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Article

Optimization of Fresh and Mechanical Characteristics of Carbon Fiber-Reinforced Concrete Composites Using Response Surface Technique

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Abstract: As a top construction material worldwide, concrete has core weakness relating to low tensile resistance without reinforcement. It is the reason that a variety of innovative materials are being used on concrete to overcome its weaknesses and make it more reliable and sustainable. Further, the embodied carbon of concrete is high because of cement being used as the integral binder. Latest research trends indicate significant potential for carbon fiber as an innovative material for improving concrete mechanical strength. Although significant literature is available on the use of carbon fiber in concrete, a limited number of studies have focused on the utilization of carbon fiber for concrete mechanical strength improvement and the reduction of embodied carbon. Following the gap in research, this study aimed to investigate and optimize the use of carbon fiber for its mechanical characteristics and embodied carbon improvements. The use of carbon fiber in self-compacting concrete lowers sagging. The greatest quantity of carbon fiber is that it reduces the blockage ratio, forcing the concrete to solidify as clumps develop. With time, carbon fiber improves the durability of concrete. Self-compacting concrete with no carbon fiber has a poor tensile strength. Experiments were conducted by adding carbon fiber at 0.2%, 0.4%, 0.6%, 0.8%, and 1.0% by weight. Fresh concrete tests including slump test and L-box test, hardened concrete tests involving compressive strength and splitting tensile strength, and durability tests involving water absorption and acid attack test were conducted. Embodied carbon ratios were calculated for all of the mix ratios and decreasing impact, in the form of eco-strength efficiency, is observed with changes in the addition of carbon fiber in concrete. From the testing results, it is evident that 0.6% carbon fiber is the ideal proportion for increasing compressive strength and split tensile strength by 20.93% and 59%, respectively, over the control mix. Response Surface Methodology (RSM) is then applied to develop a model based on results of extensive experimentation. Optimization of the model is performed and final modelled equations are provided in terms of calculating the impact of addition of carbon fiber in concrete. Positive implications are devised for the development of concrete in the future involving carbon fiber.

Keywords: carbon fiber; concrete; mechanical properties; embodied carbon; response surface methodology

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1. Introduction

Research is being performed on a global scale to improve the characteristics of concrete and make it useful in severe environmental conditions. Different forms of concrete with better characteristics and excellent performance have been produced. In these concretes, in addition to standard components, novel and unique elements are used. In addition, varied mix proportions, water-to-cement ratios, chemical and mineral admixtures, etc., have been included in the creation of new concrete processes. Self-compacting concrete is one of these innovative concretes. It is a type of concrete that is extremely easy to work with due to its ability to compact itself solely via its own mass; attain outstanding deformability during its fresh form; fill each crevice, including within confined areas and complex geometric shapes; and construct a compressed, uniform, and void-free mass whilst also retaining homogeneity. There is no need for vibration, and segregation and bleeding also do not occur [1–5]. Utilizing mineral fillers or fines and certain admixtures, self-compacting concrete enhances resistance to segregation. Self-compacting concrete must flow and fill certain molds under its own weight, pass through considerably reinforced areas, and avoid aggregate segregation.

This kind of concrete must comply with the project's placement and flow specifications [6]. Self-compacting concrete (SCC) has been used to build bridges as well as prefabricated parts. The Akashi-Kaikyo Suspension Bridge is among the most spectacular self-compacting concrete constructions [7]. In a study, Kanellopoulos et al. [6] compared the key indicators that characterize the durability of SCC (absorptivity, porosity, and chloride ion permeability) to the comparable characteristics of reference concrete. Engineers often neglect the problem of durability because they presume that strong concrete is likewise durable. This study demonstrated how specific experimental findings might lead to reliable conclusions about concerns of durability. This examination revealed a link between the different indications of durability for the particular filler additives employed in the mix designs.

