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Optimizing Mechanical and Durability Properties of Eco-Friendly Composite Materials Using Recycled Fillers and ML Techniques

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Abstract

The increasing demand for sustainable construction materials has intensified the exploration of recycled fillers as partial or full replacements for natural aggregates in composite materials. This study investigates the mechanical and durability performance of polymer matrix composites incorporating processed recycled fillers derived from construction and demolition (C&D) waste. Three distinct processing methods were employed to prepare the recycled fillers: untreated (URF), single processed (SPRF), and double processed (DPRF), with replacement levels ranging from 0% to 100%. The composite formulations were prepared using the Standard Composite Blending Method (SCBM), and their performance was evaluated through a series of mechanical and durability tests, including compressive strength, tensile strength, curing agent absorption, diffusion coefficient, and workability assessments. The results revealed that increasing recycled filler content led to reductions in strength and workability, primarily due to increased porosity and weak interfacial bonding. However, the double processed recycled filler (DPRF) consistently outperformed the other variants across all tests, demonstrating superior matrix compatibility, reduced permeability, and enhanced mechanical integrity, even at full replacement levels. Notably, the compressive strength increased from 28 to 90 days across all mixtures, indicating continued hydration and strength development. To support experimental findings, machine learning models—Polynomial Regression, Random Forest Regression, and Support Vector Regression (SVR)—were developed to predict mechanical properties based on input parameters such as filler type, replacement ratio, and curing duration. Among these, Polynomial Regression yielded the highest accuracy, with R^2 values exceeding 0.99 for tensile and flexural strength predictions. These outcomes validate the applicability of data-driven modelling in optimizing sustainable composite formulations. The study concludes that DPRF is a technically and environmentally viable substitute for natural aggregates in composite materials, and that predictive modelling can significantly enhance material design processes by enabling accurate performance estimation.

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INTRODUCTION TO ECO-FRIENDLY COMPOSITES

Composite materials, composed primarily of a polymer matrix, reinforcing fillers or aggregates, and a curing agent, have emerged as essential engineered materials in modern construction. Their adaptability, moldability into complex shapes, and the ability to utilize readily available and often natural materials make them highly favourable for structural and architectural applications. Thanks to their notable mechanical strength and stiffness, they are extensively used in infrastructure and rank among the most widely consumed construction materials—second only to water in global usage [1]. The global surge in construction activity has drastically increased the demand for such materials. Consequently, this has led to a sharp rise in the extraction of raw materials for composite fabrication, creating concerns over environmental degradation and resource depletion [2]. In India, construction and demolition (C&D) waste is a significant contributor to the total solid waste generated annually, amounting to approximately 12–14.7 million tons, of which around 7–8 million tons comprise brick and composite-related debris [3]. Tabulated in Table 1 are the specifics of C&D manufacturing in India.

C&D activities such as construction, renovation, and demolition account for nearly one-third of the total solid waste generated globally. If not properly managed, this waste can pose serious environmental and health risks. Although several studies have explored the recycling and reuse of such debris, the potential of C&D waste as a functional filler or adsorbent in composite systems has not been thoroughly examined.

This study investigates the potential of recycled C&D waste—particularly in the form of recycled aggregate fillers—to serve as reinforcement in polymer matrix composites. Previous research has highlighted their capacity to remove impurities from environmental systems, indicating their multifunctionality beyond mere structural use [4]. With increasing industrialization and urban development, both developed and developing nations are witnessing a surge in C&D waste production, often constituting 30–40% of total solid waste streams [5]. Recycling this waste into coarse fillers for composite manufacturing presents an eco-friendly solution. However, the integration of such materials introduces technical challenges, including compromised strength, poor abrasion resistance, increased permeability to moisture and ions, and thermal instability due to high porosity and weak bonding at the matrix–filler interface [6]. To address these limitations, a modified Standard Composite Blending Method (SCBM) has been proposed, aimed at improving the quality and interracial properties of recycled fillers. The SCBM enhances the interracial transition zone (ITZ) between the filler and the matrix, leading to improved composite performance [15]. In the present research, further enhancements to SCBM are introduced to develop Double Processed Recycled Fillers (DPRF), which exhibit better compatibility and improved mechanical characteristics when used in polymer-based composite systems.

OBJECTIVES OF RESEARCH

The primary aim of this study is to explore the feasibility and effectiveness of incorporating processed recycled fillers derived from construction and demolition (C&D) waste into polymer matrix composite materials. The specific objectives of the research are as follows:

- To develop high-performance Double Processed Recycled Fillers (DPRF) through mechanical and chemical treatment of C&D waste, enabling up to 100% substitution of natural fillers in the matrix phase of composite materials without compromising mechanical or durability performance.
- To evaluate the mechanical and durability characteristics of polymer-based composites reinforced with DPRF, focusing on critical performance parameters such as compressive strength, flexural strength, tensile strength, workability, and resistance to environmental degradation.
- To investigate the influence of the Standard Composite Blending Method (SCBM) on the performance of composites incorporating DPRF, and to compare its efficacy against composites made with Single Processed Recycled Fillers (SPRF) and Untreated Recycled Fillers (URF).
- To apply Machine Learning (ML) models for predicting the mechanical behaviour and long-term durability of DPRF-reinforced composites, using data-driven approaches to support optimization in material design.
- To assess the predictive accuracy of various regression-based ML techniques—including Polynomial Regression, Support Vector Regression (SVR), and Random Forest Regression—using statistical performance indicators such as R^2, Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Logarithmic Error (RMSLE).
- To visualize prediction performance through graphical representation of error metrics and residual distributions, thereby enhancing interpretability and aiding in the development of optimized, sustainable composite material formulations.

Table 1. Specifics of C&D manufacturing in India.

Constituent	Quantity generated in million tons per annum
Soil, sand and gravel	4.20 to 5.14
Bricks and masonry	3.60 to 4.40
Composite Material	2.40 to 3.67
Metals	0.60 to 0.73
Bitumen	0.25 to 0.30
Wood	0.25 to 0.30
Others	0.10 to 0.15

Furthermore, the inclusion of up to 100% recycled filler replacement aimed to evaluate the upper-limit feasibility of DPRF in structural applications comprehensively. By testing full replacement levels, the study offers insights into performance thresholds and helps define safe substitution margins, serving both scientific inquiry and practical implementation needs.

LITERATURE REVIEW

In comparison to natural aggregate composites (NAC), composite materials containing recycled aggregate (RA) typically require a higher quantity of curing agent to achieve the desired consistency and workability. This increased demand arises from the rough and porous surface of recycled fillers, which absorb more of the binder phase. Moreover, the interracial transition zone (ITZ) between recycled fillers and the new matrix is often weaker than in NAC due to the presence of residual mortar adhered to the recycled surface. This compromised ITZ results in reduced strength, a lower elastic modulus, and diminished long-term durability in recycled aggregate composites (RAC) [7].

Although much of the existing research has focused on carbonation treatment of coarse recycled aggregates (RCA), the potential benefits of treating recycled fine aggregates (RFA) should not be overlooked. Carbonation treatment involves the diffusion and dissolution of carbon dioxide (CO_2) into the pores of the adhered mortar. This reaction forms silica gel and calcium carbonate ($CaCO_3$) crystals, which help to seal micro-cracks and voids within the recycled fillers, thereby enhancing their physical properties [8].

Studies examining the inclusion of carbonated RAAs—up to 50% replacement—have shown promising improvements in mechanical and durability properties. Specifically, enhancements were observed in compressive strength (with increases of up to 15%), chloride ion resistance, and carbonation resistance. Additionally, denser microstructures were achieved, which contributed to a reduction in the corrosion potential of embedded steel reinforcements [9].

Despite these improvements, recycled aggregates derived from construction waste often possess inherently inferior characteristics, such as low bulk density, high porosity, and elevated curing agent absorption. These deficiencies stem mainly from the mechanical crushing process and the retained old mortar on the filler surface [10].

Several surface treatment strategies have been developed to enhance the quality of recycled aggregates. Among them, carbonation treatment has been widely acknowledged for increasing apparent density and reducing water (curing agent) absorption and crushing index values of treated aggregates compared to their untreated counterparts [8,10,11]. In another approach, microwave heating has been applied to remove adhered mortar effectively, thereby improving surface integrity and reducing porosity [12].

However, even after mechanical and thermal treatments, a small amount of residual mortar may remain attached to the filler surfaces. Complete removal often requires additional processing, and excessive mechanical grinding can damage the parent rock material of the recycled filler, thereby deteriorating its quality [13]. To address this, researchers have introduced hybrid treatment techniques—such as mechanical abrasion combined with pre-soaking in mild acetic acid—which have demonstrated further improvements in filler performance. Other proposed methods include thermochemical treatments and ultrasonic cleaning, both aimed at refining the surface and enhancing the filler–matrix interaction [14].

These findings underscore the importance of optimizing both the physical quality and surface chemistry of recycled fillers before their integration into composite systems. When adequately treated, recycled fillers can offer considerable benefits in terms of sustainability and cost-effectiveness without severely compromising structural performance.

COMPOSITE FABRICATION PROCESS

Matrix and Filler Composition

Aggregates

The virgin coarse aggregate (VCA) was crushed stone from the Chowki Motipura quarry in Rajasthan that had been passed through a 25 mm IS sieve. Instead of NA, we employed the single- and double-processed recycled aggregates (SPRF and DPRF, respectively) as detailed above. Aside from DPRF, both VCA and PRA (500 RVS) met the standards set forth by IS: 383-2016 [20] and IS: 2386-1999 [19]. Throughout the operation, the fine aggregate utilized complied with IS: 383-2016's grading zone-II, which was sand that was locally accessible from the Banas River. Before being air dried, all aggregates were carefully rinsed in Curing Agent to remove any unwanted contaminants such as dust, silt, or clay. Table 2 shows the aggregate distribution of their particle sizes. Figure 1 represents the flowchart of single processed recycled aggregate

Dispersing agent

Throughout the investigation, the super plasticizer employed was the chemical admixture Glenium®Ace 30 (Poly carboxylic ether-based Dispersing Agent) provided by BASF chemical firm, Mumbai, India, which conforms to IS: 9103-1999 [24]. A dark brown, Curing Agent-based solution with 40–45% solids and a density of 1215 kg/m3 is available for purchase as this super plasticizer. To regulate the slump at 120 ±30 mm, this chemical additive was used. Using a marsh cone test instrument, we checked if the super plasticizer (Glenium Ace-30) was compatible with PPC Matrix Phase during the preliminary trials.

Table 2. Particle size distribution.

Sieve size, mm	Sand % passing	NA % passing	PRA (0-RVS) % passing	PRA (500RVS) & SPRF % passing	DPRF % passing
25	100	100	100	100	100
20	100	96.24	90.23	95.41	97.0
16	100	77.56	58.87	76.83	78.13
12.5	100	50.19	42.74	51.90	51.20
10	100	27.30	22.83	28.40	29.71
6.3	100	2.48	1.75	3.50	3.97
4.75	99.50	0.82	0	0.68	0.94
2.36	94.72	0	0	0	0
1.18	77.31	0	0	0	0
0.6	60.10	0	0	0	0
0.3	19.43	0	0	0	0
0.15	3.77	0	0	0	0
0.075	0.15	0	0	0	0

Figure 1. Flow chat in the generation of single processed recycled aggregate.

Curing agent

For both the mixing and curing of the Composite Material, Curing Agent that met the specifications of IS: 456-2000 was used. The Curing Agent is potable and provided mostly by the local government.[21]

Fume of silica

One of the waste products of industries that deal with silicon or silicon alloys is silica fume. At around 2000 °C, silicon dioxide vapor is produced when electric arc furnaces convert very pure quartz to silicon. The oxidation and condensation of silicon dioxide vapor at low temperatures produces silica fume. The significant amount of Dispersing Agent needed to keep silica fume workable limits its quantity utilized as a Matrix Phase substitute. in addition to silica fume sourced from Elkem India, Navi Mumbai. [23]

The portland matrix phase

Primarily made of oxides of calcium, silicon, and aluminum, this material serves as a key binder in traditional composites such as mortar, plaster, and cement-based building materials. According to IS 1489 (Part-1):1991 standards, it is usually produced by calcining clay and limestone at temperatures between 1300°C and 1400°C. This process creates clinker, which is then ground and mixed with gypsum or other sulfate compounds to produce Ordinary Portland Cement (OPC). OPC is the most widely used type, available in various shades of grey, while white OPC is also available for aesthetic or specialty uses. Despite its common use, handling Portland cement involves health and safety risks. The material is highly alkaline (pH > 13) and can cause chemical burns or skin and respiratory irritation on contact. Long-term exposure may lead to serious health issues such as silicosis, asthma, and lung cancer due to crystalline silica and trace elements like chromium. Environmentally, producing Portland cement is energy-intensive and releases significant airborne pollutants, including nitrogen oxides (NO_2), sulfur dioxide (SO_2), dioxins, particulate matter, and carbon dioxide (CO_2), a major greenhouse gas. These environmental and health concerns have increased interest in alternative binders and greener composite options, such as those using recycled fillers, industrial by-products, and polymer matrices, which reduce ecological impact without sacrificing performance [22].

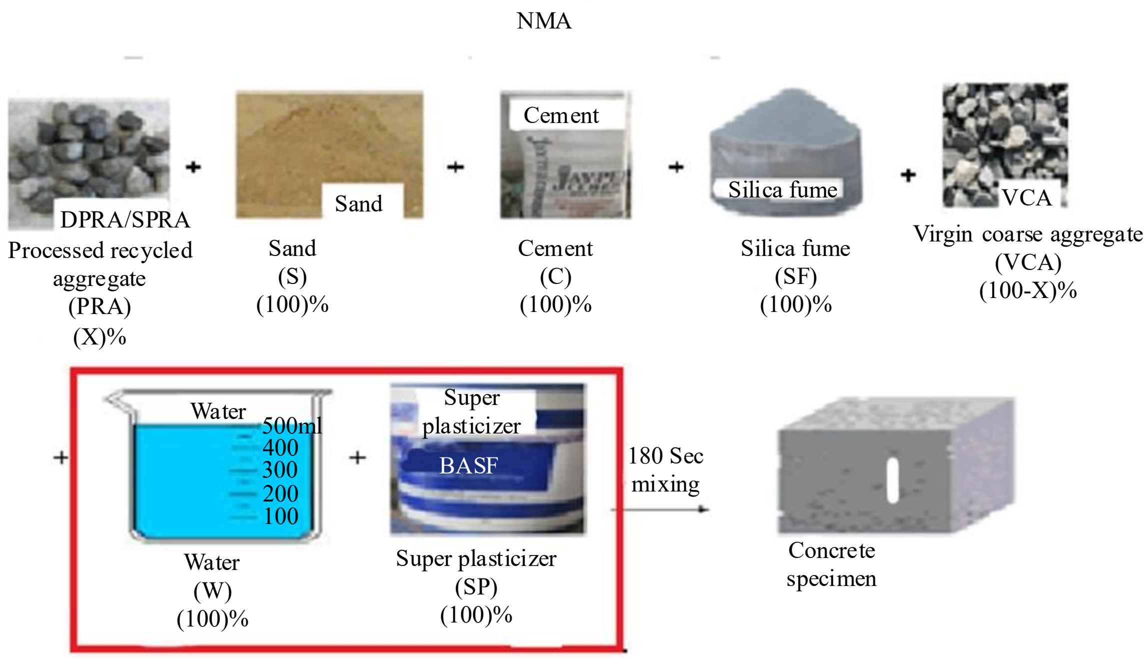

Figure 2. Standard composite blending method (SCBM).

