. (2).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

3.3.4.3 Mean *Squared Error (MSE)*

The MSE, which is sensitive to outliers, calculates the average squared error, gives more weight to larger errors, and measures the magnitude of the error. These measures provide a unique perspective on the accuracy and reliability of the model, as shown in Eq. (3).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}_i)^2 \quad (3)$$

Where, RSS is the sum of squares of residuals, $\sum(\mathrm{yi} - \hat{\mathrm{y}}\mathrm{i}\ )^2$
TSS is the total sum of squares, $\sum(\mathrm{yi} - \bar{\mathrm{y}}\ )^2$
y_i are the actual values
$\hat{y}_i$ are the predicted values
$\bar{y}$ is the mean of the actual values.
n is the number of observations

4. RESULTS AND DISCUSSIONS

4.1 Properties of Materials

Table 2 summarizes the material properties used in this research. The specific gravity of fine aggregate was 2.59. This falls within the specified range specified by **(BS EN 1097-6, 2013)** of specific gravities of fine aggregate, as 2.4 to 2.9. The crushed granite had a specific gravity of 2.71, which falls within the range of 2.5 to 2.9 as specified for coarse aggregates in **(BS EN 1097-6, 2013).** While RPA had a specific gravity of 0.53, confirming its lightweight nature for reducing structural loads in lightweight concrete applications. The compacted and uncompacted bulk densities of fine aggregate were 1525 kg/m^3 and 1340 kg/m^3, respectively. The compacted and uncompacted bulk densities of crushed stone were 1,727 kg/m^3 and 1,398 kg/m^3, respectively, both of which fall within the range of 1,200 to 1,750 kg/m^3 as specified in **(BS EN 1097-3, 1998)**. RPA's compacted and uncompacted bulk densities were 337 and 212 kg/m^3, respectively. The water absorption of the crushed stones used in the study was found to be 2.21%, which meets the requirement of **(BS EN 1097-6, 2013)**, specifying a maximum allowable value of 10% for all types of coarse aggregates and the RPA showed a water retention rate of 0.50%, suggesting low surface porosity. This helps limit water uptake in the concrete mix, leading to better durability and overall concrete performance. The aggregate impact values for crushed stone and RPA were 5.2% and 2.0%, respectively, which fall within the acceptable limit of 35% specified by (**BS EN 1097-6, 2013)** for aggregates suitable for structural concrete. The aggregate crushing values were 6.6% for crushed stone and 3.2% for RPA, both of which fall within the acceptable limit of 25% specified by **(BS EN 1097-2, 2010)**, indicating their suitability for structural concrete.

Table 2. Physical Properties of Material

Materials	Bulk Density(Kg/m³)		Specific Gravity (g)	Water Absorption (%)	Impact Value (%)	Crushing Value (%)
	Compacted	Uncompacted				
Sand	1525	1340	2.59	-	-	-
Crushed Stone	1727	1398	2.71	2.21	5.2	6.6
RPA	337	212	0.53	0.5	2	3.2

4.2 Effect of RPA as Partial Replacement of Coarse Aggregate in LWC

4.2.1 Slump Test

The workability of concrete mixes was assessed using the slump test, targeting a slump value between 75 and 100 mm. **Fig. 7** shows that workability initially improves with a 15% RPA mix but decreases as RPA content increases. This trend is attributed to RPA irregular shape which increases water demand and reduces workability, as noted by **(Huang et al., 2024).** The highest slump value of 30 mm was observed with the 15% RPA mix, where a superplasticizer was used to enhance particle dispersion and lower water demand, as supported by **(Huang et al., 2025).** Therefore, higher RPA percentages require more water to maintain adequate workability.

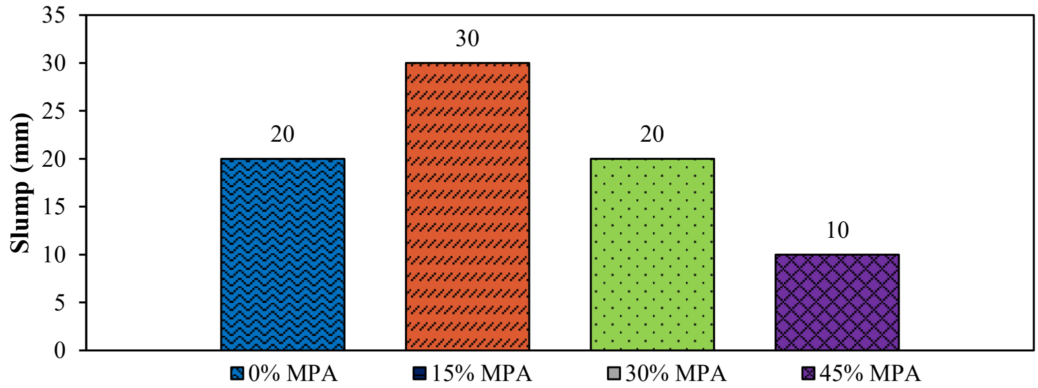

Figure 7. Slump result of concrete containing RPA.