In lieu of depending upon time-consuming artificial weathering experiments, such a connection may be utilized to predict the durability of SCC. CC mixtures offer more durability than normal vibrating concrete (NVCs), even when greater amounts of water are employed [6]. This is due to the higher amount of penalties in SCC. When alternative materials are used in place of cement [8–10], the mixture's durability is increased because the products of a pozzolanic reaction improve the packing of 10 particles inside the microstructure. Silica fume greatly inhibits the capillary absorption of the mixtures and the chloride ion permeability when used. Jiang et al. [11] conducted an experiment utilizing a rheometer to measure the rheological properties of SCC mixes containing various nanoparticles and microfillers. Nano-SiO_2, nano-TiO_2, carbon nanotubes (CNTs), carbon nanofibers, and carbon fibers are the fillers [11]. Researchers determined that perhaps the rheological qualities are affected by the filler kinds and amounts, the water/cement ratio, and the concentration of superplasticizer (SP). A little adjustment in the w/c ratio 17 may have a substantial effect on the rheological characteristics of cement paste including CNTs. A fast rate of mixing enhances the dispersal of fillers in cement matrix. Ultrasonic treatment has the potential to prevent filler aggregation and significantly decrease cement paste yield stress.

Due to filler aggregation, the yield stress of the mixtures is enhanced and must be appropriately handled before to use [11]. Fibers are often used in concrete to minimize fractures produced by drying shrinkage and plastic shrinkage. In addition, they restrict the permeability of concrete, thereby limiting water seepage. Utilizing carbon fiber in applications where high strength is needed and where it has particular qualities linked to greater toughness and superior weight reduction, due to the usage of synthetic carbon, makes it a very distinctive material [12]. Carbon fiber is very distinctive in terms of its ability to withstand vibrational stresses and stressed loading; it also has the capacity to impart the most stability to the material in which it is utilized as an addition [13,14]. As a result of its low thermal expansion, carbon fiber is very resistant to temperature rises and does not expand or contract much in comparison to other materials [15]. It is also proof that carbon fiber has a high average resistance, since it is long-lasting and is often used to cover a range of surfaces that are thought to be destroyed even by chemical assaults [16].

This study intends to determine the effects of carbon fiber on the properties of concrete, create and assess the appropriate statistical models, and then optimize mortar mixtures for infrastructure applications. This research also investigates the effect of carbon fiber particle percent and predictor variables on the fresh and hardened properties of concrete mixes using RSM design. This technology may expedite the practical implementation of fiber-reinforced concrete.

2. Background

Design of experiment, or "DOE" for short, is a particularly effective method for addressing many inputs or for making decisions [17]. For increasing the efficiency of experiments, many industrial sectors and services have been following this technique [18]. Previously, issues involving several factors were handled by using one element at a time, also known as the OVAT technique, which maintains every component but one constant and runs tests till the best results are obtained for the factor being examined. The procedure is repeated for each variable till the proper answer is found, while considering the problem's many variables. Although the process is basic and accurate, it still requires a huge datasets and several tests, that are time-consuming, expensive, and labor-intensive [19]. This is a very crucial issue for studies using construction materials like concrete. In contrast to earlier studies, which focus on a single response parameter, like the impact and quantity of substitute material on the properties of concrete, this study examines all response factors [20].

Multiple criteria, some of which are intricately interwoven, influence the overall effectiveness of high strength and self-consolidated concrete [21]. DoE lowers the amount of data necessary for effective statistical modelling by revealing the impact of each component on the analyzed dependent variable. In contrast, academics who lack appropriate topic knowledge and a well-defined technique for completing problem-solving tasks may find the variety of DoE analyses to be a hurdle [22]. DoE has indeed been widely used in recent years for the study of building materials. DoE has been applied throughout the concrete research process, from the prediction of concrete strength through to the development of design mixtures of concrete. Nondestructive testing (NDT) of ordinary concrete sometimes requires the use of numerical equations because the concrete's strength cannot be determined by NDT results alone [23].