Method for Mixing

Standard mixing method (SCBM)

To establish a baseline for evaluating the performance of modified composite formulations, this study employed the Standard Composite Blending Method (SCBM). In this process, a systematic mixing sequence was followed to ensure homogeneity and consistency across all composite batches. The mixing procedure began by loading approximately 50% of the coarse filler material—which included virgin aggregates, Single Processed Recycled Fillers (SPRF or PRF-500), and Double Processed Recycled Fillers (DPRF)—into a laboratory-grade pan mixer. This was followed by the sequential addition of fine fillers (sand), polymer matrix phase (binder), silica fume, and the remaining coarse filler content, essentially forming a layered composite mix, or what may be described as a "component sandwich." Before initiating the mixing, the curing agent and superplasticizer were pre-blended in a separate container to ensure uniform dispersion. This premixed solution was then added to the dry materials in the mixer just before blending began. The entire mixing process was continuous and uninterrupted, with a total duration of 180 seconds per batch. The mixing was performed using a laboratory pan mixer (AMIL, India), known for its precise blending capacity in composite material research. As illustrated in Figure 5, the variable 'x' denotes the proportion (in %) of natural filler replaced by recycled filler (SPRF or DPRF), with substitution levels ranging from 0% to 100% in increments of 25%. This allowed for the evaluation of performance trends across different filler replacement scenarios under consistent blending conditions [15]. Figure 2 shows the Standard Composite Blending Method (SCBM)

Generation of high-quality RA (DPRF)

The initial step in the processing of recycled aggregate (RA) involves mechanical treatment, which is aimed at improving the physical quality of the material by removing the residual mortar adhered to its surface [16]. For this purpose, discarded composite material boulders were sourced from a decommissioned pavement structure located on the campus of Jaypee University of Engineering and Technology (JUET). These boulders, aged approximately ten years, ranged in size from 100 mm to 400 mm and were manually selected to eliminate contaminants such as soil, organic matter, and other debris. Following this manual cleaning step, the boulders were mechanically crushed and sorted into two standard coarse filler fractions: 20–10 mm and 10–5 mm. Despite the initial crushing, a significant quantity of old mortar remained adhered to the surfaces, adversely affecting the quality of the recycled

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filler. To further enhance the filler's surface properties, a Los Angeles (LA) abrasion machine was employed. In this process, 10 kg batches of the crushed recycled fillers were subjected to 500 revolutions within the LA drum, using steel ball charges of various sizes and shapes. The combined effects of abrasion, impact, and attrition during this operation facilitated efficient removal of the residual mortar. After abrasion, the fillers were thoroughly washed to remove fines and dust, followed by oven drying at 110°C for 24 hours to achieve a stable moisture condition. The treated fillers were then stored in airtight containers for subsequent use in composite formulations. This optimized mechanical treatment method successfully reduced surface-bound mortar without compromising the structural integrity and interlocking capability of the aggregate particles. The resulting material from this phase of processing is referred to as Single Processed Recycled Filler (SPRF), also denoted as PRF (500) in this study [17]. Figure 3 shows the schematic depiction of mortar that has adhered to the aggregate surface

In the second stage of processing, single processed recycled aggregate (SPRF) undergoes silica fume (SF) impregnation to enhance its quality. A solution containing 5 kg of dry silica fume, 50 litters of Curing Agent, and a Dispersing Agent (1% of SF weight) was prepared using a labourer's tory pan mixer. A 50 kg batch of SPRF was soaked in this solution for 72 hours, allowing the SF to penetrate cracks and pores, further strengthening the adhered mortar. The aggregates were rinsed after washing, then let to dry for a day at 110°C in an oven before being retriggered. Approximately 60-80% of the silica fume was absorbed, significantly improving the aggregate's properties. The final product, Double Processed Recycled Aggregate (DPRF), is an excellent material for use in structural composite materials. [18] Figure 4 shows the diagrammatic representation of silica fume impregnation into the SPRF

Mix Proportion

To regulate every one of the Composite Material's characteristics, the mix percentage is a crucial variable. The Composite Material mix specifications were created in compliance with IS: 10262-2019. [24]. Table 3 shows the proportions of the planned Composite Material mix, which is M30 grade. Throughout the process, the percentage of the blend was maintained constant. Each time, RF/SPRF/DPRF were substituted for the natural aggregates in a fresh batch of mix. To create a new combination, the amount of DPRF/SPRF/RF was simply adjusted from 0 to 100 in increments of 25. The amounts of the other components, however, remain unchanged from the mix proportion. Only the quantities of DPRF, RF, and SPRF have been changed every time instead of NF. The recycled aggregates are used to replace Matrix Phases of NF at various dosages. [24,25]

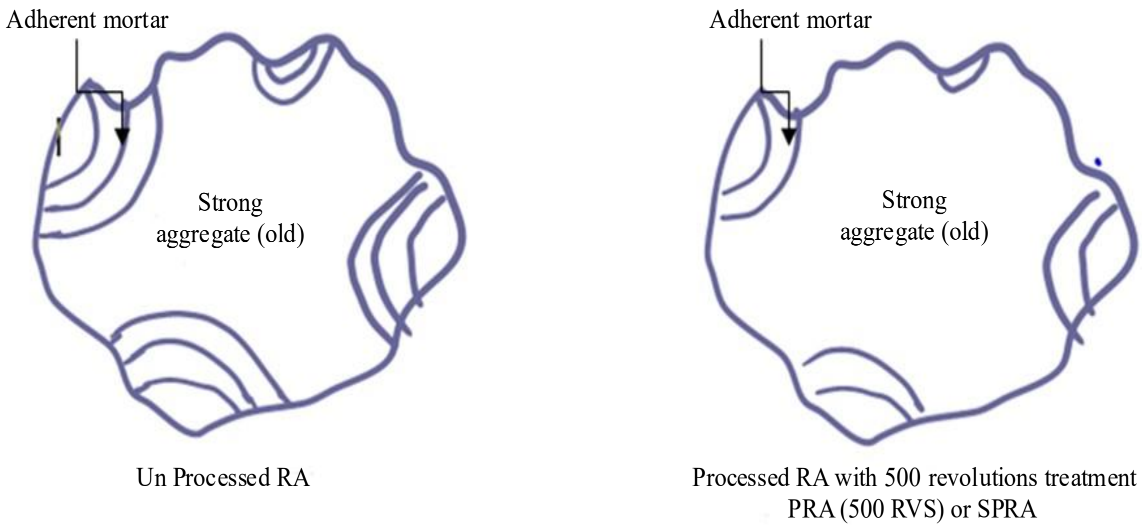

Figure 3. The schematic depiction of mortar that has adhered to the aggregate surface.

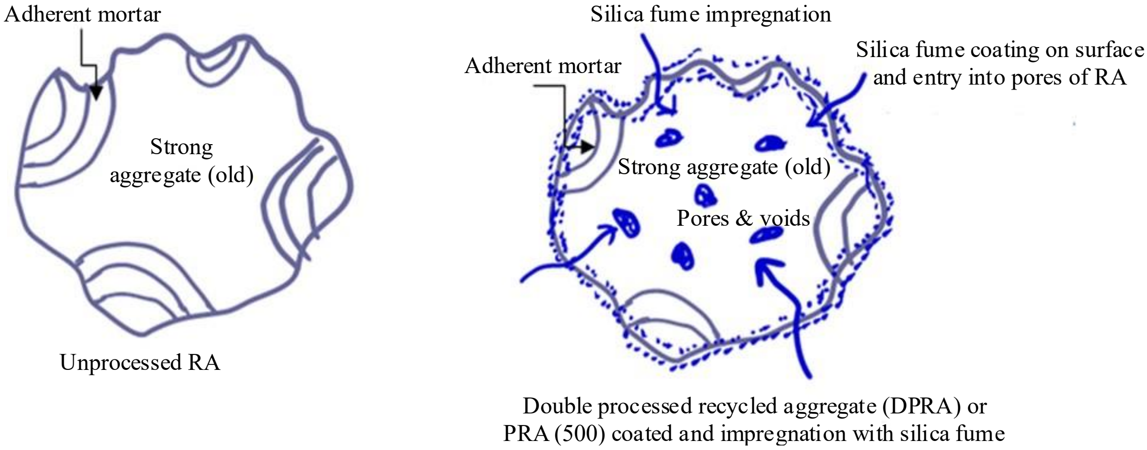

Figure 4. The diagrammatic representation of silica fume impregnation into SPRF

Table 3. The composite material mix proportion (M30).

GRA de of composite material	M30
Target Strength (28 days)	39 MPa
Slump	70 to 100 mm
Curing Agent/Matrix Phase Ratio(w/c)	0.42
Portland Pozzolana Matrix Phase (C)	350 kg
Sand (S)	695 kg
Coarse Filler (CF)	1255 kg (i.e., NF/ DPRF / SPRF / RF)
Silica fume (SF)	3.5 kg (1% of Matrix Phase weight)
Curing Agent (W)	148 kg
Super plasticizer (SP)	3.5 kg (1.0% of Matrix Phase weight)

Figure 5. Prepared specimen of SPRF.

Specimen Casting and Curing

The whole process relied on a laboratory pan mixer. To prepare the aggregates for mixing, they must first be brought to a saturated surface dry (SSD) state. The amount of VCF that was substituted with PRF varied between 0% and 100%, with a 25% rise in between. There was no variation in the designated mix percentage (M 30) throughout the research. This data is displayed in Table 5. By casting a large number of specimens for each mix, SCBM methods were used to investigate the workability, strength, and durability characteristics of the Composite Material. After 24 hours of casting, all of the steel Moulds were unmoulded and compressed using a laboratory table vibrator. Composite Material samples were immersed in the Curing Agent at 27 ±2°C until they reached the testing age. [26] Figure 5 displays the prepared specimen of SPRF.

MACHINE LEARNING MODEL

A machine learning model is a computational system developed to detect patterns and make accurate predictions or decisions when exposed to new, previously unseen data. This capability is achieved through a training process that involves large datasets, where algorithms analyze and learn underlying patterns or relationships. During training, the model continuously adjusts its internal parameters to enhance its prediction accuracy. For example, in natural language processing, machine learning models can analyze and understand the intent behind novel or unfamiliar phrases. In image recognition, they are capable of identifying and categorizing objects such as animals or vehicles. Once training is complete, the resulting model applies the learned patterns to solve real-world problems. In this research, four types of machine learning models are utilized: A variety of regression models, such as Random Forest, Support Vector, 3D Polynomial, and Linear. Each model's accuracy and performance are assessed using a variety of assessment indicators. These measures include R^2, MSE, MAE, and RMSLE (Root Mean Squared Log Error).

PERFORMANCE ANALYSIS OF COMPOSITE SPECIMENS

All experimental measurements were conducted in triplicate ($n = 3$) for each filler type, replacement percentage, and curing age. The reported results represent the average values across these replicates. Outlier detection was performed using Grubbs' test ($\alpha = 0.05$), and any confirmed anomalies were excluded and re-tested. Variability was quantified using standard deviation, and results showed acceptable consistency, with most coefficients of variation below 10%. Standard deviation values are included in the updated figures and supplementary tables to enhance reproducibility and clarity.

Workability

Figure 6 illustrates the slump values, measured in millimetres, which serve as a key indicator of the workability of freshly mixed composite materials. The observed slump values ranged significantly, from 45 mm for untreated recycled filler (URA) to 105 mm for Double Processed Recycled Filler (DPRF). This wide variation underscores the influence of processing techniques on the flow characteristics of the material. A consistent trend was identified across all recycled filler types—URA, SPRF, and DPRF —whereby the slump value decreased with an increasing dosage of recycled filler (RA). Despite this decline, all Standard Composite Blending Method (SCBM) formulations-maintained slump values above the minimum threshold of 50 mm, even at 100% replacement of natural aggregate (NA) with recycled fillers. This highlights the capability of treated fillers, particularly DPRF, to maintain acceptable workability levels, ensuring ease of mixing, placing, and compaction.

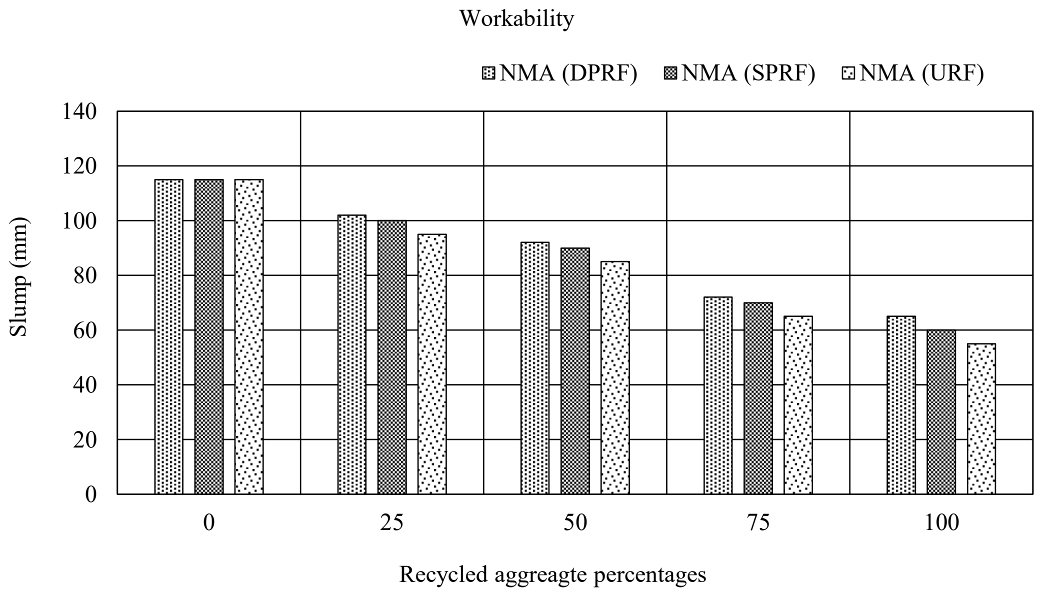

Figure 6. Evaluation of composite material slump using SCBM.

Workability is essential for ensuring uniform dispersion of composite constituents and adequate compaction without segregation. The cohesiveness of the fresh mix is also critical, and it is directly affected by the presence of adhered mortar on recycled fillers. The higher the residual mortar content, the greater the internal friction and water absorption, both of which reduce the slump. Experimental findings demonstrate that DPRF enables full (100%) replacement of NA with only a minor reduction in slump. Literature similarly supports this observation, reporting a maximum slump reduction of around 20–30% for well-processed recycled aggregates when used at full replacement levels. Moreover, across all mixing protocols and replacement ratios, DPRF consistently exhibited the highest slump values, indicating better flow behaviour. In contrast, URA showed the most severe slump reductions, followed by SPRF, with DPRF outperforming both. These results validate that double-processed recycled fillers significantly improve workability performance, making them a viable alternative to natural aggregates in composite systems, with only marginal reductions in slump even at complete replacement.

Compressive Strength

Figures 8 illustrate the compressive strength of composite materials incorporating Single Processed Recycled Fillers (SPRF or PRF–500RVS), tested after 28 and 90 days of curing, respectively. Each data point represents the average of three replicate measurements, ensuring accuracy and reproducibility of the reported values. At 28 days, the compressive strength of composites prepared using the Standard Composite Blending Method (SCBM) ranged from 85.43 MPa at 0% replacement to 62.30 MPa at 100% replacement of virgin coarse aggregate (VCA) with PRF–500RVS, in increments of 25%. After 90 days, compressive strength values increased across all mixes, ranging from 99.33 MPa (0% replacement) to 75.98 MPa (100% replacement), with finer increments of 10% replacement used for enhanced resolution. These changes negatively affect the overall strength and durability of composite materials compared to conventional systems. Increased filler replacement ratios often result in reductions in mechanical integrity, durability, and dimensional stability (e.g., shrinkage and thermal strain). Despite these effects, all composite formulations—including those with high levels of PRF—exhibited continued strength development between 28 and 90 days. This long-term strength gain reinforces the viability of using recycled fillers in structural applications when appropriate curing practices and mix designs are followed. When comparing different mixing strategies under a constant replacement level, two-stage mixing techniques consistently outperformed SCBM in terms of compressive strength. For instance, at 50% PRF–500RVS replacement, the SCBM method yielded a 28-day compressive strength of 73.23 MPa, which was lower than the value achieved using a two-stage mixing approach at the same replacement level. This suggests that mixing methodology plays a critical role in optimizing the performance of recycled filler composites. Figure 7 represents the testing of a Specimen of concrete for compressive strength. Figure 8 shows the Compressive Strength Testing.

Figure 7. Compressive strength testing.

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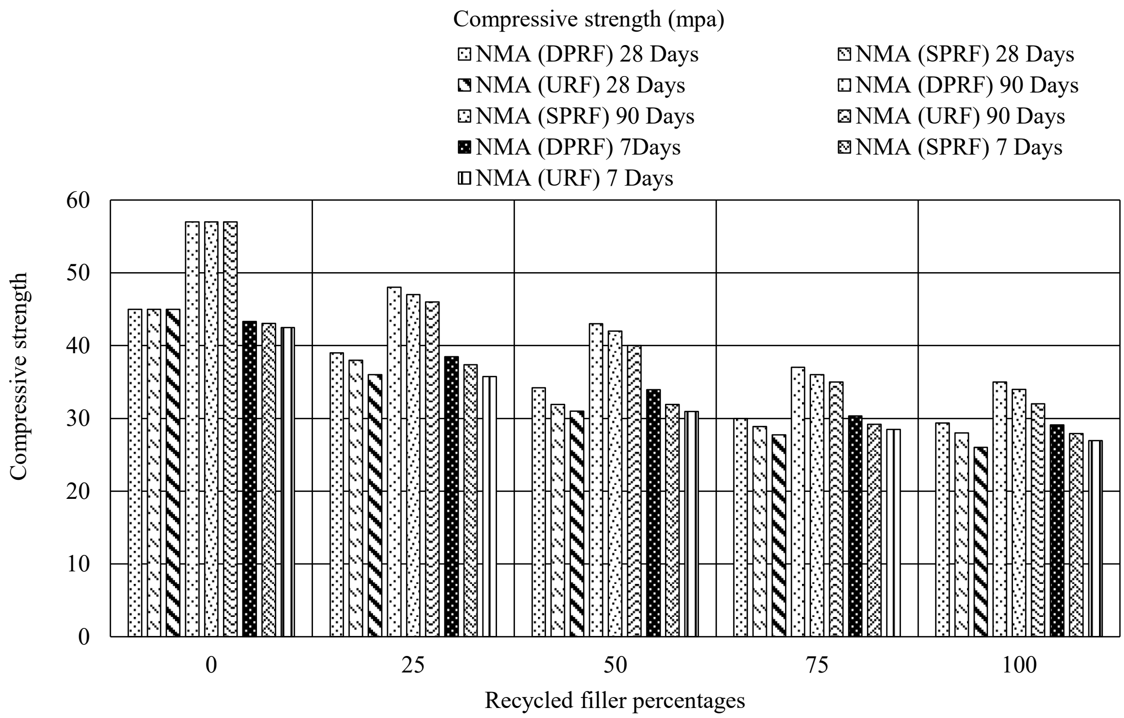

Figure 8. Strength of compressive composite material after 28 and 90 days of SCBM addition.

Curing Agent Absorption

Figure 9 presents the variation in curing agent absorption across composite materials incorporating Single Processed Recycled Filler (PRF–500RVS) at different replacement levels. In freshly mixed composites, free curing agent is consumed primarily through hydration reactions of the matrix phase and evaporation, both of which are essential in the initial setting and hardening process. It was observed that composite mixes containing recycled fillers absorbed significantly more curing agent than those prepared with natural aggregates. This is primarily due to the presence of adhered mortar on the surface of recycled aggregates, which introduces high porosity and increased moisture demand. According to established benchmarks, a curing agent absorption rate below 3% is considered low and indicative of good material compactness. In this study, SCBM composite mixes exhibited curing agent absorption values ranging from 0.45% to 1.55% after 28 days, with PRF–500RVS replacing virgin coarse aggregates (VCA) in 10% increments from 0% to 100%. The elevated absorption in recycled aggregate composites is attributed to the microstructural flaws of the adhered mortar—specifically, the abundance of micro voids, cracks, capillaries, and interracial gaps. These features facilitate higher permeability and hinder the formation of a strong bond between the matrix phase and the filler, ultimately reducing the composite's strength and durability. Furthermore, loosely adhered and highly porous mortar fragments act as weak zones, interrupting the continuity of the composite matrix. As the PRF–500RVS content increases, a gradual rise in curing agent absorption is observed, reflecting the influence of micro-defects and surface irregularities on the composite's moisture dynamics. Despite these challenges, mechanical treatment of recycled fillers—especially via two-stage processing techniques—significantly improves their surface quality and physical integrity. By reducing the volume of adhered mortar and enhancing surface compactness, these processes directly contribute to lower porosity and improved durability of the resulting composites. However, even after treatment, some residual mortar and surface voids persist, which underscores the need for continuous optimization in aggregate processing protocols. Compared to the traditional SCBM approach, composites made using two-stage treated fillers exhibited substantially improved durability indicators, including reduced curing agent absorption and enhanced resistance to permeability-driven degradation.