4.2.2 Density

Fig. 8 shows the average density of concrete samples after 28 days for all mixes. According to (**BS EN 12390-7, 2019),** the density of structural lightweight concrete typically ranges between 1,300 and 2000 kg/m^3, which serves as the standard limit for classifying concrete as lightweight for structural applications. Concrete density is significantly influenced by the specific gravity of aggregates, with higher specific gravity leading to denser concrete **(Dehwah et al., 2015)**. The RPA used in this research has a lower bulk density compared to conventional coarse aggregate, resulting in reduced density for concrete mixes with RPA. At 28 days, the control samples had a density of 2347 kg/m^3, while the 15%, 30%, and 45% RPA mixes had densities of 2135 kg/m^3, 1996 kg/m^3 and 1895 kg/m^3 respectively, reflecting reductions of approximately 9.03, 14.96 and 19.26% compared to the control. However, only the 30 and 45% RPA mixes fall within the structural lightweight concrete density range specified by **(BS EN 12390-7, 2019)** and are therefore suitable for structural use.

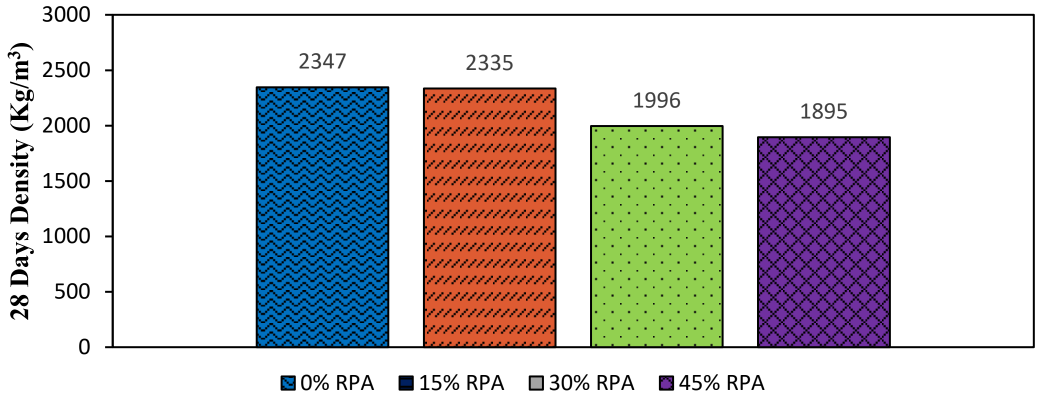

Figure 8. Density of concrete containing RPA at 28 days

4.2.3 Compressive Strength

Fig. 9 shows compressive strength tests for lightweight concrete with RPA replacing 15, 30 and 45% of conventional coarse aggregate. The replacement resulted in reduced compressive strength, which may likely be due to the different characteristics of the RPA such as size, shape and quality, causing inconsistent performance **(Qasim and Jassam, 2022)**. The control sample achieved the highest compressive strength of strength of 32.59 N/mm^2 at 56 days, exceeding the target design strength of 30 N/mm^2 specified for 28 days. RPA concrete samples showed a linear reduction in compressive strength with decreases of 9.33, 16.14 and 22.40% for 15, 30 and 45% RPA content, respectively. Both control and RPA samples reached about 90% of their 28 day compressive strength. However, higher RPA content led to lower compressive strength likely due to reduced workability and increased porosity at 30 and 45% RPA levels **(Jayasinghe et al., 2023).** Despite this, all RPA concrete samples met the (**BS EN 206, 2000)** minimum requirement of 17 N/mm^2 for 28 days compressive strength of structural lightweight concrete. Therefore, RPA can replace up to 45% of conventional aggregates without significantly affecting compressive strength.