Typically, simple linear regression (SLR) with a scatter plot is employed in this case. Innovative methods of evaluation, like the Response Surface Method [24], are now useful for generating very perfect and detailed predictions. DoE procedures are particularly effective for determining potential material replacement [25]; a significant proportion of recent publications adopt a more sophisticated method for analyzing test results [26]. Several replacement materials, including tyre rubber [27], fly ash [28], as well as others, have been evaluated utilizing various DoE methods. In other studies, a response surface technique [29], methods of curve fitting [30], or ANNs-based approaches are utilized to improve novel design methodologies of concrete, which frequently incorporate the use of standard environmental waste components.

3. Response Surface Methodology (RSM)

RSM technique is the design of experiment (DoE) approach utilized to explore the effect and interrelationships of numerous response variable elements. Similar to the classic Taguchi approach, the primary goal is to simplify the testing procedure and optimize the results. As per Bradley et al. [31], the RSM approach entails interpreting the response surface form, along with the local maximum (+1), minimum (−1), and ridges route, and identifying the optimal response site. The RSM model analyses the combined impact of the first order, second order, and combination influence among the components, in order to generate a design for a response surface that specifies the ideal settings for the response variable. As with other experimental design (DoE) techniques, the RSM technique employs a numerical approach to solve a problem, consequently reducing the number of lab tests as well as the expense and duration of the research [32]. Moreover, it evaluates the interplay of components to improve the model's precision and dependability. However, empirical data are matched to a quadratic order, that may not adequately reflect all curved systems [33].

Even while RSM offers a thorough analysis tool for results and discoveries, it cannot dictate the data collecting method. In contrast to the Taguchi method, which employs the Orthogonal Array, different data collection methods exist. Box-Behnken design (BBD), 3 levels (3 k) full factorial designs, central composite design (CCD), Doehlert design matrix (DM), and other methodologies are applied. As the number of levels increases, the numbers of tests required increases, resulting in poor data collection performance [34]. Consequently, it has limited applications in comparison to RSM. Numerous research studies [35] have examined the efficacy of the remaining three methods. In comparison to traditional designs, optimal experimental designs have gained popularity during the last ten years. This is owing to their adaptability and capacity to deal with a greater array of issues than traditional designs [36].

Design Expert 13 software was used for this study's Response Surface Methodology (RSM), encompassing experimental designs, mixtures proportioning, constructing mathematical models, and optimization of the mixture. Carbon fiber is employed as the independent variable in this investigation so that its impact on the properties of concrete during fresh and hard state may be investigated.

4. Materials and Experimental Methods

4.1. Materials

For the purposes of this investigation, type I ordinary Portland cement (OPC) was used. Additionally, binder material meeting the requirements of ASTM C150M-15 [37] was utilized. The carbon fiber was purchased from local suppliers since it is one of the essential ingredients that must be incorporated into the concrete; thereby, no concessions were made during the materials acquisition process. Following the vendor's standard specifications for carbon fiber, the material's qualities were evaluated utilizing the existing equipment to validate its acceptability for concrete manufacturing and additional testing processes [7]. In order to manufacture stronger concrete, it was necessary to monitor the growth of the carbon fiber in the concrete, as well as the structure of the carbon fiber, to ensure optimal contact between the carbon fiber and the concrete parts.

However, care was taken to guarantee that the carbon fiber used in the creation of concrete and subsequent testing was of industrial grade 36 and has all of the features of carbon fiber. It was preserved to demonstrate that the maximum strand length of the carbon fiber must not exceed 10 mm, and that the technique of inserting the fiber into other concrete components maximizes the durability and testing processes. Microsilica used in this study was also obtained from local vendor. After that, the material was delivered; its density and other characteristics were verified. It was discovered that its characteristics are inextricably connected to lower absorption of water and a greater capacity to be absorbed into materials with the proper size of particles or diameter. A nearby supplier was selected for the coarse aggregate. Locally available fine aggregate was utilized for the research. In order to manufacture self-compacted concrete, a superplasticizer with a density of 1200 kg per meter cube was purchased from local supplies and used only to meet the concrete's water needs. Carbon fiber and superplasticizers are often cross-matched to identify any chemical ingredients that may have a detrimental effect on the structure of fiber.