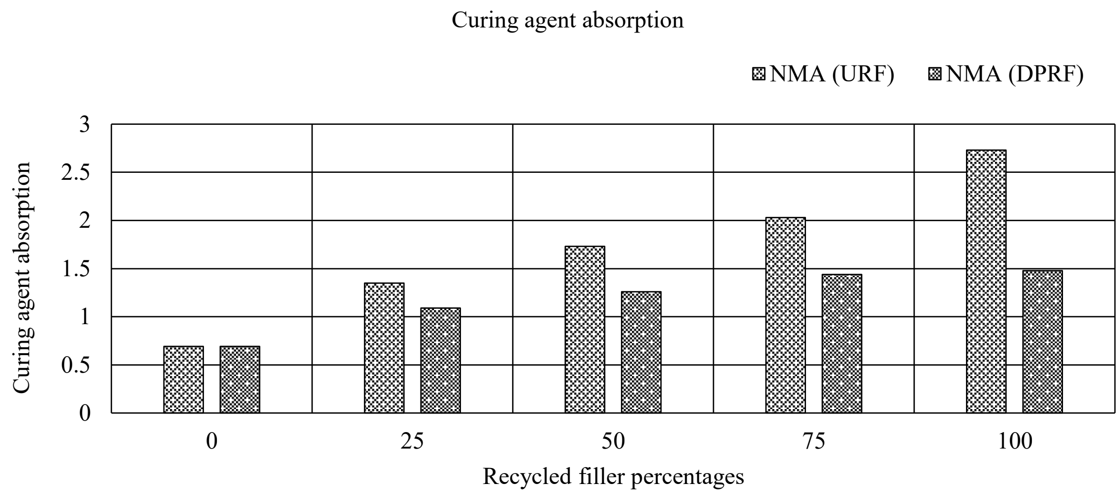

Figure 9. Curing agent absorption after 28 days.

Diffusion Coefficient

As you can see in Figures 10 and 11, the diffusion coefficient data for 28 days and 90 days are shown. Steel in reinforced Composite Material will corrode if air, Curing Agent, and chloride get inside. The expansion of the steel volume increases the likelihood of Composite Material cover cracking and spalling. In terms of Composite materials' strength and durability, ITZ is often a crucial component. As the curing period increases, the diffusion coefficient usually decreases. The diffusion coefficient findings in SCBM after 28 days ranged from 2.58 X10^{-4} to 3.96 X10^{-4} g/mm2/min 0.5, with PRF (500RVS) replacement Matrix Phase VCA at levels ranging from 0% to 100% step-by-step. Similarly, when VCA replacement with PRF (500RVS) increases by 10% at a time from 0% to 100%, the diffusion coefficient values after 90 days in SCBM ranged from 1.27 10^{-4} to 2.4 X10^{-4} g/mm^2/min 0.5. Large pores are also the result of a lack of proper mixing time in the Composite Material. As the material ages, its diffusion coefficient improves from 28 days to 90 days as a consequence of the continual hydration process. The Matrix Phase's hydration process reduces the size and volume of the small holes over time. Using two-stage mixing processes, a thin film is formed around the RA's perimeter after fractures, cavities, pores, fissures, voids, etc. are filled. This thin film prevents the pores from connecting.

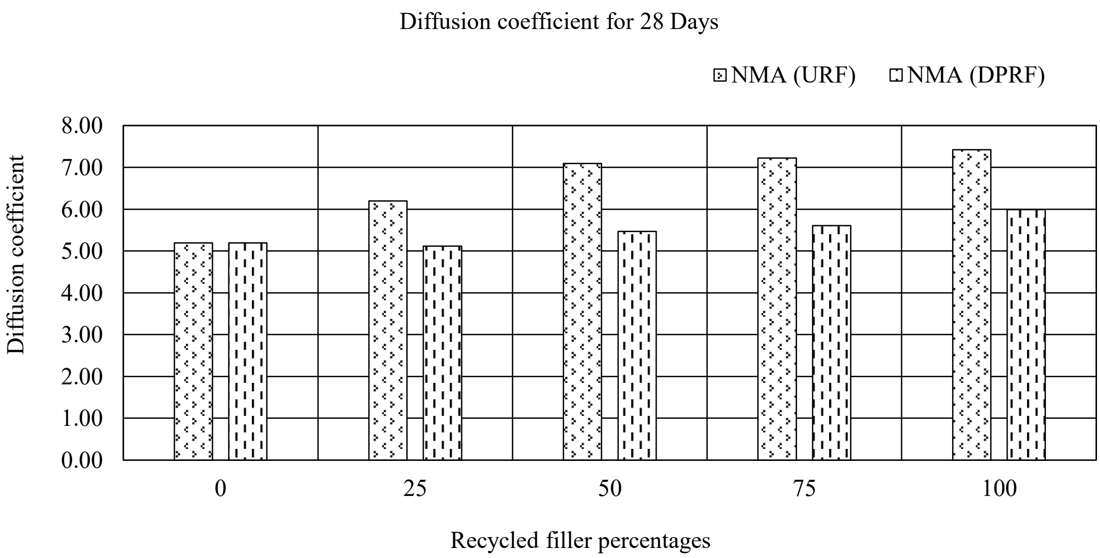

Figure 10. Diffusion coefficient of composite material at 28 days.

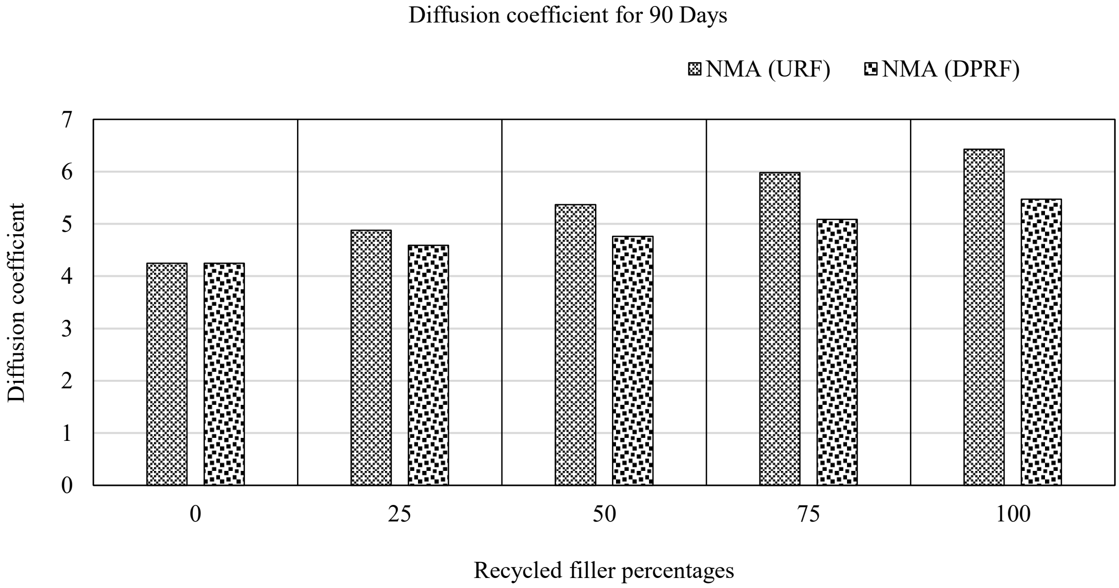

Figure 11. Diffusion coefficient of composite material at 90 days.

Permeability or Electrical Resistivity Tests

The Permeability Test (RCPT) findings for Composite Material mixes at 28 and 90 days are displayed in Figures 12, respectively. Chloride ion penetration is frequently improved by adding recycled solid material. Conversely, the penetrability resistance of natural and recycled aggregate Composite Material to chloride ions was enhanced by mineral admixtures. A range of 1823 coulombs to 3210 coulombs was observed in the 28-day permeability or electrical resistivity test results in SCBM, with PRF (500RVS) replacement Matrix Phase levels ranging from 0% to 100% in 25% increments. In a similar vein, the range of 90-day permeability or electrical resistivity tests results in SCBM was 1316–2546 coulombs, with PRF (500RVS) replacement Matrix Phase VCA at levels ranging from 0% to 100% in 25% increments.

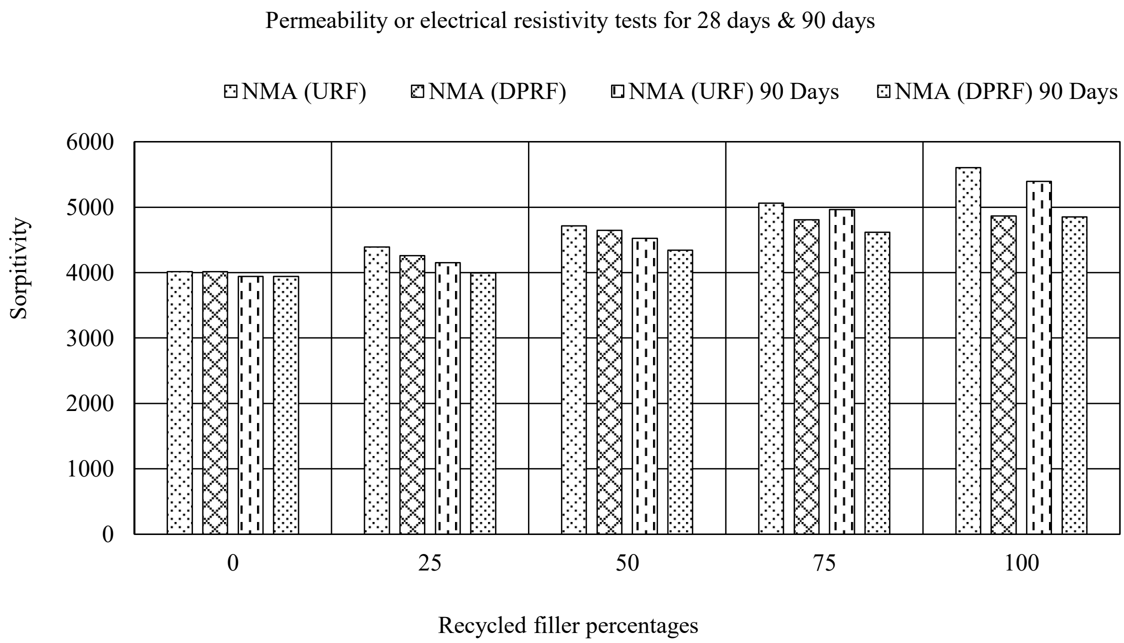

Figure 12. Permeability or electrical resistivity tests of composite material at 28 & 90 days.

Thermal Expansion

The experimental results of thermal expansion for each combination following 112 drying days are shown in Figure 13. The pace of shrinkage steadily slows down after the first week. Many elements affect the thermal expansion, which is a complicated process. The components, the temperature and relative humidity of the surrounding air, the Composite Material's age, the size of the part or structure, and the drying environment are some of these variables. A lower Curing Agent binder Ratio, which indicates the amount of evaporable Curing Agent in the Matrix Phase Tious paste and the rates at which Curing Agent may migrate towards the specimen's surface, results in less thermal expansion. When mortar was added to the RF, the volume of the paste (old new) increased, which led to an increase in the amount of thermal expansion in the Composite Material. The thermal expansion results for SCBM varied from 510 X 10^-6 to 1172 X 10^-6, respectively, with PRF (500RVS) replacement Matrix Phase Matrix Phase Cing VCA at values ranging from 0% to 100% in 25% increments.

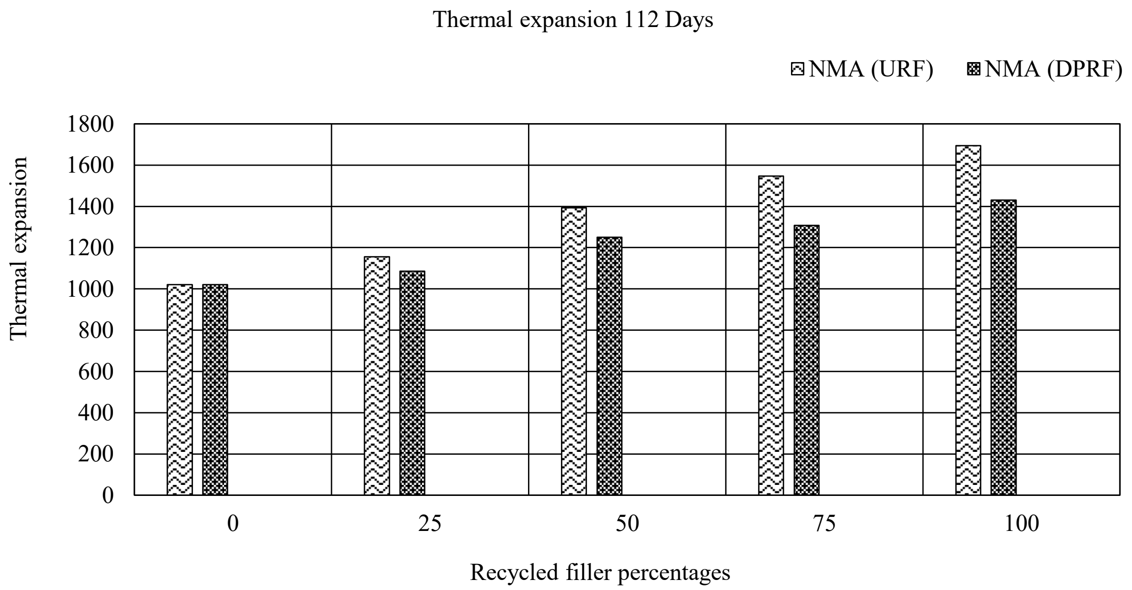

Figure 13. Thermal expansion, 112 days later.

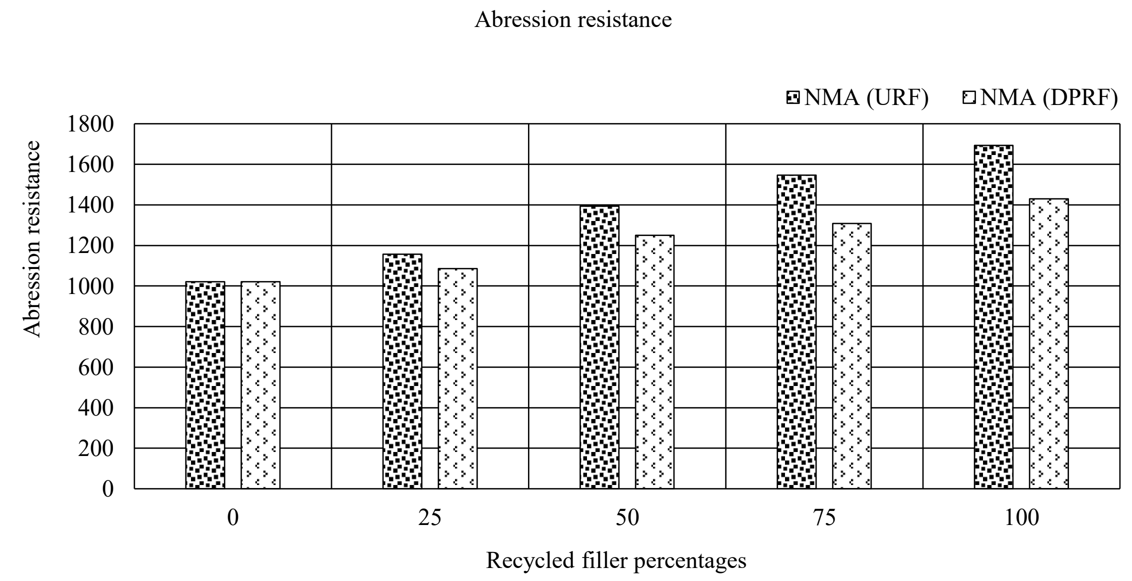

Figure 14. Abrasion resistance of aggregate.

Abression Resistance

Figure 14 displays the results of the abrasion resistance test. Composite Material abrasion loss should be expressed as a percentage loss, with results aveRA ged to the nearest 0.01 g. for a total of 12 surface s (4 surface as per cube). In geneRA l, the abrasion resistance goes down when the RA content becomes more. The abrasion resistance of SCBM RA nged from 8 X10-3 to 79 X10-3, with 25% increments between 0% and 100% when the PRF (500RVS) replacement Matrix Phase levels for VCA.

Flexural Strength

From Figure 15 the 7,28, and 90 days after curing, Figure shows the flexural strength of Composite Material prepared with PRF (500RVS) using various mixing procedures (SCBM). For every degree of replacement Matrix Phase Matrix Phase Matrix Phase, the findings represent an Average of three measurements. From 0% to 100% in 25% increments, the flexural strength typically falls across all curing duration and procedures (DPRF, SPRF, URF) as the PRF replacement Matrix Phase level of VCA (500RVS) becomes higher. At 0% Matrix Phase, flexural strength values were the highest across all methods, ranging between 4.5 MPa and 5.1 MPa. Using the DPRF method, examples of such values are about 4.7 MPa after 7 days, 5.0 MPa after 28 days, and 5.2 MPa after 90 days. When the replacement Matrix Phase Matrix Phase Matrix Phase amount was increased to 50%, the flexural strength dropped to around 4.1-4.4 MPa after 7 days, 4.3-4.6 MPa after 28 days, and 4.5-4.8 MPa after 90 days. The exact values vary by technique. At 100% replacement Matrix Phase Matrix Phase Matrix Phase, the flexural strength dropped significantly across all curing periods. For example, SCBM-URA at 7 days recorded approximately 3.7 MPa, while DPRF at 90 days reached 4.3 MPa. The overall trend indicates that increasing the recycled aggregate content leads to a reduction in flexural strength, consistent with expected behaviour due to weaker interracial bonding and higher porosity associated with recycled aggregates. Regardless of the decrease, all techniques show a steady rise in strength from 7 to 90 days, indicating that hydration and pozzolanic processes are still going on. Among the three approaches, DPRF consistently demonstrated slightly higher flexural strength values at all replacement Matrix Phase Matrix Phase Matrix Phase levels and curing duration s, followed by SPRF and URF.