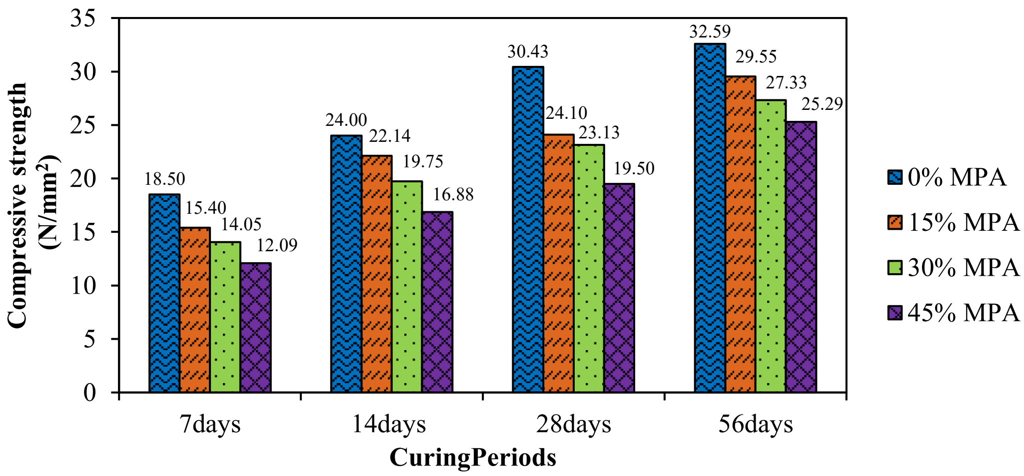

Figure 9. Decrease in compressive strength of concrete containing RPA

4.2.4 Water Absorption

Water absorption refers to the ability of a material to absorb water, which affects its durability and performance. According to **(BS EN 13755, 2008)**, the maximum water absorption for a material should be less than 10% of its dry weight. The average water absorption at 7, 14, 28 and 56 days for concrete mixes with 0, 15, 30 and 45% RPA replacement was recorded and presented. The 28 days water absorption for the 15% RPA mix was 2.50%, while the control was 2.66%. Including 30 and 45% RPA increased water absorption to 3.37 and 7.58%, respectively as shown in **Fig. 10**. This indicates that higher RPA content increases water absorption due to the porous nature of the samples **(Zhong et al., 2024)**. Higher porosity leads to increased void spaces, allowing more water to penetrate as noted by **(Wang et al., 2022).**

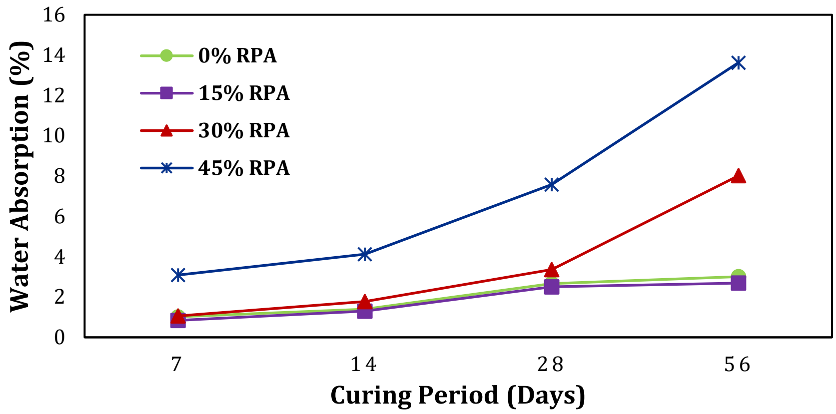

Figure 10. Water absorption of concrete containing RPA

4.2.5 Sorptivity

Sorptivity measures the absorption of water through tiny pores in concrete, indicating its microstructure and durability. According to (**BS EN 480-5, 2005)**, the sorptivity of concrete should not exceed 0.55 mm/s$^{1/2}$. Low sorptivity indicates better resistance to water penetration, enhancing concrete durability. From the experimental results in **Fig. 11**, the sorptivity index for the control sample varied from 0.040 to 0.024 mm/s$^{1/2}$, measured from 5 to 60 minutes. The 15% RPA mix showed a decrease from 0.038 to 0.0235 mm/s$^{1/2}$.

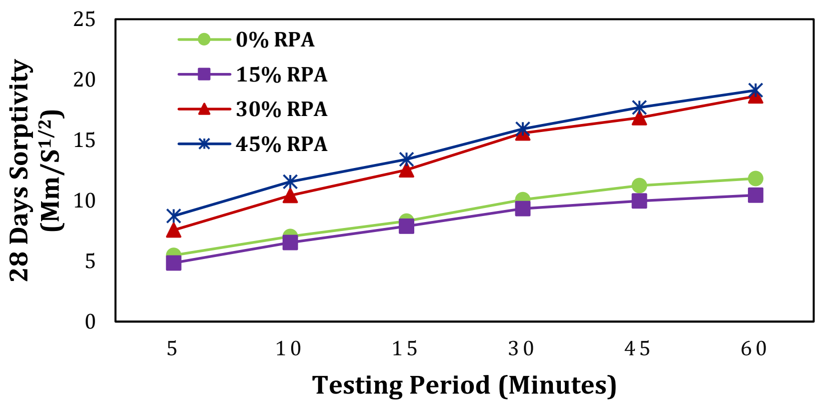

Figure 11. Sorption of concrete containing RPA at 60 minutes

However, inculding 30% and 45% RPA increased sorptivity due to void formation, as established by **(Zhong et al., 2024)**. High percentages of RPA can weaken the interfacial bond between RPA and the cement matrix there by increasing water ingress **(Soares et al., 2025)**. Despite this, all tested samples fell within the acceptable limits set by **(BS EN 12390-8, 2009)**, making them suitable for structural lightweight concrete applications.

4.3 Relationship between Sorptivity and Water Absorption

Fig. 12 shows the relationship between sorptivity and water absorption in RPA lightweight concrete. Higher sorptivity is associated with increased water absorption, reflecting a more porous and interconnected pore structure that facilitates faster water penetration. In contrast, materials with lower sorptivity generally exhibit lower water absorption due to their denser microstructure. Sorptivity and water absorption decrease with longer curing periods, although factors such as pore size distribution and environmental conditions can independently influence these properties. The inclusion of RPA into concrete showed reduced sorptivity and water uptake at 15% replacement but increased levels at 30 and 45% replacement. Linear regression analysis showed a strong correlation between these properties, suggesting that sorptivity values can be use to predict water absorption reliably, and vice versa, which is confirmed by the high R^2 values.