4.2. RSM and Mix Proportioning

Following recommendations from ACI 211.1-91, the controlled concrete (including no carbon fiber) was developed [37]. Mix design using response surface methodology, containing varying percentages of carbon fiber, was carried out with design expert 13 software. Carbon fiber is an independent variable, RSM involves the manipulation of this independent variable and represents its actual effect on the dependent variable [38]. The mix percentage was executed using the design expert 13 software's best design option.

From 0% to 0.8% carbon fiber content was included in a variety of composite mixtures. Relevant replies for this inquiry include tests done on fresh and hard concrete (slump cone, L-box test, compressive strength of concrete, split tensile strength, absorption of water, acid attack test, embodied carbon, and eco-strength efficiency). All other mix ingredients (coarse aggregate, fine aggregate, micro silica, water, and superplasticizer) were held constant, whereas RSM created multiple mixes with varying carbon fiber contents. Mix proportions generated by RSM are presented in Table 1.

Table 1. Mix proportioning.

MIX	Binder Kg/m^3	CF (%)	Micro Silica Kg/m^3	C.A Kg/m^3	F.A Kg/m^3	Water Kg/m^3	SP (%)
CF 0%	503.5	0.00%	26.5	890	740	195	1
CF 0.20%	503.5	0.20%	26.5	890	740	195	1
CF 0.40%	503.5	0.40%	26.5	890	740	195	1
CF 0.60%	503.5	0.60%	26.5	890	740	195	1
CF 0.80%	503.5	0.80%	26.5	890	740	195	1
CF 1%	503.5	1%	26.5	890	740	195	1

4.3. Preparations of Samples

All the dry materials like cement and aggregates were properly mixed into the mixture for more than 2 min, and then water and superplasticizer were added. That mixture was properly mixed for a few minutes into the concrete mixture. As the concrete was being prepared, carbon fiber was sprinkled onto it gradually. After the concrete was properly mixed, samples were cast. For slump cone testing, samples were collected in compliance with JIS A 1115 and JIS A 1138. To measure the slump of concrete, a slump cone was utilized. The L-box test was carried out using an apparatus that was compatible with both JIS A 1115 and JIS A 1138. The goal of this evaluation is to determine SSC's pass rate and recruitment potential. The duration of time it takes to go from a starting position 200 mm away to a starting position 400 mm on the horizontal is quantified. Compressive strength samples with dimensions of 100 mm $\times$ 100 mm $\times$ 100 mm were produced according to ASTM C78/C78M, while split tensile strength samples with dimensions of 100 mm and height of 200 mm were casted according to ASTMC496 and tested on the 7th and 28th day of casting. The sample preparation of this research work is shown in Figure 1.

Figure 1. Sample preparation.

5. Results and Discussion

5.1. Fresh Characteristics Examination

5.1.1. Slump Flow-Test

According to the data, the inclusion of carbon fibers clearly has a significant impact on the accessibility of concrete, as represented by the results of slump tests as shown in Figure 2. It is clear that the width of the droop decreases continuously when carbon fiber is added, demonstrating that the inclusion of carbon fiber has a direct effect on the strength of concrete, which may impede the actual adoption of carbon fiber in construction. As per EFNARC's reference standards, it is evident that the necessary slump value is 650 mm; thus, if the slump falls within the specified range, it is okay. The value of slump for the control mix CF0% was found to be 711 mm. In comparison to the control sample, the addition of 0.20% carbon fiber reduces slumps by 2.30% in the CF0.20% sample and by 4.55% in the CF0.40% sample. Increasing the carbon fiber content to 0.60% decreases sag by 6.91%, while increasing fiber content to 0.80% reduces sag by 9.38%; at CF1%, sag reduction rises by 11.92%.

According to previous studies done by Iftekar gull et al., adding 1% carbon fiber to concrete reduces slump by 27 mm. The test findings suggest that the starting value of the slum is aligned with the standard limit; thus, the findings are acceptable. Nonetheless, when the carbon fiber percentage rises, the workability decreases, resulting in various design limits for the concrete that are unable to meet if the carbon fiber contact is raised above 0.8%. Ultimately, the workability is diminished due to the interaction between fiber and concrete parts.