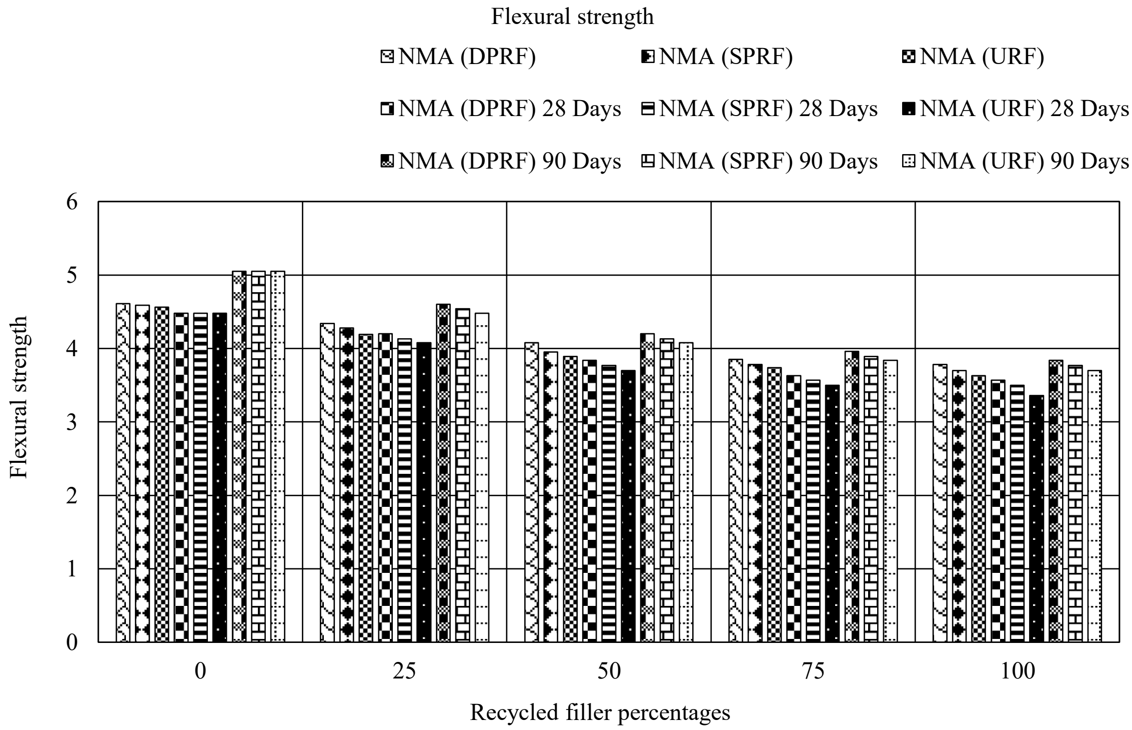

Figure 15. Flexural strength of composite material at 7Days, 28Days & 90Days.

Tensile Strength

Figure 16 illustrates the tensile strength behaviour of composite materials incorporating Single Processed Recycled Filler (PRF–500RVS) in combination with Double Processed Recycled Filler (DPRF), Single Processed Recycled Filler (SPRF), and Untreated Recycled Filler (URF), evaluated at 28 and 90 days of curing. The reported values represent the average of three independent tests conducted for each replacement level. Across all mixing strategies, the results reveal a clear trend: tensile strength decreases progressively as the recycled filler replacement ratio increases from 0% to 100%, in increments of 25%. At 0% replacement, where only natural aggregates are used, tensile strength peaks, ranging from 3.6 MPa to 4.1 MPa, with the highest strength (approximately 4.1 MPa) achieved by the SCBM-DPRF mix at 90 days.

As recycled filler content increases, tensile strength diminishes. For example:

- At 50% replacement, values range between 3.0 MPa and 3.4 MPa, depending on the filler type and curing period.
- At 100% replacement, the strength drops further to 2.8 MPa–3.2 MPa, with URF consistently showing the lowest performance among all tested mixes.

Despite this downward trend, tensile strength improved for all mixtures from 28 to 90 days, indicating that hydration continues over time, contributing to further matrix densification and bond development.

Among the three filler types, DPRF consistently exhibited the highest tensile strength at each replacement level and curing duration, highlighting the effectiveness of double processing in improving filler–matrix bonding and reducing surface porosity. SPRF showed intermediate performance, while URF resulted in the lowest tensile strength across all conditions—particularly at higher replacement levels—due to its weak interface and high porosity.

Machine Learning-Based Forecasting of Composite Behavior

In this we have discussed about the prediction model of polynomial regression of comparison strength, Flexible Strength and Tensile Strength. We have also found out the R-sq and MES values of SCBM with different aggregate. To ensure model robustness and prevent overfitting, 5-fold cross-validation was employed during training for all machine learning models (Linear Regression, Polynomial Regression, SVR, and Random Forest). Each dataset was split into five subsets, and the training-testing cycle was repeated five times, with performance metrics averaged across folds. This approach enhances the credibility of the reported model accuracies and supports generalizability in future applications.

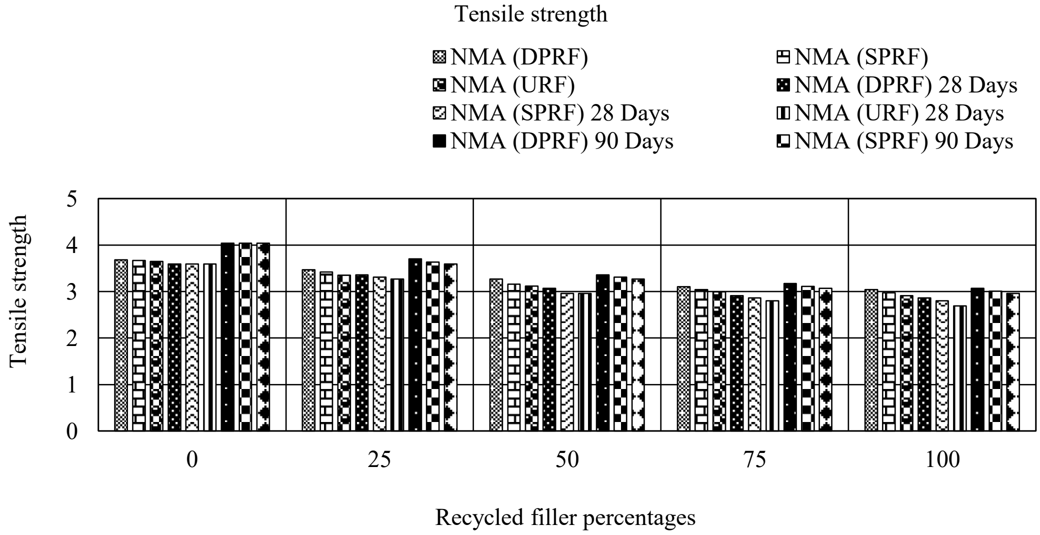

Figure 16. Tensile strength of composite material at 7Days, 28Days & 90Days.

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Machine Learning-Based Forecasting of Compressive Strength

To find out how the proportion of recycled aggregate and the number of curing days influenced the selected Composite Material feature (such workability or strength), we employed a 3D polynomial regression model in figure 17. The picture illustrates the spatial relationship between the dependent variable and the independent variables (Recycled Aggregate Percentage and Days) using both the RA w data points and the fitted polynomial surface. The blue scatter points represent the experimental data collected, while the smooth orange surface denotes the polynomial model's approximation. The nonlinear trend in the data is captured by the model, showing that both factors have a considerable impact on the Composite Material behavior. The concave shape of the surface suggests an optimal Range of recycled aggregate use beyond which the performance may diminish. This visualization aids in understanding the interactive effects of material composition and curing time, highlighting the predictive capability of polynomial regression in modeling complex relationships in sustainable Composite Material mix design. After this we have done 3 different type of machine learning model to which are linear regression, SVR and forest regressor model. By theses model we find out the different matrix values are i.e. R-square, MASE, MSE.RMSLE and MAPE. Which are below in Table 4.

The accuracy of machine learning models in forecasting real-world performance indicators, such as DPRF, SPRF, and URA, was evaluated using four regression techniques: Random Forest Regression, Support Vector Regression (SVR), Polynomial Regression, and Linear Regression. The combined actual versus predicted plots (Figure 18) provide a visual insight into each model's accuracy. Out of the four, Polynomial Regression emerged as the most accurate, achieving the highest coefficient of determination ($R^2 = 0.91$) and the lowest error values (MSE = 1.57, MAE = 1.57, and RSLMEQ = 0.0575). The tight clustering of points along the ideal fit line illustrates the model's excellent performance in capturing nonlinear trends in the data.

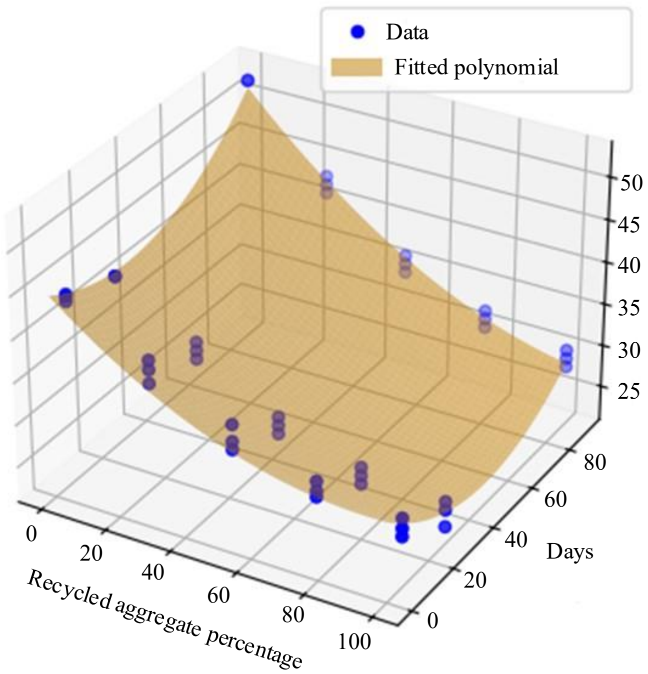

Figure 17. Polynomial regression model of compressive strength (SCBM)

Table 4. Different matrix values are i.e. R-square, MASE, MSE.RMSLE and MAPE.

Machine learning model	R-sq.	MSE	MAE	RMSLE
Linear regression	0.85	7.26	1.96	0,0752
Polynomial regression	0.91	1.57	1.57	0.0575
Support vector regression (SVR)	0.79	10.07	2.54	0.087
Random forest regression	0.83	8.33	2.33	0.083

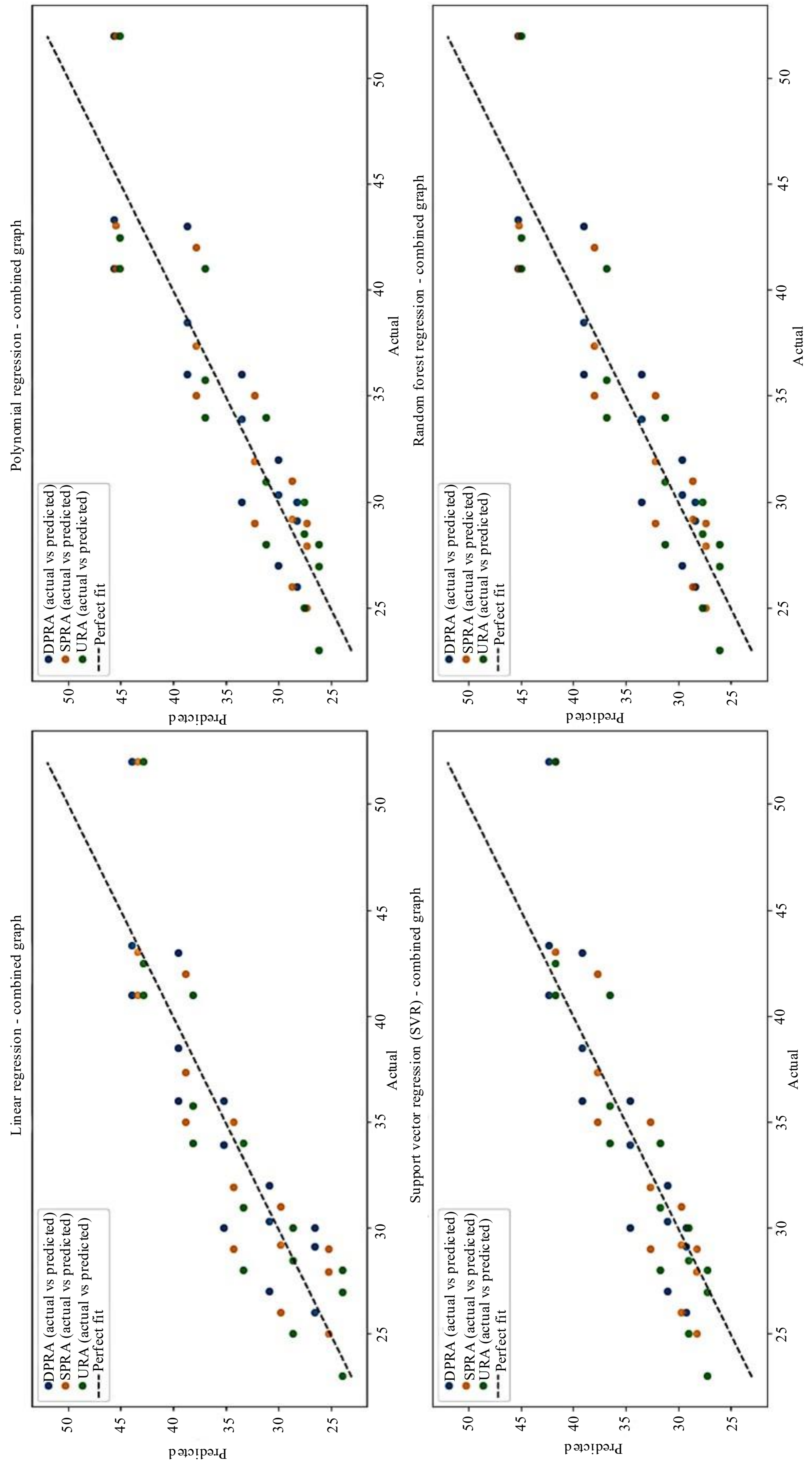

Figure 18. Comparison of actual vs. predicted values for compressive strength.

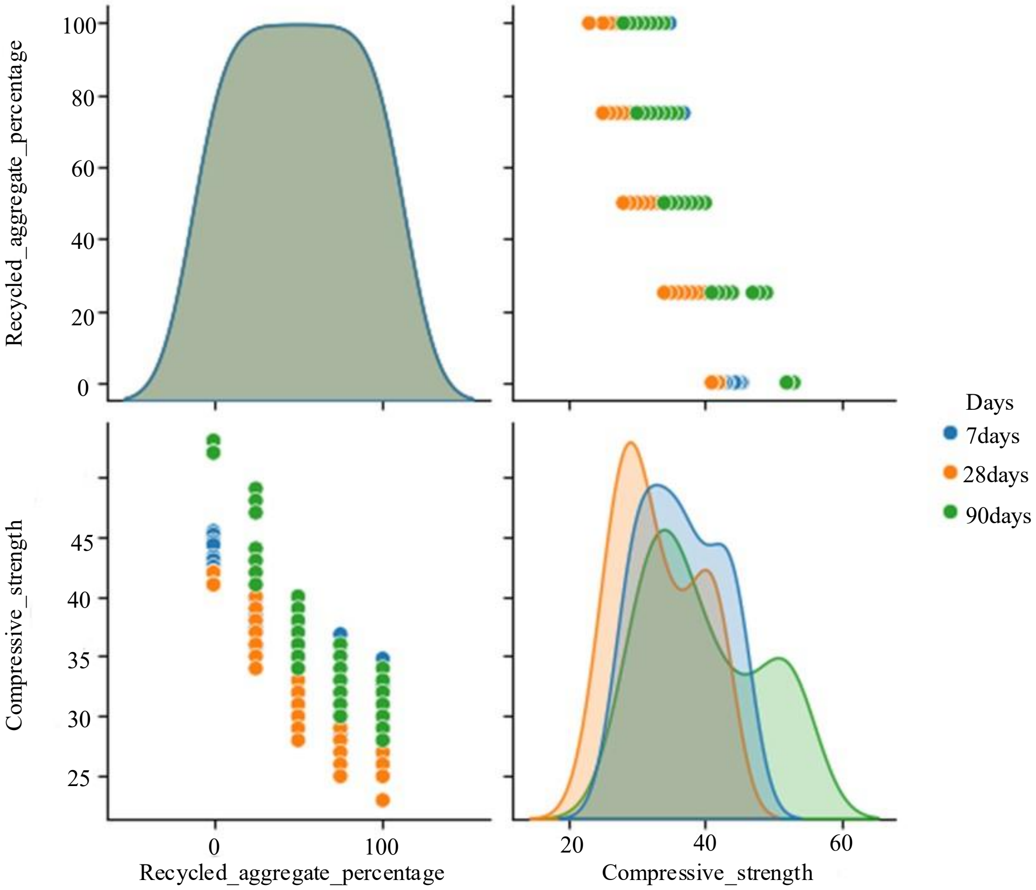

Figure 19. Relationship between recycled aggregate percentage and compressive strength at different curing ages (7, 28, and 90 days).

The SVR model, although more sophisticated than linear regression, showed a relatively lower predictive performance with $R^2 = 0.79$, MSE = 10.07, MAE = 2.54, and RSLMEQ = 0.087. This indicates that while SVR can handle nonlinearity, its performance may be sensitive to hyperparameter tuning and kernel selection. The scatter plot for SVR shows a moderate deviation from the perfect fit line, particularly at the extremes of the prediction Range. Nevertheless, SVR remains a viable option due to its robustness and flexibility, especially in datasets with smaller sample sizes or noise.

Random Forest Regression offered a better balance, with $R^2 = 0.83$, MSE = 8.33, and MAE = 2.33, benefiting from its ensemble nature and ability to model complex feature interactions. However, it did not outperform Polynomial Regression in this scenario. Linear Regression, despite its simplicity and interpretability, showed limitations with an $R^2 = 0.85$ and MSE = 7.26, indicating a reduced capacity to model the nonlinear behaviour of the dataset.