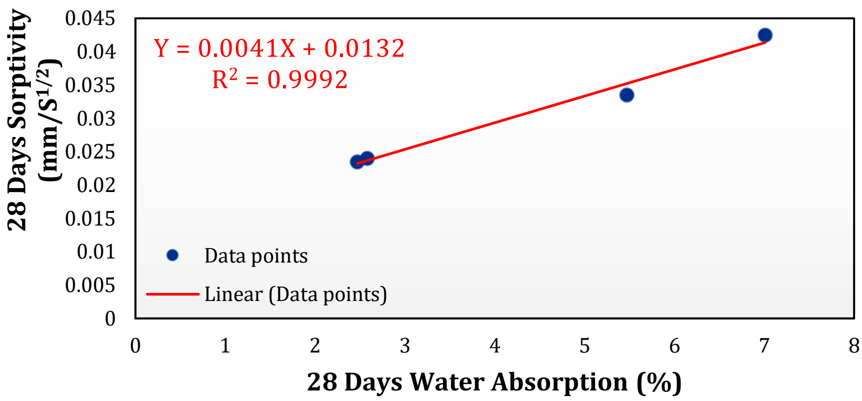

Figure 12. Relationship between sorptivity and water absorption

$S = 0.0041\ WA + 0.0132$ ($R^2 = 0.9992$)
Where, S = Sorptivity (mm/s$^{1/2}$); WA = 28 Days water absorption (%)

4.4 Development of Predictive Models

This section shows the predicted durability properties of RPA concrete, where RPA partially replaced by conventional coarse aggregate in lightweight concrete at 0, 15, 30 and 45%. Durability predictions were performed using ANN, KNN, and RF models. Due to the need for large datasets for effective machine learning, the experimental datatset was augmented with synthetic data generated using CTGAN, a machine learning library use for generating complex datasets.

4.4.1 Simulation and Analysis Results

The study evaluated the durability properties of RPA concrete using computational intelligence techniques. A dataset of 500 entries, combining experimental and augmented data, was created using the CTGAN library in Python. The dataset includes parameters such as cement content (C), water content (W), superplasticizer (SP), coarse aggregate (CA), fine aggregate (FA), RPA, test age (A), slump value (S), density (D), and compressive strength (CS). The data were divided into a training set (70%, 350 samples) and testing set (30%, 150 samples). The training set was used to develop robust predictive models, while the test set evaluated the models accuracy in predicting durability properties.

As shown in **Tables 3** and **4**, the statistical analysis of the dataset revealed key variables such as the maximum, minimum, mean, and standard deviation for the input and output variables. Differences were handled by replacing them with median values, maintaining data integrit y and consistent distribution. This process ensured that no attribute had more than 5% outliers, as shown in **Table 5**.

Table 3. The Statistical Parameters of Water Absorption Model.

Variables	Count	Mean	Standard deviation	Minimum	Maximum
Water	500	150.68	19.42	128	207
Cement	500	348	0	348	348
Fine	500	745	0	745	745
Coarse	500	836.6	210.92	338	1391
SP	500	1.99	1.64	0	4.48
RPA	500	75.56	42.32	0	174
Age	500	50.24	23.31	7	92
Slump	500	17.1	8.15	0	38
Density	500	1951.08	223.68	1393.35	2624.47
Strength	500	29.61	7.86	5.58	44.38
WA (%)	500	4.88	5.17	0	20.78

Table 4. The Statistical Parameters of the Sorptivity Model**.**

Variables	Count	Mean	Standard deviation	Minimum	Maximum
Water	500	155.15	20.02	130	201
Cement	500	348	0	348	348
Fine	500	745	0	745	745
Coarse	500	855.39	216.17	343	1400
SP	500	2.58	3.39	0	4.33
RPA	500	70.95	43.59	0	175
Age	500	28	28	28	28
Time	500	37.25	25.22	0	96
S (mm/s$^{1/2}$)	500	0.036	0.014	0.006	0.074

Table 5. Analysis of the Outliers for all the Variables**.**

Water absorption											
Variables	**W**	**C**	**F**	**C**	**SP**	**RPA**	**Age**	**S**	**D**	**CS**	**WA (%)**
Outliers	0	0	0	0	0	0	0	0	0	0	7
Sorptivity											
Variables	**W**	**C**	**F**	**C**	**SP**	**RPA**	**Age**	**T**	**S (mm/s$^{1/2}$)**		
Outliers	0	0	0	0	0	0	0	0	0		

4.4.2 Prediction of Water Absorption Properties of Concrete RPA

Water absorption is a key durability property that indicates the resistance of concrete to moisture penetration and possible degradation. High water absorption can weaken concrete, reduce compressive strength and increase the risk of deterioration. **Table 6** shows the training and testing results for ANN, KNN and RF models predicting the water absorption of RPA concrete at different ages.

Table 6. Performance Evaluation of Water Absorption Models.