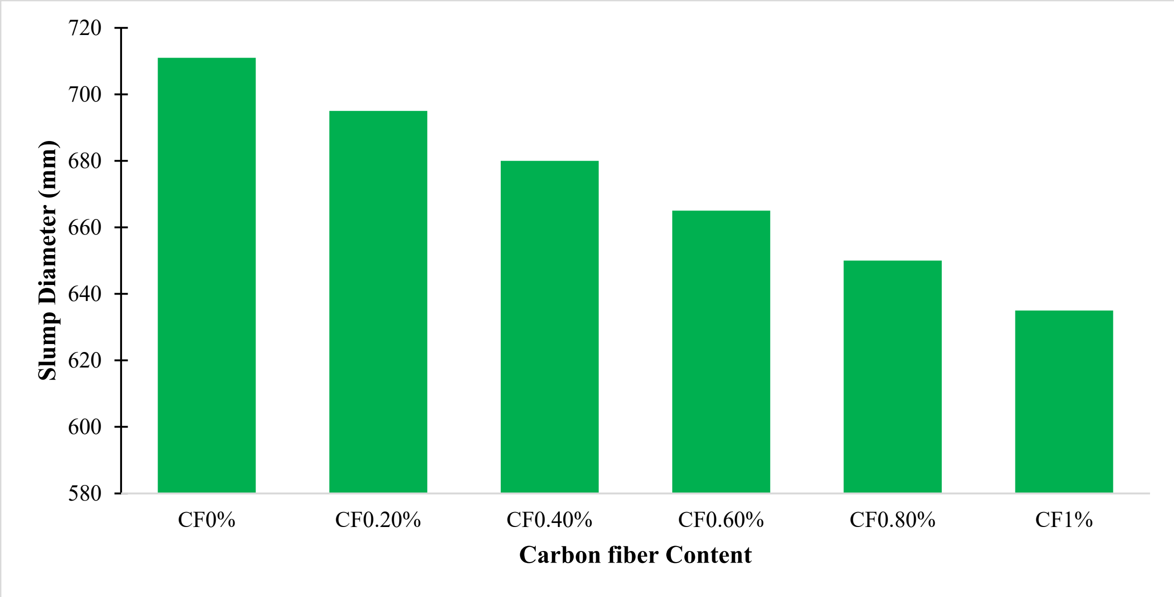

Figure 2. Slump flow Test.

5.1.2. L-Box Test

The workability from the L-box test is also acquired, and it can be seen that the workability decreases continually as the carbon fiber content increases. As anticipated, the outcomes are the same since the inclusion of carbon fiber lowers the amount of concrete available, making it difficult for self-compacting concrete to find further applications. According to standard standards, it is obvious that the needed value must be more than 0.8, and all of the measured values are greater than 0.8, indicating good workability with a carbon fiber concentration of 0.8% or less. Figure 3 demonstrates that adding 1% fiber content to CF1% decreases the developing ratio excessively.