In summary, Polynomial Regression proved to be the most suitable model for this study, while SVR, despite its theoretical strength, may require further optimization to reach comparable levels of performance. The significance of carefully selecting and fine-tuning machine learning models for use in research predicting Composite Material materials is shown by this investigation.

The scatter and density plots illustrate the distribution and correlation between Recycled Aggregate Percentage and Compressive Strength over three curing periods-7, 28, and 90 days shown in figure 19. In general, compressive strength declines as the percentage of recycled aggregate increases, although strength recovery is improved with longer curing duration s, especially 90 days. Highlighting the impact of curing period on strength growth, the distribution patterns of compressive strength with time may be seen in the kernel density estimates (KDEs).

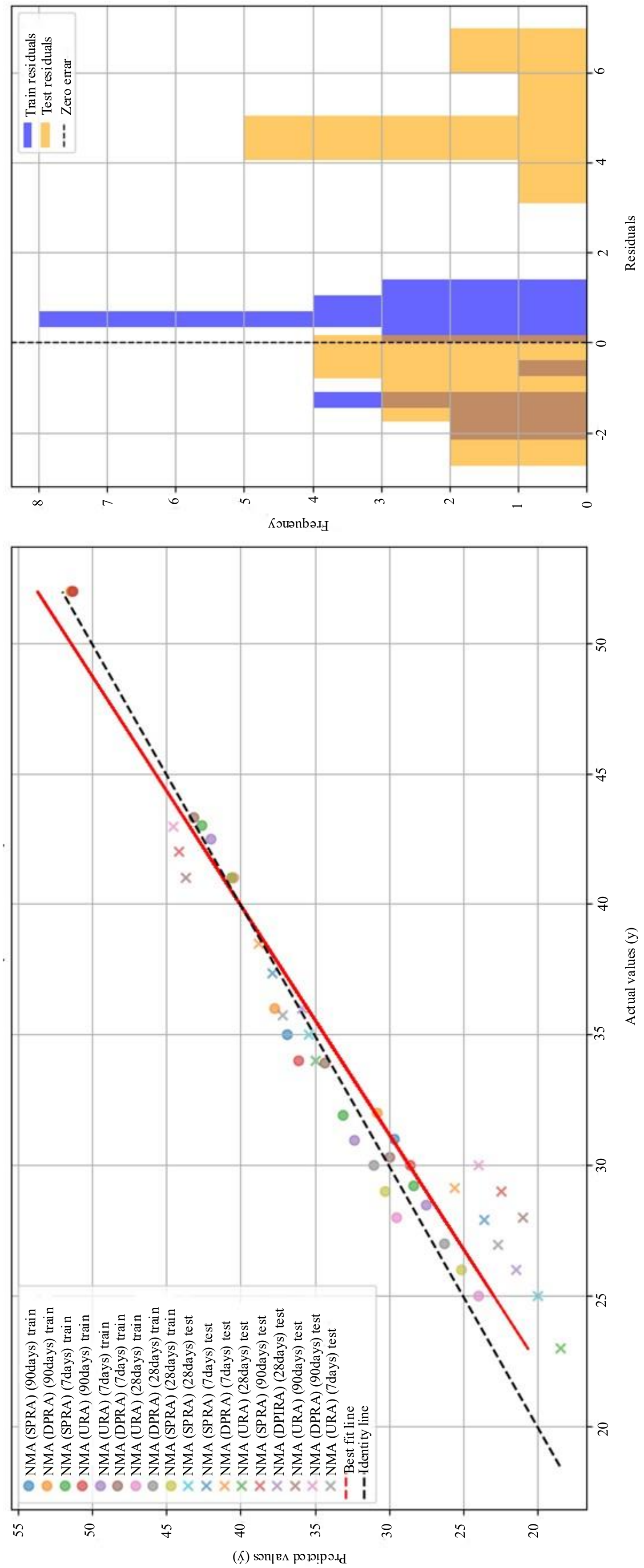

Figure 20. Residual model of compressive strength.

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Predication Model Error & Residual Model for Compressive Strength

The provided Figure 20 presents a dual-panel visualization of model prediction performance. A scatter figure comparing real values (x-axis) and predicted values (y-axis) for both the training and testing datasets is shown in the left panel, headed "Combined Prediction Error (TRA in & Test)". Different markers and colours represent various conditions, including multiple duration (7, 21, 90 days) and two models labelled SPRF and DPRF.

The solid red line shows the best-fit regression line of the predictions, while the dashed black line represents the ideal 1:1 relationship (identity line) where predictions perfectly match actual values. A close alignment of points along the identity line indicates higher prediction accuracy. The right panel, titled "Residual Distribution", shows a histogram m of residuals (the difference between actual and predicted values) for both the training (blue) and testing (orange) datasets. The vertical dashed line at zero represents perfect predictions. The trap in residuals appear more cantered around zero, while the test residuals are more spread out and skewed, suggesting that the model performed better on the training data compared to the testing data. This visualization collectively helps evaluate the model's predictive accuracy and generalization performance across different conditions.

The Figure 21 displays a scatter plot titled "Combined Prediction Error with Best-Fit Line", which visualizes the performance of a predictive model. Each coloured dot represents a predicted value plotted against the actual value, categorized by different combinations of experimental conditions, such as model type (DPRF, SPRF, URA) and curing periods (7, 28, and 90 days). The expected values are shown on the y-axis, and the actual values are shown on the x-axis.

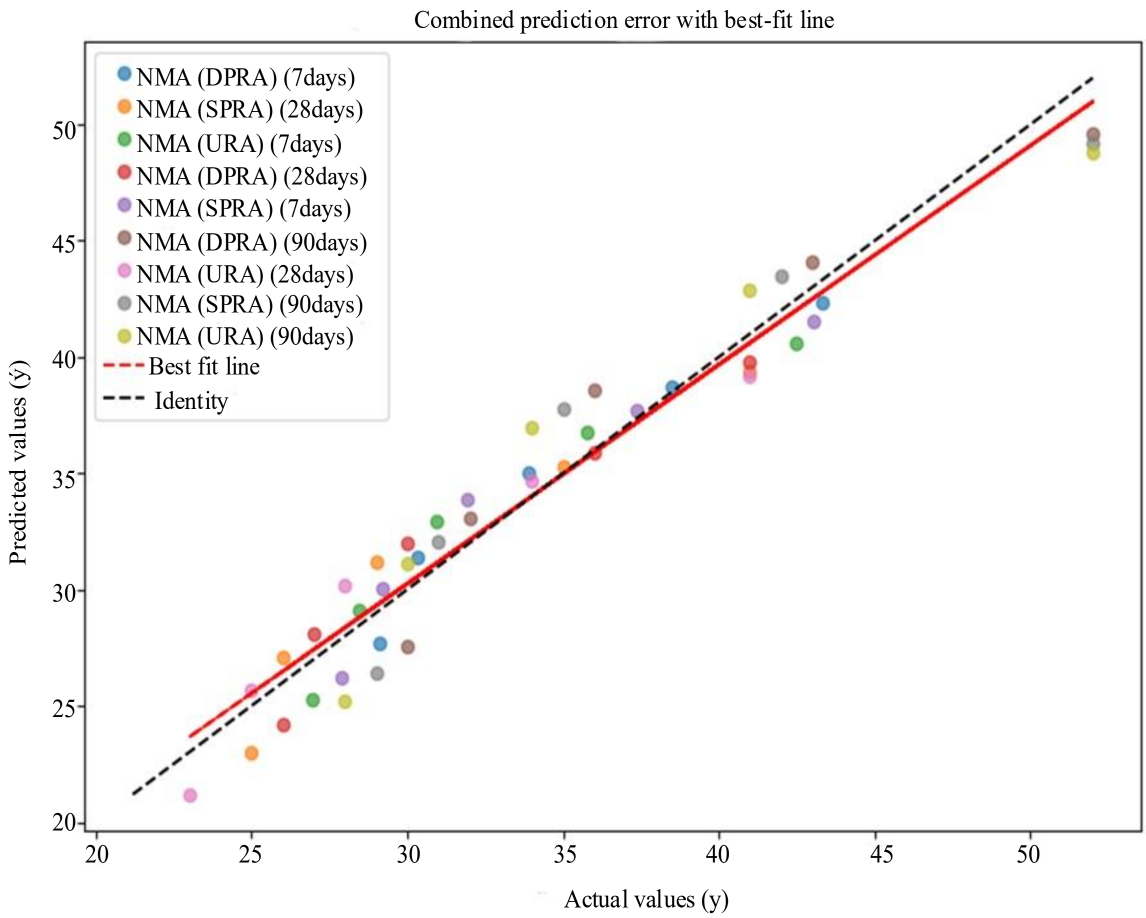


Figure 21. Combined prediction error with best-fit line.

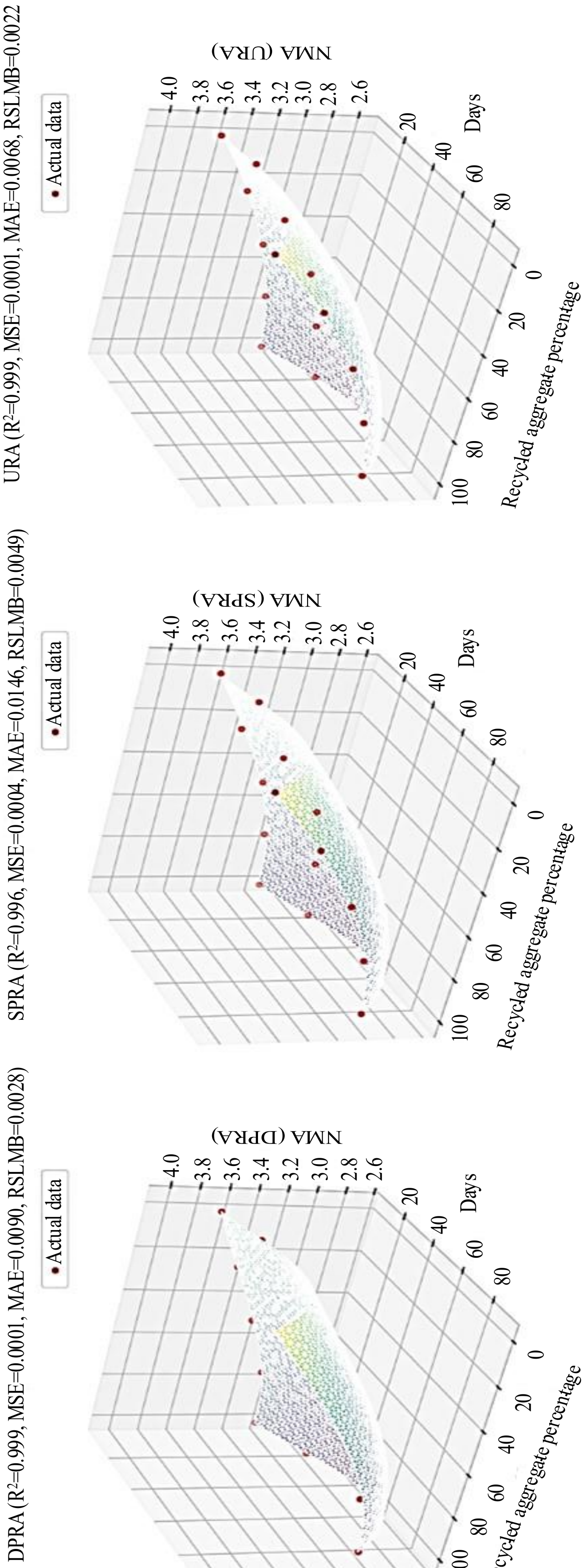


Figure 22. Polynomial regression model of flexible strength (SCBM)

Two important reference lines are included:

- The dashed black line represents the identity line, When the actual values are equivalent to the expected values. Predictions that lie on this line are perfect.
- The solid red line is the best-fit line, showing the trend of the predicted data in relation to the actual values.

The close alignment of most points along these lines—especially near the identity line—indicates that the model predictions are fairly accurate across all conditions. The best-fit line being close to the identity line also reinforces the reliability of the model, suggesting that it well for different datasets and curing duration s.

Machine Learning-Based Forecasting of Flexible Strength

The 3D surface plots of figure 22 for DPRF, SPRF, and URA models illustrate the predictive response of SCBM (Normalized Mix Assessment) values as functions of both Recycled Aggregate Percentage and curing time (Days). These visualizations offer an intuitive understanding of how different recycled aggregate levels and duration affect the Composite Material properties.

Each plot shows a continuous and smooth surface, indicating the model's ability to capture nonlinear interactions between the input variables. The red dots, representing actual experimental data, are closely aligned with the surface predictions across all three models, suggesting a high degree of conformity and minimal deviation.

- In the DPRF plot, the surface trends downward as the recycled aggregate percentage increases, reflecting the decreasing SCBM values with higher replacement Matrix Phase levels. This pattern holds consistently over time, showing that curing duration has a positive but slightly diminishing effect at higher aggregate percentages.
- The SPRF surface reflects a similar curvature, with a smooth decline in SCBM as the replacement Matrix Phase Ratio increases, yet the influence of curing time appears slightly more variable, highlighting subtle shifts in hydration behaviour.
- In the URF visualization, the model successfully reproduces the gradual slope and contour transitions, capturing the combined effects of aging and aggregate replacement Matrix Phase on Composite Material performance. The surface shape confirms the model's capability in reproducing real-life variations across both independent variables.

These plots collectively affirm the effectiveness of the chosen modelling approach-particularly in capturing complex, nonlinear dependencies-while also enhancing interpretability. The clear correspondence between predicted surface and actual data supports the reliability of these models for practical applications in sustainable Composite Material design.

From figure 23 The comparative scatter plots provide a visual benchmark of the predictive performance across four machine learning models-Linear Regression, Polynomial Regression, Support Vector Regression (SVR), and Random Forest Regression. Each plot shows how closely the predicted SCBM values (DPRF, SPRF, URA) align with their actual counterparts, with a reference diagonal line representing the ideal scenario of perfect prediction.

Table 5. Different matrix values are i.e. R-square, MASE, MSE.RMSLE and MAPE.

Machine learning model	R-sq.	MSE	MAE	RMSLE
Linear Regression	0.864	0.0140	0.098	0.0278
Polynomial Regression	0.99	0.001	0.0090	0.0028
Support Vector Regression (SVR)	0.858	0.0146	0.106	0.0275
Random Forest Regression	0.974	0.0027	0.0398	0.0117

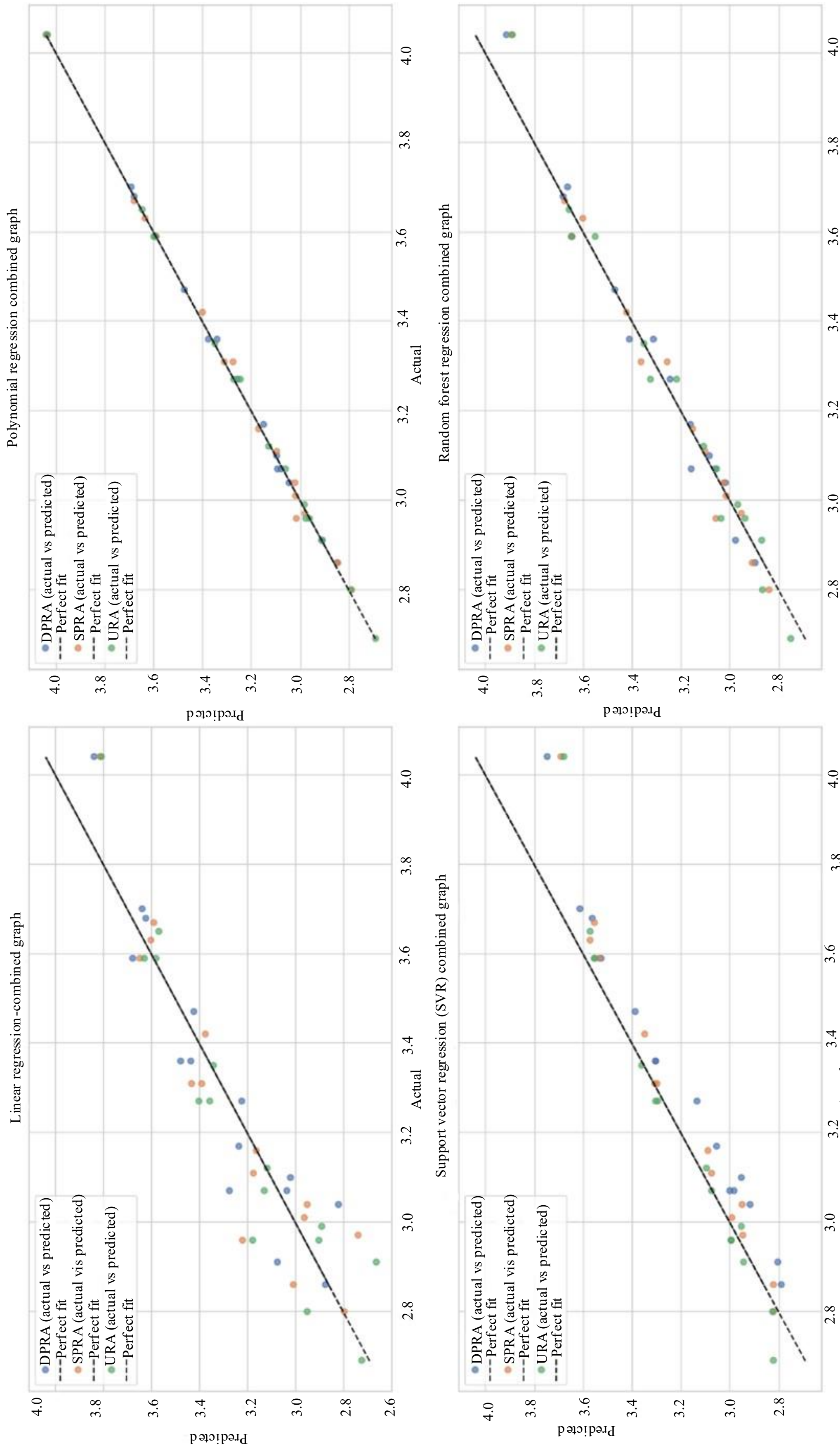


Figure 23. Comparison of actual vs. predicted values for flexible strength.