Models name	**Training results**		
	R^2	**MAE**	**MSE**
ANN	0.9997	0.0555	0.0077
KNN	1.00	0.0010	0.0010
RF	0.8515	1.4717	3.6896
	Testing results		
ANN	0.9989	0.0945	0.0299
KNN	1.00	0.0010	0.0010
RF	0.8118	1.8479	5.6642

Figs. 13 and **14** show that both ANN and KNN models accurately predicted the measured water absorption values of RPA concrete. The R^2, MAE and MSE values of the ANN model were 0.9997, 0.0555 and 0.0077, respectively. On the training data and 0.9989, 0.0945 and 0.0229, respectively in the testing data. The KNN model performed very well with R^2, MAE and MSE values of 1.0, 0.001 and 0.001 for the training and test sets, respectively. The R^2, MAE and MSE values obtained by the RF model on the test set are 0.8118, 1.8479 and 5.6642, respectively as shown in **Table 6. Fig. 15** shows the residual plot of the R^2 train and test results of water absorption for the RF model. These results are consistent with the findings of **(Deng *et al.*, 2018)**, who reported R^2 values of 0.95 when predicting water absorption in concrete pavements using KNN models. The high value of R^2 indicates that KNN can reliably predict the water absorption of RPA concrete.

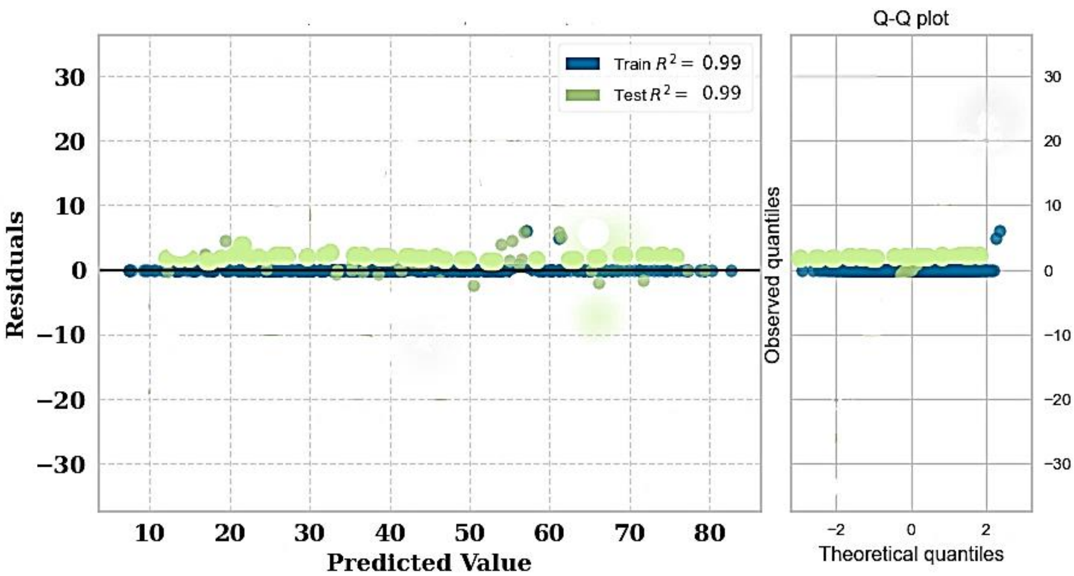

Figure 13. Residual plot of the train and test R^2 score of water absorption for ANN model.

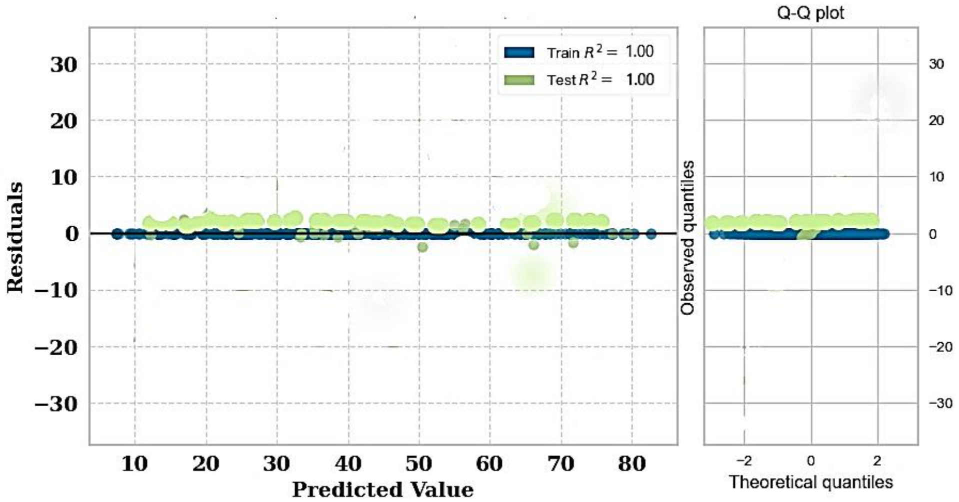

Figure 14. Residual plot of the train and test R^2 score of water absorption for the KNN model.