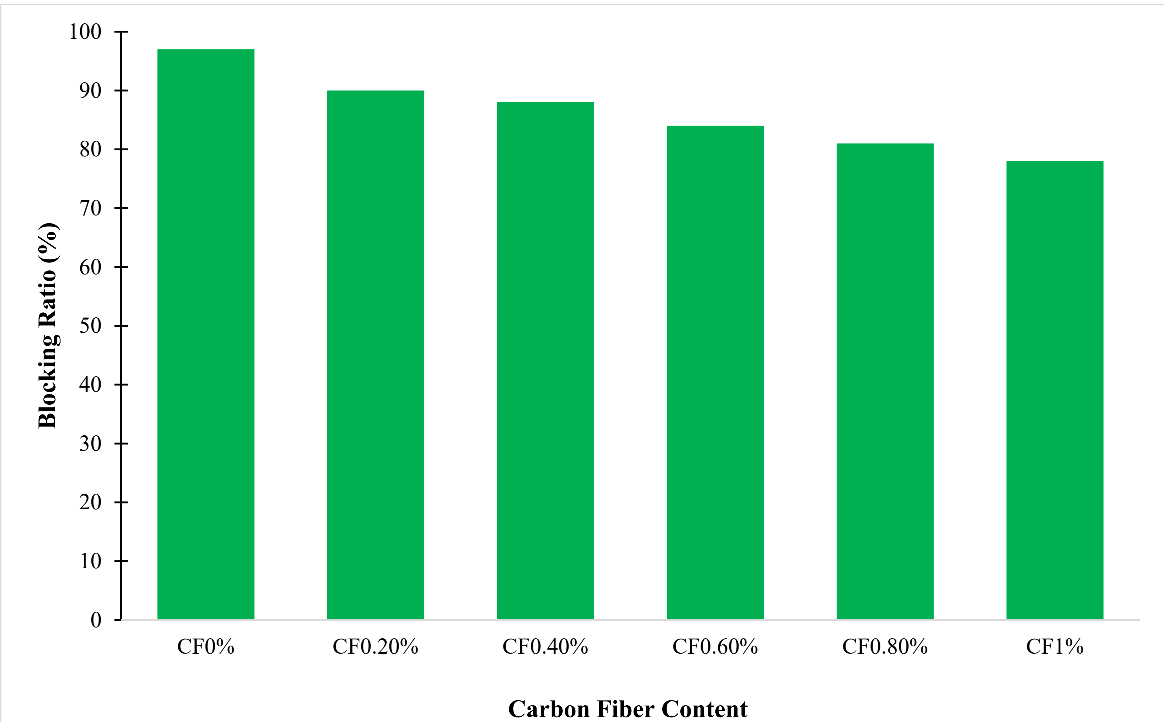

Figure 3. L-Box test.

The 0.8% is the best level for adding carbon fiber to concrete in order to improve its workability and remain within the permissible range. Otherwise, it might hinder the ability of self-compacting and carbon-fiber-based concrete to function better in accordance with planned environmental outcomes. Overall, the data indicates that the L-box test yields superior results and the ideal value of carbon fiber, which must be maintained when incorporating it into concrete buildings. In previous studies done by Nadeem et al. [39], they also found that the H1/H2 ratio decreases by increases in the fiber content, and suggested that 0.6% of fiber content gives better result for maintain the workability.

5.2. Compressive Strength

Figure 4 demonstrates that the cubical samples were tested for compressive strength after 28 days. However, the addition of carbon fiber enhances the concrete's compressive strength up to a specific threshold, beyond which it decreases as shown in Figure 5. By adding 0.20% fiber, compressive strength improves by 13.98 percent; by adding 0.40% fiber, it increases by 16.29%; and by adding 0.60% carbon fiber, compressive strength increases by a maximum of 20.93%. By adding 0.80% fiber, the compressive strength starts to decline; adding 1% fiber only enhances the concrete's compressive strength by 10%. The compressive strength test demonstrates that, by the addition of 0.6% carbon fiber, concrete's compressive strength starts to diminish (Figure 5). As a result of the production of fiber agglomerates, which leads to the development of voids in the concrete, the addition of carbon fibers more than 0.6% lowered the compressive strength of the concrete [40].

Figure 4. Compressive strength laboratory testing.

According to earlier research, the ideal quantity of carbon fiber that may have an optimistic impact on the concrete's compressive strength is 0.60% [39]. According to research conducted by Andrey Nevsky et al. [41], adding more than 1% fibers to concrete diminishes its compressive strength. Furthermore, the addition of 0.20% carbon fiber produced the greatest gain in compression strength.