- Linear Regression reveals a general alignment trend but with noticeable dispersion, particularly at the lower and higher ends of the actual values. This suggests that while it captures the overall pattern, its simplicity limits its capacity to model complex nonlinear behaviours inherent in the data.
- Polynomial Regression, in contrast, shows a tight clustering of predicted values along the diagonal line, reflecting a highly accurate model fit. The minimal spread and consistent proximity to the ideal line indicate its strength in modelling curved relationships and interactions between input variables.
- Support Vector Regression (SVR) performs similarly to Linear Regression in terms of alignment but exhibits slightly more deviation across all three datasets. This indicates a moderate ability to model complexity but with limitations in capturing finer nuances.
- Random Forest Regression demonstrate strong predictive agreement, with most points tightly grouped near the diagonal. Its performance illustrates robustness and adaptability, effectively modelling nonlinearity while resisting oversitting, making it well-suited for heterogeneous datasets like this one.

Overall, the Polynomial and Random Forest models visually outperform the others, showing better generalization and fidelity to actual data trends. These plots emphasize the importance of selecting models capable of handling nonlinear relationships in materials research, especially when dealing with complex factors like aggregate composition and curing time.

From Figure 24 The KDE and scatter plot presented provides a deeper understanding of how the SCBM (Normalized Mechanical Attribute) varies with changing percentages of recycled aggregate across three curing periods (7, 28, and 90 days). It is evident from the scatter plot that the SCBM values are going lower as the recycled aggregate percentage goes up. Because of poorer bonding, greater porosity, or the intrinsic unpredictability of recycled aggregates, performance gradually decreases with larger replacement Matrix Phase levels. This trend is evident across all curing duration s, although the rate and extent of decline vary.

The kernel density estimates (KDE) offer further insight into the distributional behaviour of SCBM values at different ages:

- At 7 days, the SCBM distribution is slightly shifted toward higher values, reflecting early strength development typical of initial hydration reactions.
- At 28 days, the distribution tightens and moves lower, indicating that the influence of recycled aggregates becomes more pronounced over time.
- At 90 days, the spread of SCBM widens again, suggesting that longer curing may help recover some of the mechanical strength, possibly due to pozzolanic activity or microstructural densification.

The KDE for Recycled Aggregate Percentage shows a uniform distribution, suggesting that the data sampling across different replacement Matrix Phase levels was well-balanced and comprehensive.

Overall, this plot highlights the clear inverse relationship between recycled content and mechanical performance for DPRF, while also emphasizing the temporal effects of curing-especially the potential for strength recovery at extended ages. Such insights are vital when optimizing mix designs that aim to balance sustainability and structural performance. The SPRF scatter and KDE plots reveal a comparable descending trend in SCBM as the recycled aggregate percentage increases. This confirms a consistent pattern observed with DPRF: increasing recycled content negatively influences mechanical attributes. However, SPRF shows a more noticeable spread in data points, especially at mid to hire replacement Matrix Phase levels, suggesting a higher sensitivity of this mix to changes in aggregate quality and curing conditions.

Looking at the KDE curves for different curing duration s:

- 7-day curves are skewed toward higher SCBM values, reflecting early age strength development.
- 28-day data become more centralized, showing a slight dip in overall performance.
- 90-day distributions, although slightly broader, show that some mixes retain or recover strength over time, though not uniformly across all samples.

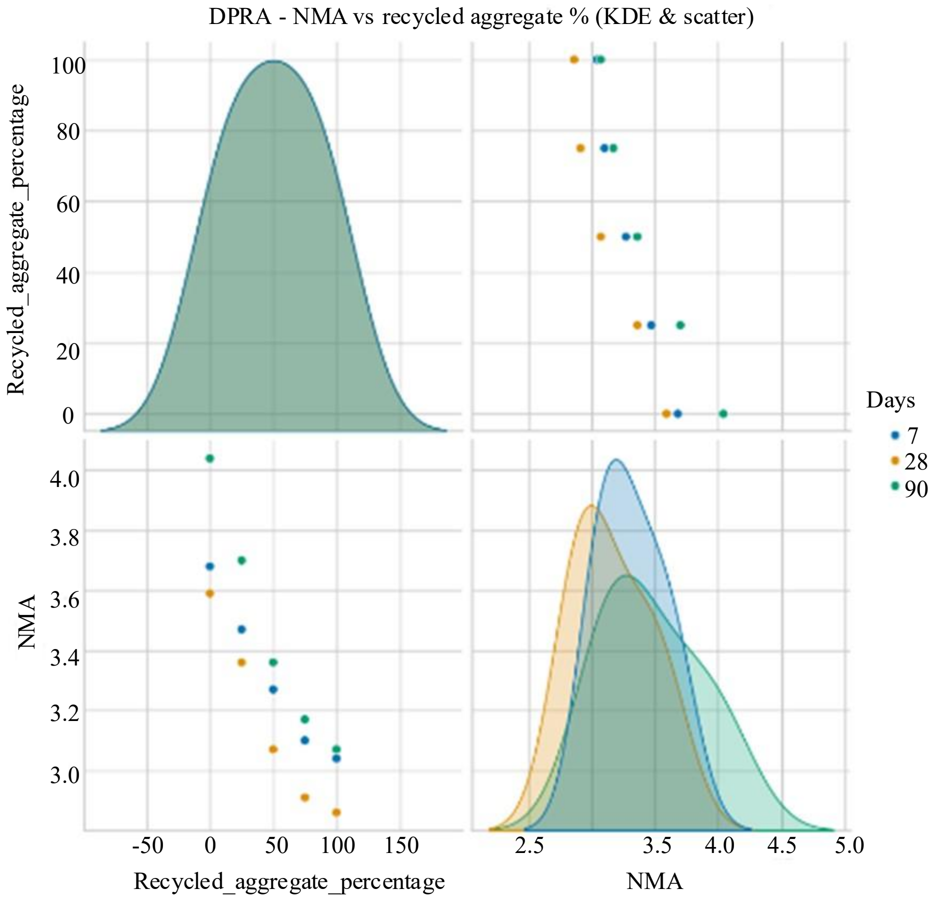
These visual cues imply that SPRF responds to long-term curing, but with greater variability, indicating that mix consistency or interaction effects (e.g., mineral admixtures, moisture levels) could play a more prominent role in this mix design.

In the URA plots, we again observe the expected decrease in SCBM with increasing recycled content. However, what sets URA apart is its relatively tighter clustering of data points, especially at lower replacement Matrix percentages. This suggests better performance consistency and potentially more robust behaviour against the inclusion of recycled aggregates.

KDE plots reinforce this interpretation:

- 7-day strength remains relatively strong, maintaining a tight peak near the upper SCBM values.
- 28-day shows a slight dip but remains cantered with minimal skew.
- 90-day curves appear slightly elevated and broader, indicating enhanced long-term hydration and strength development potential despite the recycled content.

URA thus demonstrates a more stable and predictable response over time, which could make it a more suitable choice for mixes requiring performance retention even at moderate-to-high replacement Matrix Phase levels.



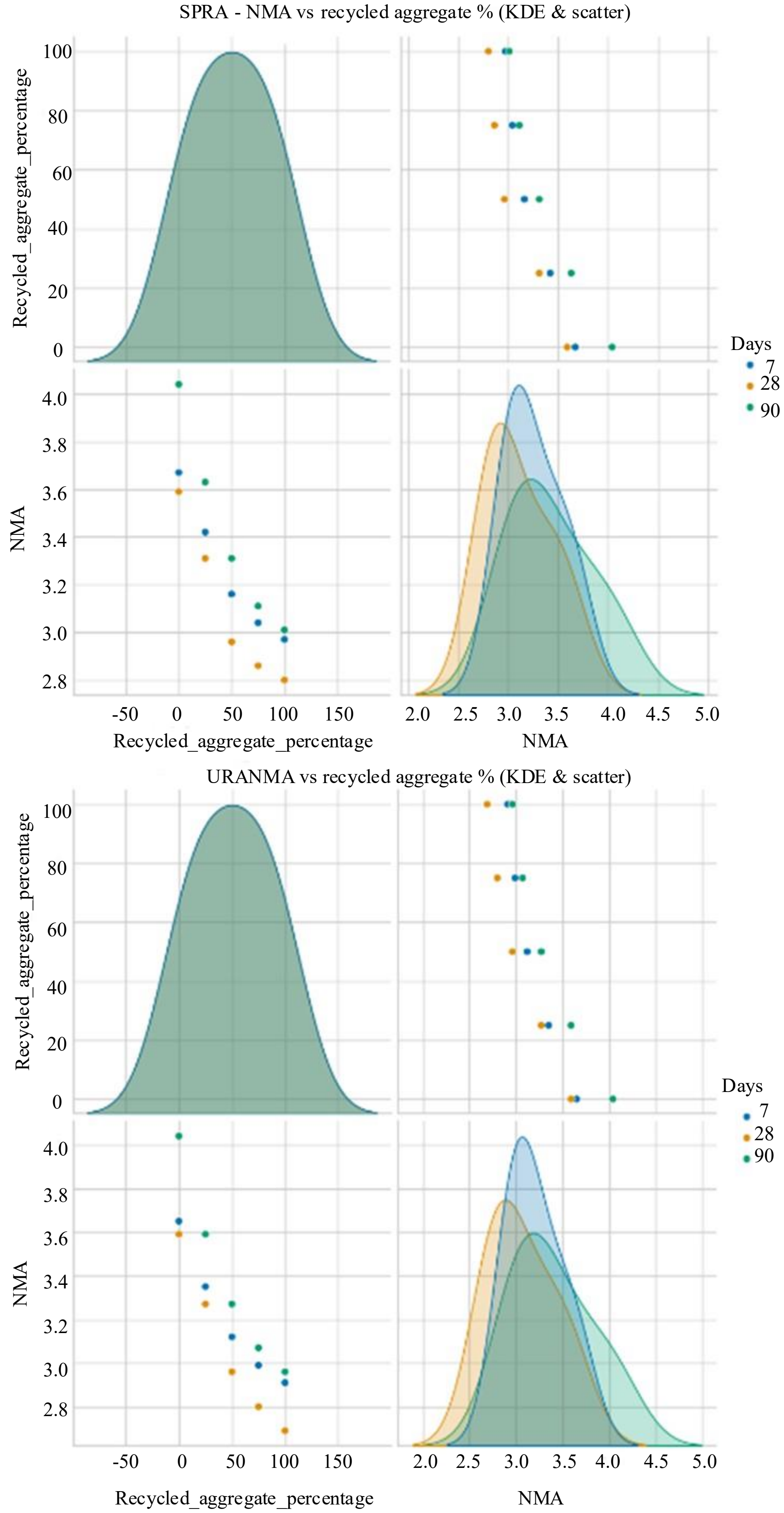


Figure 24. Relationship between recycled aggregate percentage and adaptive strength at varying curing ages (7, 28, and 90 days).

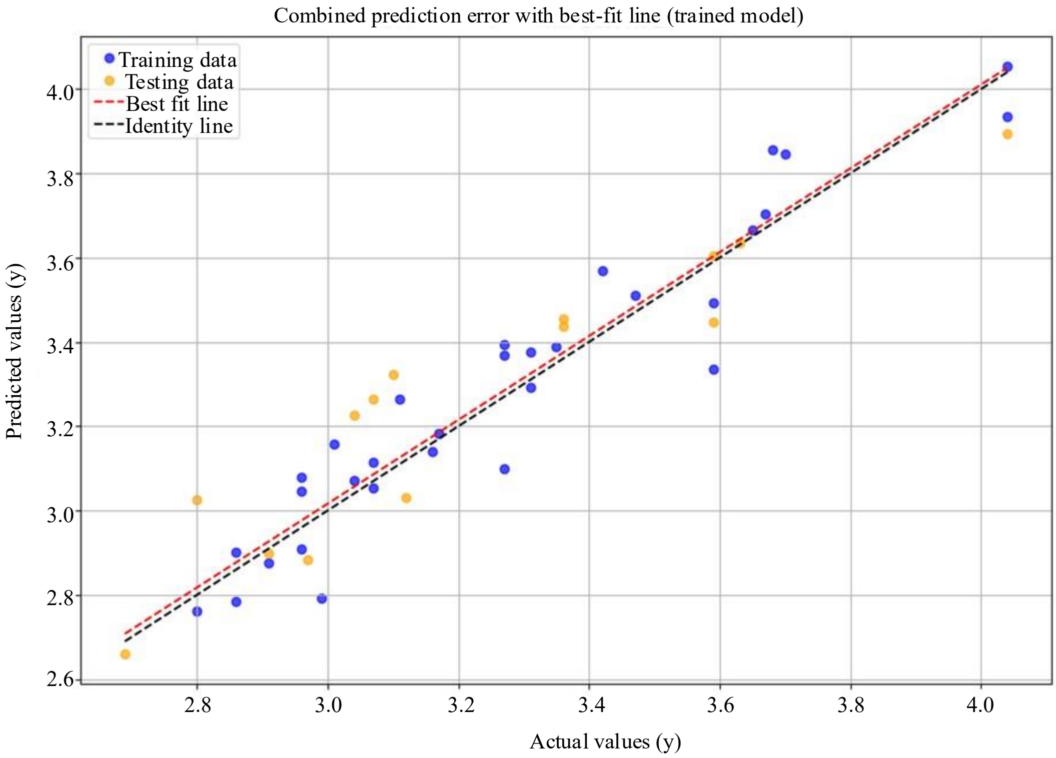


Figure 25. Combined prediction error with best-fit line.

Predication Model Error and Residual Model for Flexible Strength

The Figure 25 shown is a scatter plot titled "Combined Prediction Error with Best-Fit Line (Trained Model)", where the anticipated and actual values from the training and testing datasets are graphically compared. The x-axis displays the actual values, while the y-axis displays the anticipated values from the Trained model. Training data is indicated by blue markers, whereas testing data is indicated by orange markers.

Two key reference lines are included in the plot:

- The dashed black line represents the identity line, which is where all points would lie if the predictions were perfectly accurate.
- The best-fit line, which displays the general trend of the model's predictions in relation to the actual values, is the dashed red line.

Most of the data points cluster around these lines, especially the identity line, indicating that the model performs reasonably well in both training and testing phases. However, minor deviations from the identity line suggest small prediction errors, which is common in real-world modelling. Overall, the visualization supports the conclusion that the model has a good generalization capability with a consistent trend across both datasets.

Figure 26 The residual analysis, represented through the scatter plot and histogram m, offers insight into the prediction accuracy of the Trained model. In the scatter plot, residuals-Plotted against the actual values, the difference between the actual and expected values is computed. Points from the training data are shown in blue, while those from the testing data appear in orange. Most residuals are distributed close to the zero line, indicating that there are only little variations between the model's predictions and the actual data. Similarly, the histogram m shows the frequency of residuals for both training and testing data. The residuals are mostly centered around zero, forming a relatively balanced distribution without significant skewness. This indicates that the errors are Randomly distributed and generally small in magnitude. Overall, both visualizations suggest that the model performs reliably, with minimal bias and consistent accuracy across both the training and testing datasets.

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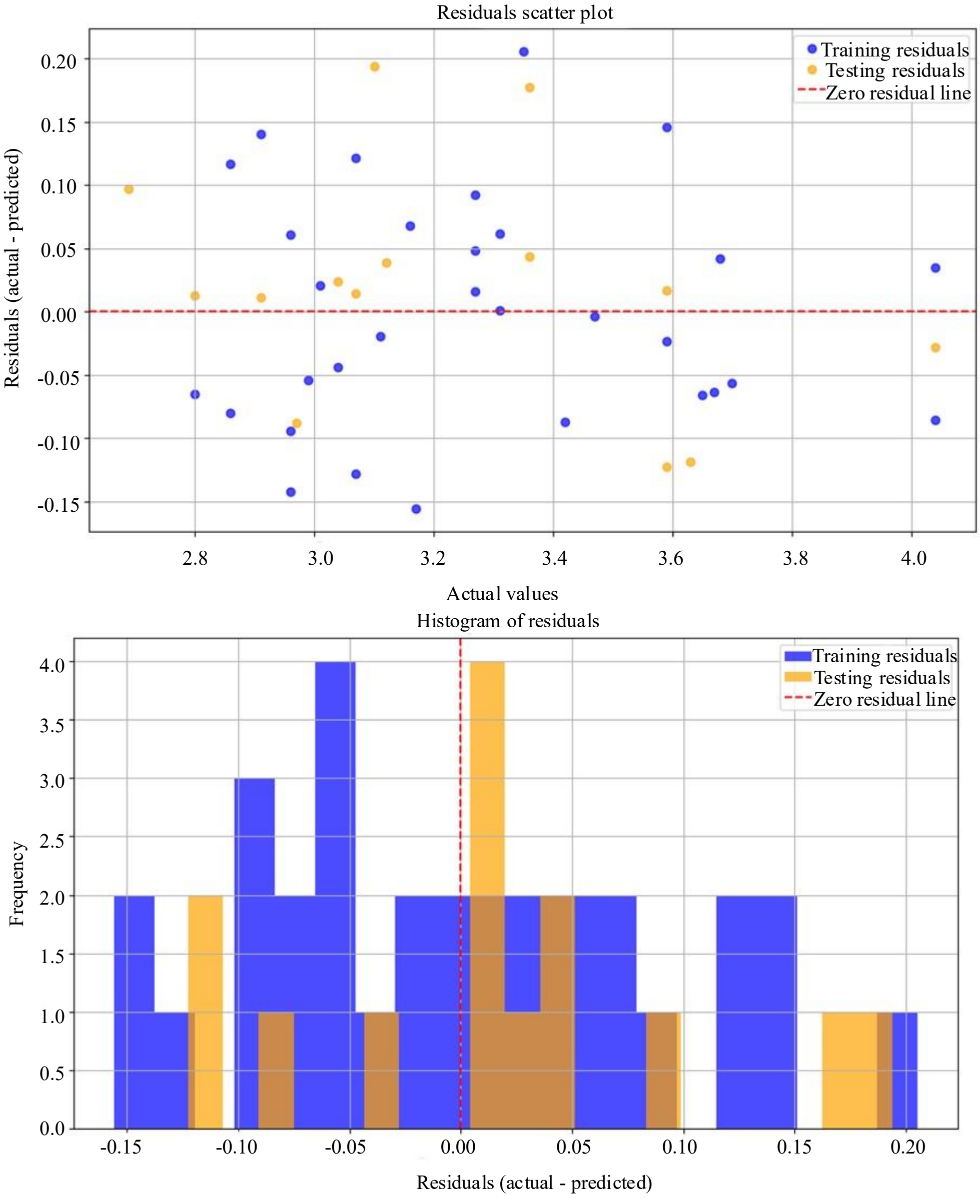

Figure 26. Represents the residual model of flexible strength

Prediction Model on the Tensile Strength

From Figure 27, the 3D polynomial regression models of Figure 24 for DPRF, SPRF, and URF demonstrate strong predictive capability in estimating the Normalized Mix Assessment (SCBM) based on recycled aggregate percentage and curing duration.