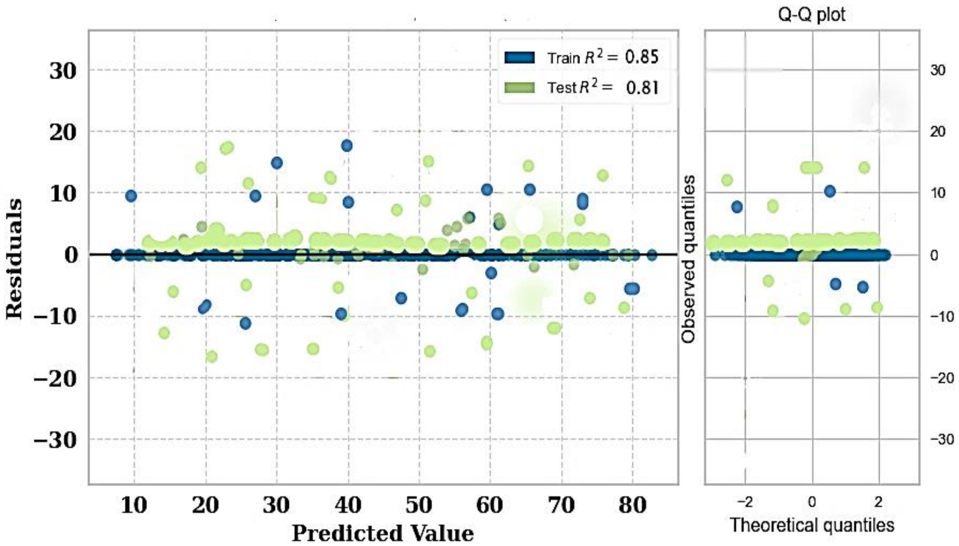

Figure 15. Residual plot of the train and test R^2 score of water absorption for RF model.

4.4.3 Predicting RPA Concrete Sorptivity Properties Using Machine Learning

Sorptivity, a critical durability property, measures the ability of concrete to absorb liquid or gas through capillary action under a hydraulic gradient. High sorptivity levels increase the risk of chemical deterioration and alkali silica reaction (ASR). This phase of the study evaluates the predicted sorptivity properties of RPA concrete using ANN, KNN and RF models. **Table 7** shows the performance evaluation for the training and testing datasets. The ANN model showed that the predictions closely match the measured sorptivity values. The R^2, MAE and MSE values of the experimental dataset obtained by the ANN model are 0.9998, 0.0117 and 0.0002 respectively. The KNN model performed very well with R^2, MAE and MSE values of 1.0, 0.001 and 0.001 for the training and test datasets. The R^2, MAE and MSE values of the experimental data obtained by the RF model are 0.8189, 0.3303 and 0.1755, respectively as shown in **Table 7**. These results are consistent with those of **(Duan, 2024),** who reported R^2 values ranging from 0.90 to 0.95 when predicting sorptivity in concrete pavements using KNN models.

Table 7. Performance Evaluation of Sorptivity Models.

Models name	Training results		
	R^2	MAE	MSE
ANN	0.9994	0.0138	0.0005
KNN	1	0.001	0.001
RF	0.8147	0.3058	0.1507
	Testing results		
ANN	0.9998	0.0117	0.0002
KNN	1	0.001	0.001
RF	0.8189	0.3303	0.1755

Figs. 16 to **18** illustrate the residual plot of the train and test R^2 score of ANN, KNN, and RF models for sorptivity values of RPA concrete.

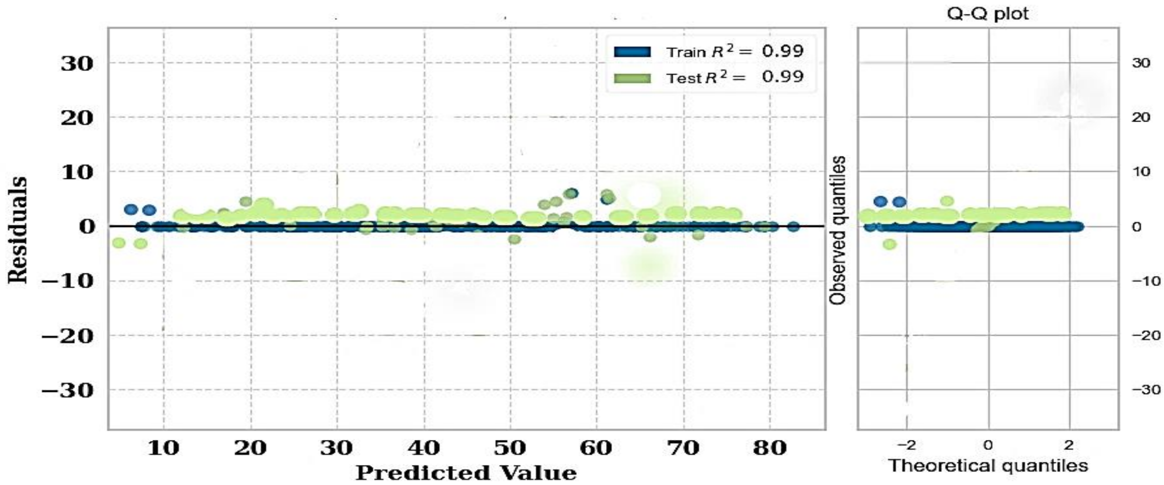

Figure 16. Residual plot of the train and test R^2 score of sorptivity for ANN model.