- The DPRF model closely matches the observed data, and its smooth surface accurately represents the connection between the input variables and SCBM. The curvature reflects a distinct trend where strength initially decreases with higher recycled content but gradually recovers with increased curing time.
- For the SPRF model, the predictive surface is also well-fitted, though slight deviations from actual data points can be observed in certain regions. This suggests that while the model captures the overall trend accurately, there may be some sensitivity to input variations in the mid-range of aggregate percentages.
- The URF model presents a highly stable and consistent surface closely aligning with the distribution of actual observations. This suggests excellent generalization across the full range of recycled content and curing periods, making it particularly suitable for long-term predictions.

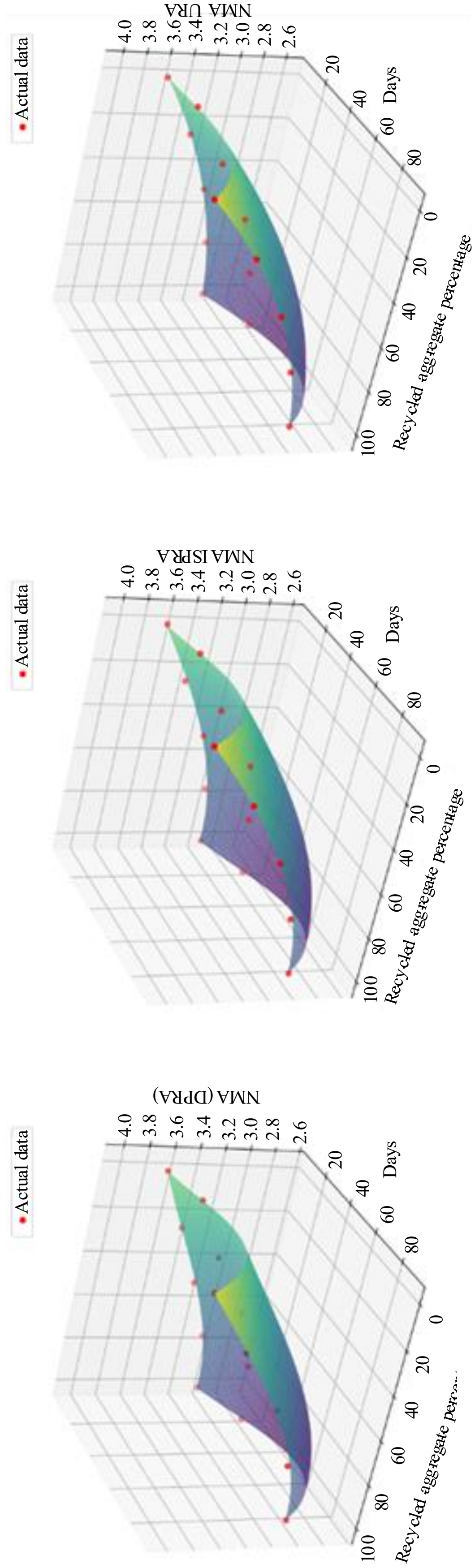

Figure 27. Polynomial regression model of tensile strength (SCBM).

Table 6. Different matrix values are i.e. R-square, MASE, MSE.RMSLE and MAPE.

Machine learning model	R-sq.	MSE	MAE	RMSLE
Linear regression	0.861	0.0140	0.0988	0.0278
Polynomial regression	0.996	0.0004	0.0146	0.0049
Support vector regression (SVR)	0.096	0.0109	0.0656	0.0222
Random forest regression	0.974	0.0030	0.0389	0.0122

Across all three models, the surface plots confirm that polynomial regression is well-suited to capturing the nonlinear relationships inherent in Composite Material behaviour when using recycled materials. The precise alignment between the predicted surface and actual data points indicates that the models are both accurate and reliable. Table 6 represents the Different matrix values

Figure 28 describes the Regression models' accuracy in predicting DPRF, SPRF, and URF values relative to actual values, allowing us to evaluate their performance. These models included Linear Regression, Polynomial Regression, Support Vector Regression (SVR), and Random Forest Regression.

- Linear Regression shows a moderate correlation, with a noticeable spread of data points around the perfect fit line. While it captures the general trend, there is some visible underfitting, especially in boundary regions.
- Polynomial Regression provides an excellent visual match with the actual data. Data points for all three types (DPRF, SPRF, and URF) align closely along the perfect fit line, indicating that the model captures nonlinear relationships effectively. The consistency and tight clustering suggest it generalizes well across the range.
- SVR (Support Vector Regression) displays moderate scatter in predictions. Although it aligns with the general trend, the visual gap between predicted and actual values in various areas reflects a less precise fit. This suggests a limited ability to model the underlying complexity in the data.
- Random Forest Regression also demonstrates strong performance, with most points clustering near the ideal fit line. It handles variability better than SVR and linear regression, indicating its strength in modelling nonlinear patterns without oversitting.

In summary, Polynomial and Random Forest Regression emerge as the most visually robust models for predicting SCBM values, capturing both trend and variance with high precision. These models are particularly well-suited for scenarios where accurate estimation across diverse material compositions and curing duration is essential.

Figure 29 describe the KDE and scatter plot reveal a clear inverse relationship between the Recycled Aggregate Percentage and SCBM across all curing duration (7, 28, and 90 days). A falling SCBM rating is indicative of steadily declining workability or strength-related performance as the proportion of recycled aggregate rises.

Distribution Analysis

- The Recycled Aggregate Percentage follows a near-uniform distribution across all data points.
- The SCBM values for each curing period exhibit distinct Gaussian-like distributions, with the 7-day samples showing slightly higher peak values compared to 28 and 90-day samples.

Scatter Patterns

- The scatter distribution highlights the downward trend of SCBM with increasing recycled content.
- Across curing duration s, 90-day mixes (green dots) show relatively higher SCBM stability than early-age mixes, suggesting some recovery in matrix structure over time.

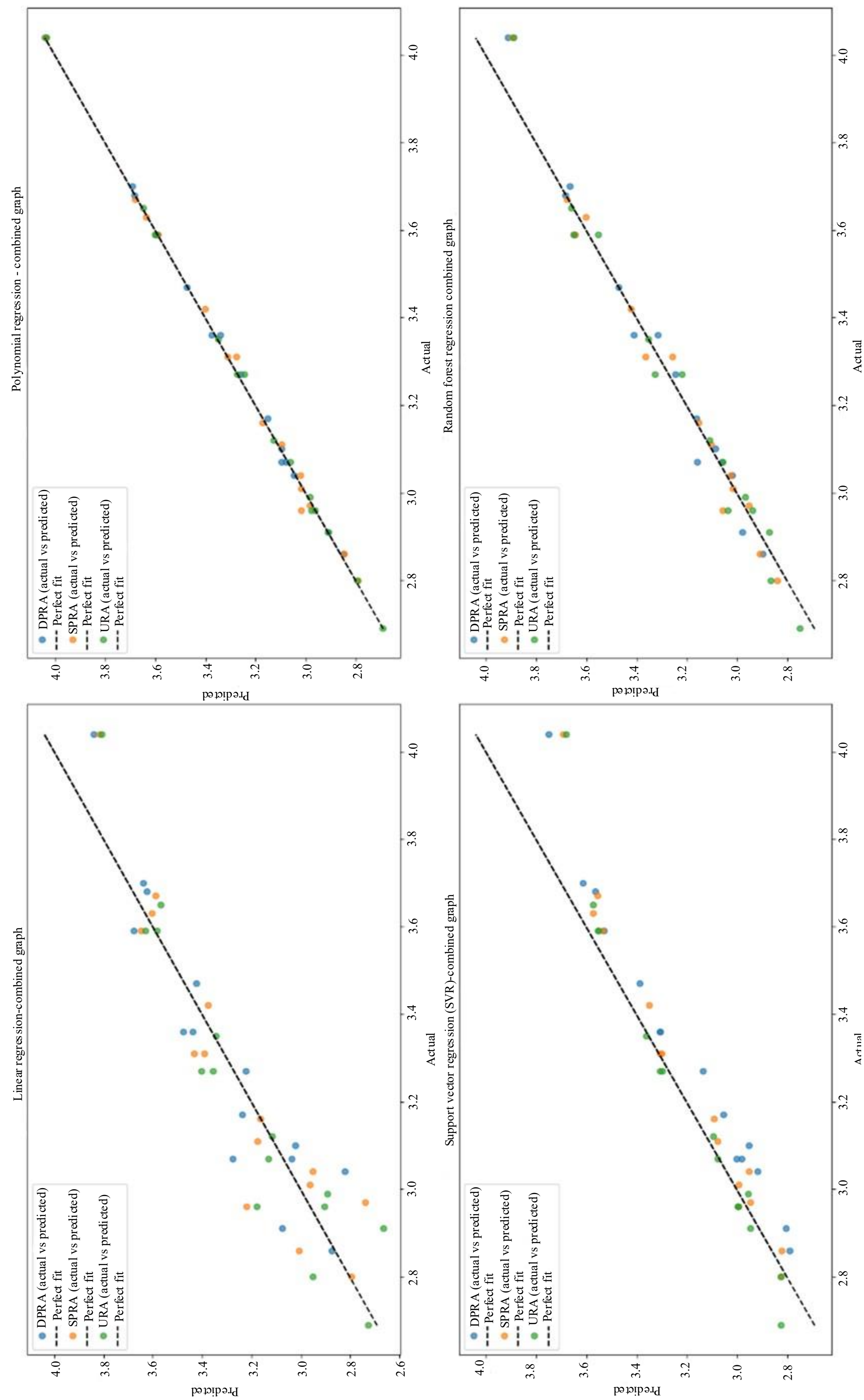

Figure 28. Comparison of actual vs. predicted values for tensile strength.

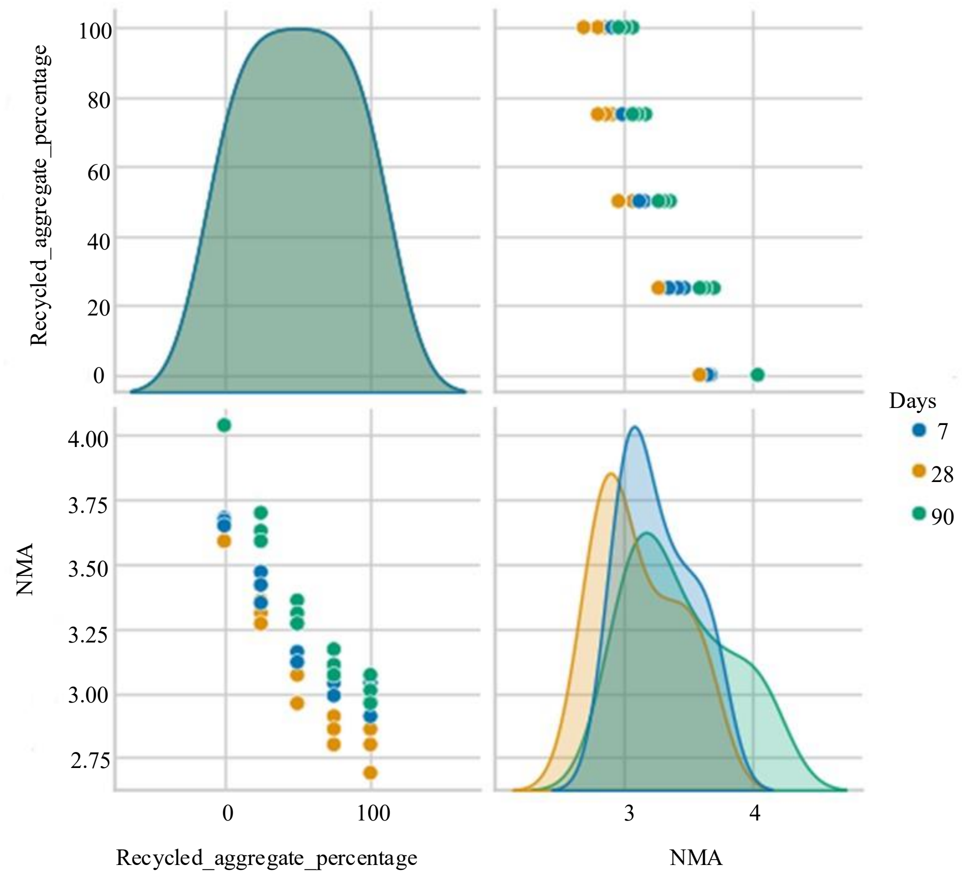

Figure 29. Relationship between recycled aggregate percentage and tensile strength at different curing ages (7, 28, and 90 Days).

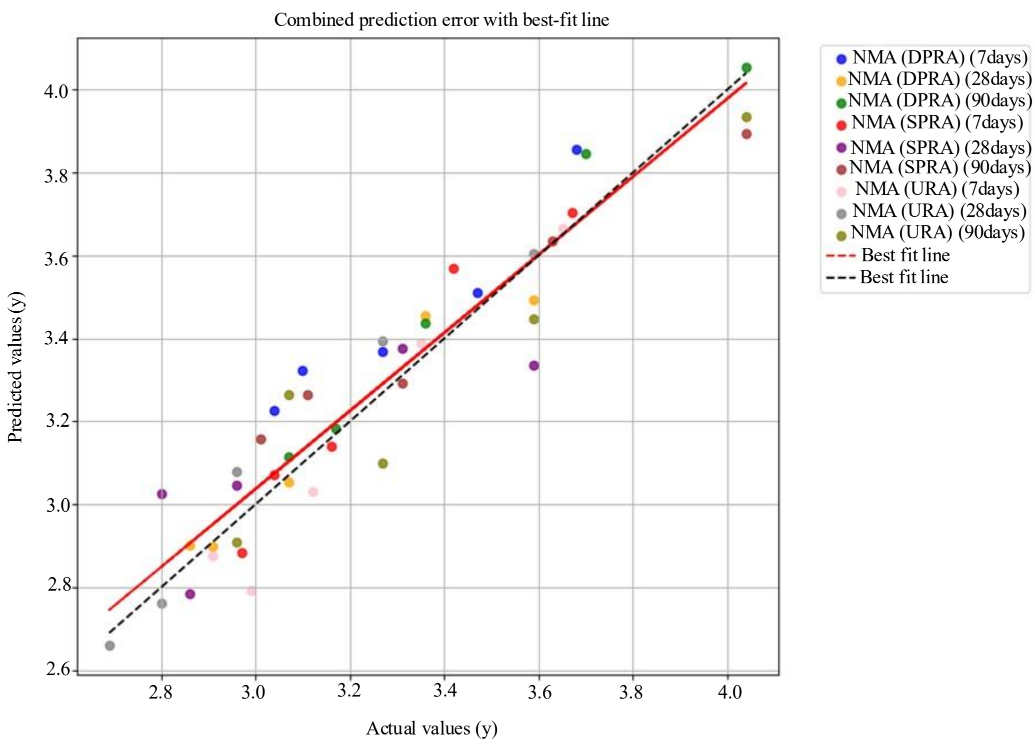

Figure 30. Combined prediction error with best-fit line.

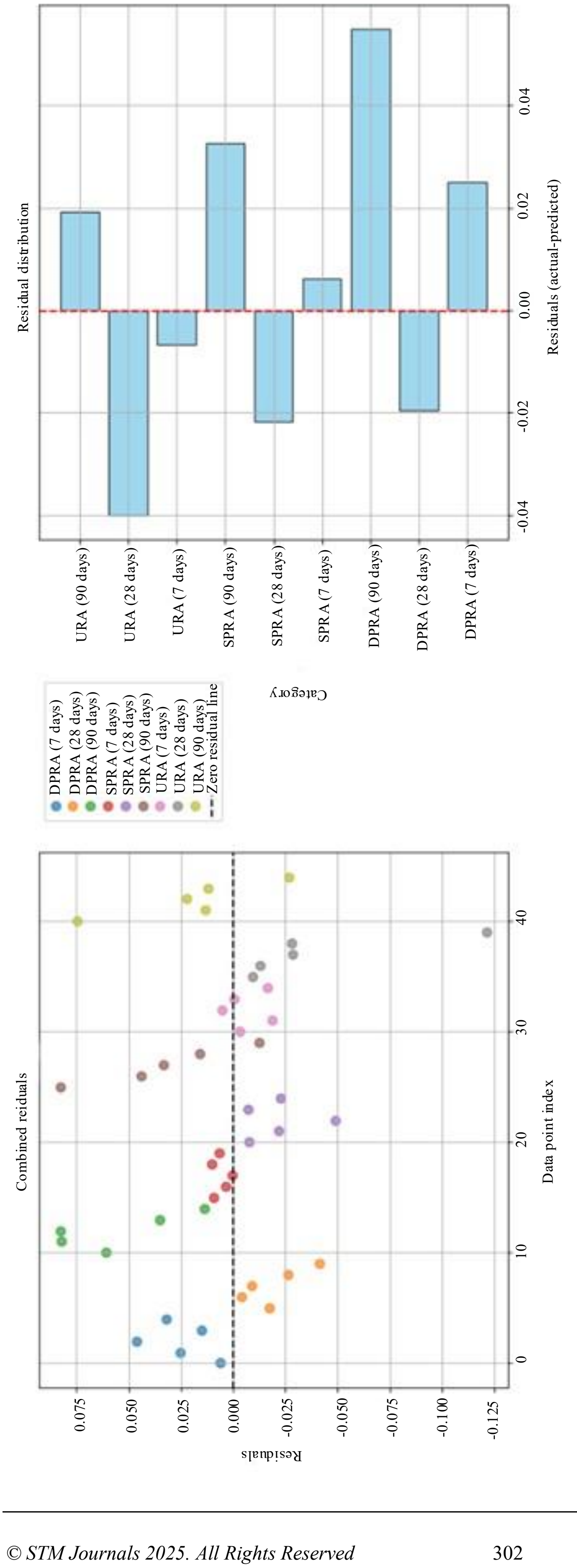

Figure 31. Residual model of tensile strength.