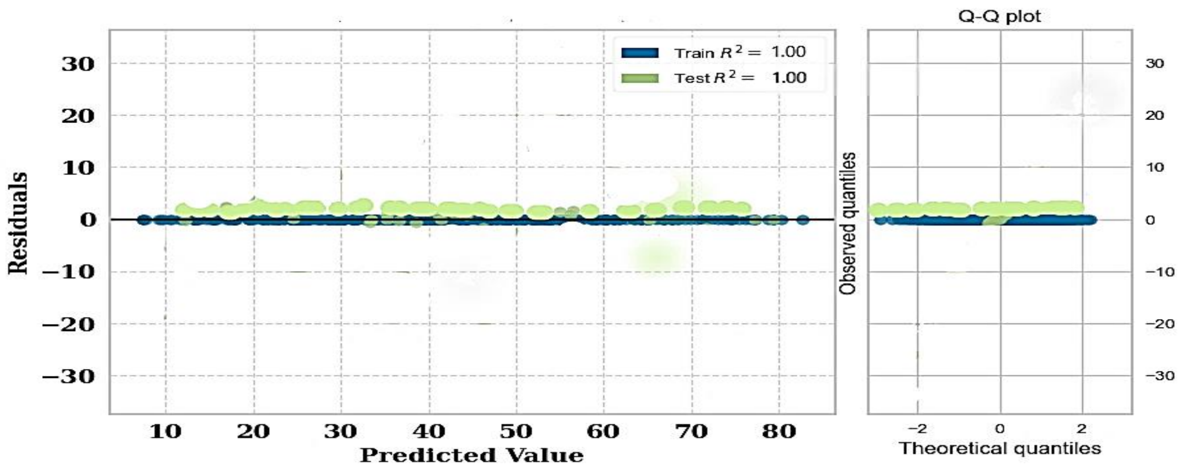

Figure 17. Residual plot of the train and test R^2 score of sorptivity for KNN model.

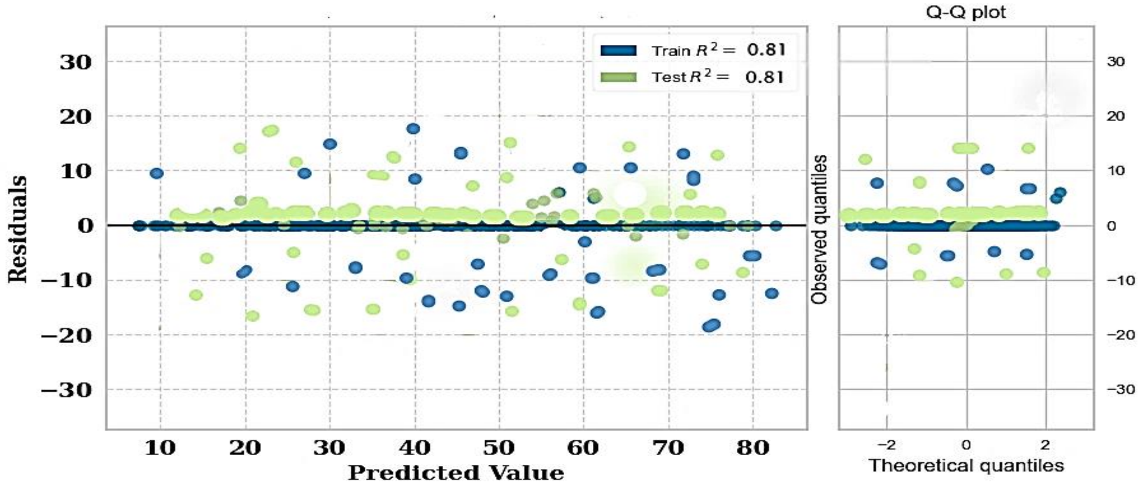

Figure 18. Residual plot of the train and test R^2 score of sorptivity for RF model.

5. CONCLUSIONS

After extensive laboratory testing, observations, analysis, and discussion on the effect of RPA on concrete properties and the potential of predictive models to predict durability, the following conclusions were reached:

- The determination of properties for both conventional crushed stone and recycled plastic aggregate (RPA) revealed distinct differences in their physical properties. The RPA exhibited a notably lower density and a water retention value of 0.50%, indicating reduced mass and low surface porosity compared to crushed stone. Despite these differences, both aggregate types met the requirements for compacted and uncompacted bulk density as specified in BS EN 1097-3, confirming their suitability for use in concrete production. Furthermore, the aggregates demonstrated excellent mechanical performance, with aggregate impact and crushing values of 5.20 and 6.60% for crushed stone, and 2.00 and 3.20% for RPA, all falling well within the permissible limits defined by BS EN 1097-6 and BS EN 1097-2. These results indicate that both materials possess sufficient mechanical strength to be considered for structural concrete applications.
- The 15% RPA replacement fresh concrete showed better workability than the control mix, while the 45% replacement concrete showed the lowest slump value, likely due to the irregular shape of the RPA and the rough surface structure that affected the flow of water. The inclusion of RPA reduced the density of the concrete compared to traditional aggregates, reflecting its lighter nature.
- The compressive strength of RPA concrete decreases with increasing replacement percentage due to the lower rigidity of RPA compared to traditional coarse aggregate, showing an inverse relationship between replacement percentage and strength properties.
- At 28 days of curing, the compressive strength of RPA concrete decreased with higher replacement percentages, attributed to its lower rigidity compared to traditional coarse aggregates, with reductions of 10.94, 14.65 and 15.69% for 15, 30 and 45% RPA replacement, likely due to reduced rigidity and increased void content which disrupt the bond between the aggregate and cement paste, reducing cohesion and strength.
- Water absorption and sorptivity decreased with 15% RPA replacement but increased at higher percentages compared to the control. This increase is due to the void space in the interfacial transition zone, which allows easy water penetration.
- Prediction models using K-Nearest Neighbors (KNN) consistently provide the most

accurate predictions of water absorption and sorptivity property of RPA concrete. KNN shows the best performance with the lowest error and the highest R^2 score of 0.001 and 1.00 in all evaluations. Artificial neural networks (ANN) also show strong predictive capabilities, serving as a reliable alternative to KNN. In contrast, Random Forest (RF) shows inaccurate predictions, indicating the need for further optimization to improve its performance in predicting the properties of these materials.

Credit Authorship Contribution Statement

Muhammad Fuad Umar: Writing-original draft, Formal analysis, Investigation, Jamilu Yau: Supervision, Agboola Shamsudeen Abdulazeez: Validation, Methodology, Review & editing, Shabi Moshood Olawale: Validation, Software, Aliyu Bukar: Review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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التنبؤ بخصائص المتانة للخرسانة باستخدام الركام البلاستيكي المعاد تدويره كبديل جزئي للركام الخشن

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الخلاصة

يتسبب التخلص من النفايات البلاستيكية في مشكلات بيئية خطيرة، منها تدهور الأراضي والمسطحات المائية، وانبعاث الغازات الدفيئة، وتلوث التربة، وغيرها. تهدف هذه الدراسة إلى فحص استخدام الركام البلاستيكي المعاد تدويره (RPA) كبديل جزئي للركام الخشن التقليدي في الخرسانة خفيفة الوزن من حيث الوزن. تم إعداد خلطات خرسانية تحتوي على نسب مختلفة من RPA(0%، 15%، 30%، و45%)، وتمت معالجتها لمدة 7، 14، 28، و56 يومًا. أظهرت النتائج أن إدخال RPA في الخرسانة أدى إلى انخفاض في الكثافة ومقاومة الانضغاط كلما زادت نسبة الاستبدال. انخفضت الكثافة من 2,347 كجم/م³ عند 0 RPA %إلى 1,895 كجم/م³ عند نسبة استبدال 45%. وبالمثل، انخفضت مقاومة الانضغاط بعد 28 يومًا من 30.43 نيوتن/مم² (العيّنة المرجعية) إلى 19.50 نيوتن/مم² عند نسبة استبدال 45%، مما يعكس الكثافة النوعية المنخفضة وضعف التماسك في RPA مقارنةً بالركام الخشن التقليدي .أظهرت النتائج أيضًا أن الخرسانة المحتوية على 15% من RPA أظهرت معدل امتصاص منخفض للماء بلغ 2.50% وقيمة امتصاصية (sorptivity) مقدارها 0.0235 مم/ثانية²/¹، مقارنة بالعينات المرجعية التي أظهرت امتصاصًا للماء بنسبة 2.66% وقيمة امتصاصية 0.024 مم/ثانية²/¹. ومع ذلك، أظهرت العينات التي تحتوي على ما يصل إلى 30% من RPA نتائج تفي بالحد الأدنى لمتطلبات الخرسانة الهيكلية خفيفة الوزن .كما استخدمت الدراسة نماذج تعلم الآلة، بما في ذلك الشبكات العصبية الاصطناعية(ANN) ، وأقرب الجيران(k–NN) ، وغابة القرارات العشوائية(RF) ، للتنبؤ بخصائص المتانة للخرسانة المحتوية على .RPA من بين هذه النماذج، أظهر نموذج k–NN أعلى دقة في التنبؤ، حيث بلغت قيمة معامل التحديد$R^2 = 1.00$ ، مع متوسط خطأ مطلق (MAE) ومتوسط الخطأ التربيعي (MSE)قدره 0.001 لكل من بيانات التدريب والاختبار .تشير هذه النتائج إلى أن استخدام RPA المعالج في الخرسانة لا يوفر بديلًا مستدامًا للركام الطبيعي فحسب، بل يساهم أيضًا في تحسين متانة الهياكل الخرسانية الناتجة.

الكلمات المفتاحية :الشبكة العصبية الاصطناعية، أقرب الجيران، غابة القرارات العشوائية، خرسانة الركام البلاستيكي المعاد تدويره، الامتصاصية، امتصاص الماء.