This image illustrates the importance of optimizing the percentage of recycled aggregate utilized in Composite Material, particularly when early performance optimization is being sought for.

Predication Model Error and Residual Model for Tensile Strength

Figure 30 illustrate that the scatter plot illustrates the combined prediction error of the model across various curing periods and additive types for SCBM Composite Material. Each point on the graph represents a predicted value plotted against the actual value, with distinct colors indicating different combinations such as curing duration (7, 28, and 90 days) and types of additives (DPRF, SPRF, and URF). The identity line, where the predicted values would be identical to the actual values (i.e., perfect prediction), is shown by the dashed black line. Based on the model's predictions, the best-fit line is the solid red line. The model seems to have strong prediction accuracy, since most data points are close to the identification line and the best-fit line is aligned. Minimal dispersion from the identity line implies consistent performance across all sample types and curing periods, reinforcing the model’s reliability in estimating the flexural strength of SCBM Composite Material with different additives.

You can see a detailed breakdown of residuals for different Composite Material mixes and cure times in the Figure 31. The left subplot, titled "Combined Residuals," illustrates the residuals (i.e., the difference between actual and predicted values) for each data point across all categories, including DPRF, SPRF, and URF at 7, 28, and 90 days. Each category is represented by a distinct color, and a horizontal dashed line at zero highlights the baseline where predictions perfectly match actual values. Most residuals are closely clustered around this line, indicating a relatively accurate prediction performance. On the right, the "Residual Distribution" plot presents the mean residuals for each category using a horizontal bar chart. Categories such as DPRF (90 Days) and URF (28 Days) show higher deviations, suggesting slight overprediction or underprediction in those cases. The red dashed vertical line represents zero residual, serving as a visual reference to assess the direction and magnitude of prediction errors. OveRA ll, the residual plots demonstrate that the prediction model performs reasonably well across all categories, with only minor discrepancies observed in certain cases.

Feature Selection and Validation

The input features-filler type, replacement ratio, and curing duration—were selected based on their physical significance and experimental control in the study. To validate feature independence, a Variance Inflation Factor (VIF) analysis was conducted, and all input features had VIF values < 5, indicating low multicollinearity. Additionally, Random Forest-based feature importance scores were used for sensitivity analysis, revealing that curing duration and filler type had the highest predictive influence on composite behavior.

DISCUSSION

Using the Standard Composite Blending Method (SCBM) and varying proportions of treated and unprocessed recycled coarse particles, this study investigated the mechanical and durability properties of Composite Material in detail. The experimental analysis focused on a number of performance para meters, including workability, abrasion resistance, flexural strength, tensile strength, Curing Agent absorption, diffusion coefficient, thermal expansion, and rapid chloride ion permeability.

- *Workability*: The slump values decreased with increasing reinforcement content across all composite formulations. This trend is primarily attributed to the porous and irregular surface texture of the recycled fillers, which increases the demand for the curing agent due to higher surface area and absorption characteristics. Among the three filler types—Double Processed Recycled Filler (DPRF), Single Processed Recycled Filler (SPRF), and Untreated Recycled Filler (URF)-DPRF exhibited the best workability, maintaining acceptable slump values even at 100% replacement of the natural filler in the matrix phase. This enhanced performance is credited to the improved surface quality and reduced porosity achieved through double processing, which minimizes the negative impact on flowability and handling characteristics of the composite material.

- *Compressive strength*: As the RF concentration increased, there was a slow but steady decrease in compressive strength. The poor quality of the RA —which contains imperfections like holes, fractures, and leftover mortar—is to blame for this. The fact that Composite Material kept becoming stronger between days 28 and 90 indicates that the long-term hydration effects were still there. The results showed that DPRF was the best kind of rate all replacement Matrix Phase levels.
- *Flexural strength*: As with compressive strength, flexural strength decreases as concentration rises. This is primarily because the interface transition zone (ITZ) has a lower binding strength between the RA and Matrix Phase paste. The strength was becoming better even while it was falling overall. Consistently producing greater flexural strength among the techniques evaluated, DPRF showcases the benefits of proper RA processing.
- *Tensile strength*: As predicted by the larger porosity and weaker ITZ in RA -based Composite Material, As the concentration of RA increased, the tensile strength of RA C dropped. The results at 28 and 90 days showed that DPRF mixes retained the most tensile strength, followed by SPRF and URF. The Matrix Phase in tensile strength over time reinforces the role of ongoing hydration in improving matrix density and internal bonding. Even at 100% replacement Matrix Phase, the strength loss remained within manageable limits when DPRF was used, showing its viability for structural use.
- *Curing agent absorption and diffusion coefficient*: The existence of microcracks and porous adhering mortar caused an increase in Curing Agent absorption and diffusion coefficient as the RA concentration rose. However, DPRF mixes had better resistance to Curing Agent ingress, reflecting the benefits of mortar removal and surface refinement.
- *Chloride ion permeability (RCPT):* Chloride ion permeability rose with RF content but reduced significantly between 28 and 90 days due to pore structure refinement through continued hydration. This indicates better durability at later ages, especially in processed aggregate mixes.
- *Thermal expansion:* The thermal expansion was found to be proportional to the RA content. The reason for this is because the drying process impacts both the volume change and moisture loss due to the greater Curing Agent absorption capacity of RF and the increasing volume of old mortar. However, shrinkage remained within acceptable limits, particularly for DPRF mixes.
- *Abrasion resistance:* The abrasion resistance declined with higher RA percentages due to weaker surface hardness of RF compared to natural aggregates. Nonetheless, the performance was still adequate for non-extreme wear environments, with DPRF once again outperforming other types.

The study successfully demonstrates that machine learning techniques, coupled with visual Exploration, is able to provide light on the intricate relationship between curing age and recycled aggregate constituents. Among all models and regions studied, Polynomial Regression emerged as the most robust, supporting its integration into future predictive models for sustainable Composite Material applications. Using a range of machine learning algorithms and visual analytics, the Normalized Mixing Assessment (SCBM) is utilized in this study to ascertain the impact of various curing intervals and recycled aggregate percentages (7, 28, and 90 days). The comprehensive approach integrates regression modelling, KDE-scatter analysis, and 3D surface visualization to understand performance behaviour and prediction capability.

Relationship Between Recycled Aggregate Percentage And SCBM

The KDE and scatter plots reveal a consistent inverse relationship between the recycled aggregate content and SCBM across all ages. A lower SCBM means that as the amount of recycled aggregate increases, the Composite Material's quality or workability decreases. Lower SCBM values at early ages (7 and 28 days) show greater microstructural weakness owing to higher porosity and the weaker character of recycled aggregates, and this tendency is particularly noticeable at these ages. However, by 90 days, there's a mild improvement, implying microstructural healing and pozzolanic activity.

3D Polynomial Regression Surface Fit

The 3D polynomial regression plots provide a spatial understanding of how SCBM evolves with both Recycled Aggregate Percentage and Days:

- All three regions (DPRF, SPRF, URF) exhibit highly accurate polynomial surface that align closely with actual data points.
- The DPRF and URF zones show R^2 values of 0.999, indicating near-perfect prediction fit. This suggests the behaviour in these zones is highly predictable under polynomial regression.
- The SCBM surface decreases with rising recycled content but gradually increases with curing time, reinforcing the earlier observed recovery trend.

Comparative Model Behaviour

From the combined actual vs. predicted plots across four models:

- Polynomial Regression showed near-perfect alignment with the actual data points, confirming it as the most suitable for capturing non-linear relationships in this dataset.
- Random Forest Regression also exhibited excellent performance with minimal deviation and strong clustering near the perfect fit line.
- Linear Regression and SVR were less effective due to the underlying non-linearity in the data, reflected in wider residual spread and underperformance in capturing complex relationships.

Implication for Sustainable Composite Material Mix Design

The combination of machine learning modelling and visualization reveals key trends essential for sustainable Composite Material development:

- While higher recycled aggregate usage negatively impacts early-age performance, careful optimization and extended curing can mitigate these effects.
- Advanced regression models-particularly Polynomial and Random Forest-offer powerful tools for predictive mix design, allowing for accurate forecasting of Composite Material performance under varying material replacement levels.

Prediction Model Error and Residual Model

The outcomes of the residual analyses and the series of figures show that the model that was created to estimate the mechanical characteristics of recycled aggregate-based Composite Material and additives such as DPRF, SPRF, and URF performed well across a range of curing duration (7, 28, and 90 days).

The model's excellent predictive accuracy was confirmed by scatter plots comparing real and expected values along the identity line in both the compressive and flexural strength tests.

The best-fit lines closely tracked this identity line, confirming once more that the model successfully identifies underlying patterns in the data. Residual plots, both in scatter and histogram formats, confirmed that errors are small and largely cantered around zero, with no signs of major systematic bias. While certain conditions—such as DPRF at 90 days or URF at 28 days—showed slightly larger deviations, the residuals remained within acceptable limits, indicating consistent model performance across diverse input scenarios. The overall trend points to a model that generalizes well from training to testing datasets, making it suitable for practical applications in predicting Composite Material behaviour under different curing and additive conditions.

Limitations of Double Processed Recycled Fillers (DPRF)

While the study demonstrates the technical viability and improved performance of Double Processed Recycled Fillers (DPRF) in polymer-based composites under standard curing and loading conditions, we acknowledge that limitations exist—especially under extreme environmental or structural stress scenarios.

Specifically, Potential Limitations of DPRF Include

1. *Freeze-thaw sensitivity:* The residual porosity—even after double processing—could allow moisture ingress and expansion under cyclic freezing, potentially weakening the interfacial bond and causing microcracking. This behaviour was not evaluated in the current study and requires targeted durability testing.

2. *Long-term creep and fatigue:* Under sustained or repetitive loading (e.g., in bridges or pavements), recycled fillers may exhibit greater deformation due to microstructural heterogeneity and incomplete bonding zones. Long-term fatigue studies are essential to quantify this risk.
3. *Chemical resistance:* While curing agent absorption and chloride diffusion were assessed, aggressive environments involving acidic, sulphate, or alkali conditions were not tested. These could compromise matrix–filler integrity, particularly where old mortar is retained.
4. *Scale-up variability*: DPRF performance depends on consistent processing (mechanical and silica fume impregnation). In field applications, variability in feedstock quality and treatment precision could affect reproducibility.

Sustainability Implications of DPRF (Double Processed Recycled Filler)

Resource efficiency & waste reduction: The use of DPRF directly contributes to reduced reliance on virgin aggregates and enables high-value reuse of construction and demolition (C&D) waste. This supports circular economy goals by diverting waste from landfills and reducing natural resource extraction.

Embodied energy and carbon emissions: While DPRF undergoes additional processing, the overall embodied energy and CO_2 emissions are expected to be significantly lower compared to natural aggregates, especially when accounting for mining, transportation, and environmental costs. A brief comparative discussion based on literature (added in the revised manuscript) now reflects this.

Durability and lifecycle: DPRF-based composites exhibited improved long-term mechanical performance and reduced permeability, suggesting an extended service life and reduced maintenance demand. These are crucial indicators for sustainable infrastructure and have now been explicitly mentioned.

Circular economy metrics: The DPRF approach reintegrates waste into structural applications, reducing raw material consumption and enabling more sustainable construction practices.

CONCLUSION

This study looked at how different percentages of reinforcement affected the mechanical properties and workability of Composite Material after it had been cured for different lengths of time. This research sheds light on the practicality and efficiency of recycled aggregate in green building by methodically examining the actions of DPRF, SPRF, and URF in a controlled environment. While an increase in RA concentration affects Composite Material's workability and strength, the results show that a balanced percentage may be attained to promote environmental sustainability while maintaining structural integrity. Integrating recycled aggregate in Composite Material presents a viable pathway toward sustainable construction. While challenges exist, strategic mix optimization and quality control measures can unlock its full potential. The results add to the increasing amount of evidence in favor of using greener construction materials, paving the way for more resilient and environmentally responsible Infar structure development.

- *High replacement matrix phase feasibility:* Properly treated recycled aggregates-especially DPRF - may substitute natural coarse aggregates up to 100% with little impact on strength and durability.
- *Mechanical performance:* Although strength properties-compressive, flexural, and tensile-declined with increasing RA content, the use of DPRF minimized this reduction. The continued strength development from 28 to 90 days confirms the long-term potential of RA C, particularly with proper curing and mix design.
- *TRA its of longevity*: Staying power Inherent porosity was the primary cause of the increasing Curing Agent absorption, diffusion coefficient, chloride permeability, and thermal expansion as the RA Concentration rose. However, these issues were effectively mitigated by adopting advanced processing techniques. DPRF consistently provided the best results in minimizing durability losses.

- *Processing methods matter:* The type and quality of RA treatment significantly affect the performance of RA C. Among all approaches, DPRF showed superior mechanical strength and durability due to better surface texture, reduced porosity, and improved ITZ.
- *Sustainability implications*: Using recycled aggregates in Composite Material aligns with sustainable building goals by reducing dependency on virgin resources and removing waste from construction and demolition. The findings of this study support the notion that recycled materials might be effectively incorporate ted into building structures without significantly changing how well they function.
- To minimize performance loss, it is strongly recommended to use Double Processed Recycled Aggregate (DPRF) even when employing 100% recycled aggregate. Recycled aggregate Composite Material's strength and durability are greatly enhanced while it cures, particularly within the first 90 days.
- The experimental findings clearly show that mechanical performance decreases as the recycled aggregate content rises. This is because the interracial bonding weakens, the porosity increases, and adhering mortar is present. The application of double processing (DPRF) helped to reduce these impacts and yielded consistently higher workability, strength, and durability outcomes.
- These behaviors were measured and predicted using four machine learning models: Random Forest Regression, Support Vector Regression (SVR), Polynomial Regression, and Linear Regression. R^2,

MSE, MAE, and RMSLE were some of the statistical criteria used to assess their efficacy. Considering the compressive, flexural, and tensile strengths:

- Polynomial Regression consistently outperformed all other models:
  - Compressive Strength: $R^2 = 0.91$, MSE = 1.57
  - Flexural Strength: $R^2 = 0.99$, MSE = 0.001
  - Tensile Strength: $R^2 = 0.996$, MSE = 0.0004
- These findings validate its exceptional capacity to simulate intricate, nonlinear connections between input factors and Composite Material strength.
- Random Forest Regression performed second best overall, especially in modelling tensile and flexural strengths, showing robust performance and generalization with minimal oversitting.
- Linear Regression, while simple and interpretable, failed to capture the nonlinear behaviour of the dataset fully, especially at higher replacement Matrix Phase levels and early curing periods.
- Support Vector Regression (SVR) displayed moderate performance but was the least consistent, likely due to sensitivity to kernel Para meters and data distribution.
- The model demonstrates robust predictive capability for both compressive and flexural strength properties, with minor deviations observed under specific curing or material conditions. This confirms the viability of using machine learning approaches for performance prediction in sustainable Composite Material formulations, particularly those incorporating recycled aggregates and industrial by-products.

The scatter plot illustrates the combined prediction error of the model across various curing periods and additive types for SCBM Composite Material. Each point on the graph represents a predicted value plotted against the actual value, with distinct colors indicating different combinations such as curing duration (7, 28, and 90 days) and types of additives (DPRF, SPRF, and URF). The identity line, where the predicted values would be identical to the actual values (i.e., perfect prediction), is shown by the dashed black line. Based on the model's predictions, the best-fit line is the solid red line. The model seems to have strong prediction accuracy, since most data points are close to the identification line and the best-fit line is aligned. Minimal dispersion from the identity line implies consistent performance across all sample types and curing periods, reinforcing the model’s reliability in estimating the flexural strength of SCBM Composite Material with different additives.

While this study confirms the technical and environmental viability of Double Processed Recycled Fillers (DPRF) in polymer-based composites, several limitations warrant further investigation. Notably, the residual porosity, despite dual processing, may increase sensitivity to freeze-thaw cycles and chemical exposure in aggressive environments, such as those involving acids, sulphates, or alkalis. Additionally, the long-term behavior of DPRF under creep and fatigue loading remains unquantified and may present durability concerns in heavily trafficked or load-bearing structures. Furthermore, consistent performance relies on tightly controlled processing conditions; variability in feedstock quality and treatment precision during large-scale implementation could impact reproducibility. Despite these challenges, DPRF offers strong sustainability benefits, including substantial reductions in virgin aggregate demand and landfill waste, contributing directly to circular economy objectives. Its comparatively lower embodied energy and carbon footprint, coupled with enhanced long-term durability, position DPRF as a promising material for sustainable infrastructure development. These attributes support broader environmental goals while promoting high-performance, resource-efficient composite design.

FUTURE SCOPE

Based on the findings of this study, several actionable recommendations can be made for field engineers and materials designers.

- The Double Processed Recycled Filler (DPRF) demonstrated the capability to replace up to 100% of virgin coarse aggregates in polymer matrix composites without significant loss in workability or mechanical integrity, making it a viable and sustainable alternative for non-load-bearing and moderately loaded structural applications.
- For enhanced durability-especially in aggressive environments such as coastal or industrial regions—DPRF-based composites are preferred due to their reduced permeability and improved resistance to chloride ion diffusion.
- The performance of these materials improves substantially with longer curing durations; thus, delayed loading or extended curing schedules should be considered in field deployment. To maintain optimal workability, the use of high-range water-reducing admixtures (e.g., Glenium Ace-30) is recommended.
- Additionally, the SCBM protocol and the two-step DPRF processing method should be standardized in quality assurance procedures to ensure consistency across production batches. Finally, the validated machine learning models developed in this study-particularly polynomial regression-offer a predictive toolset that engineers can use to estimate composite performance based on filler type, dosage, and curing time, thereby reducing reliance on costly trial-and-error mix design processes

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