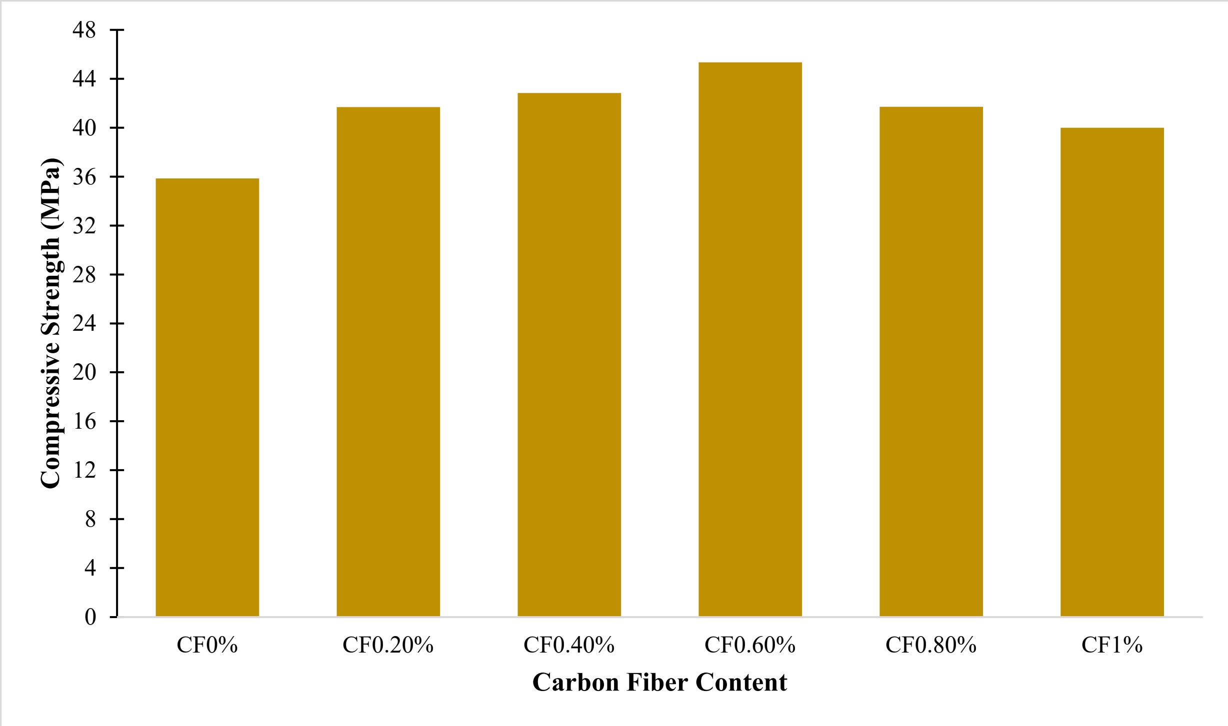

Figure 5. Compressive strength.

5.3. *Split Tensile Strength*

The cylindrical samples were used for splitting tensile strength of concrete as shown in Figure 6. According to the findings of split tensile strength test, the addition of carbon fiber to concrete boosts its tensile strength to some degree as displayed in Figure 7. Concrete with 0.60% carbon fiber provides the best results for tensile strength at the optimal fiber percentage. By adding 0.20% (CF0.20%) of carbon fiber, the tensile strength improves by about 56%; by adding 0.40% (CF0.40%) of fiber, the strength increases by approximately 57%; and by adding 0.60% (CF0.60%) of fiber, the strength increases by approximately 59%. When fiber concentration exceeds 0.60%, tensile strength begins to decrease. The addition of 0.80% (CF0.80%) fiber enhances tensile strength by 56%, which is less than CF0.60%. The addition of 1% fiber enhances the strength by 53%, which is lower than the strength of CF0.60%. When the amount of carbon fiber goes above 0.6%, the split tensile strength of the concrete begins to decline, as shown by the data; this is because the production of fiber agglomerates results in the development of void, which causes the strength of concrete to decrease [40].

The tensile strength of concrete with 0.20 percent carbon fiber is 17.5 percent higher than the tensile strength of concrete without scattered carbon fibers [41]. The relationship between concrete's compressive strength and split tensile strength is presented in Figure 8. The value of "R" shows that there is a strong corelation between concrete's compressive and tensile strength. Equation presented in Figure 8. can be utilized to find out split tensile strength or compressive strength, if anyone of them is given.

Figure 6. Split tensile strength laboratory testing.

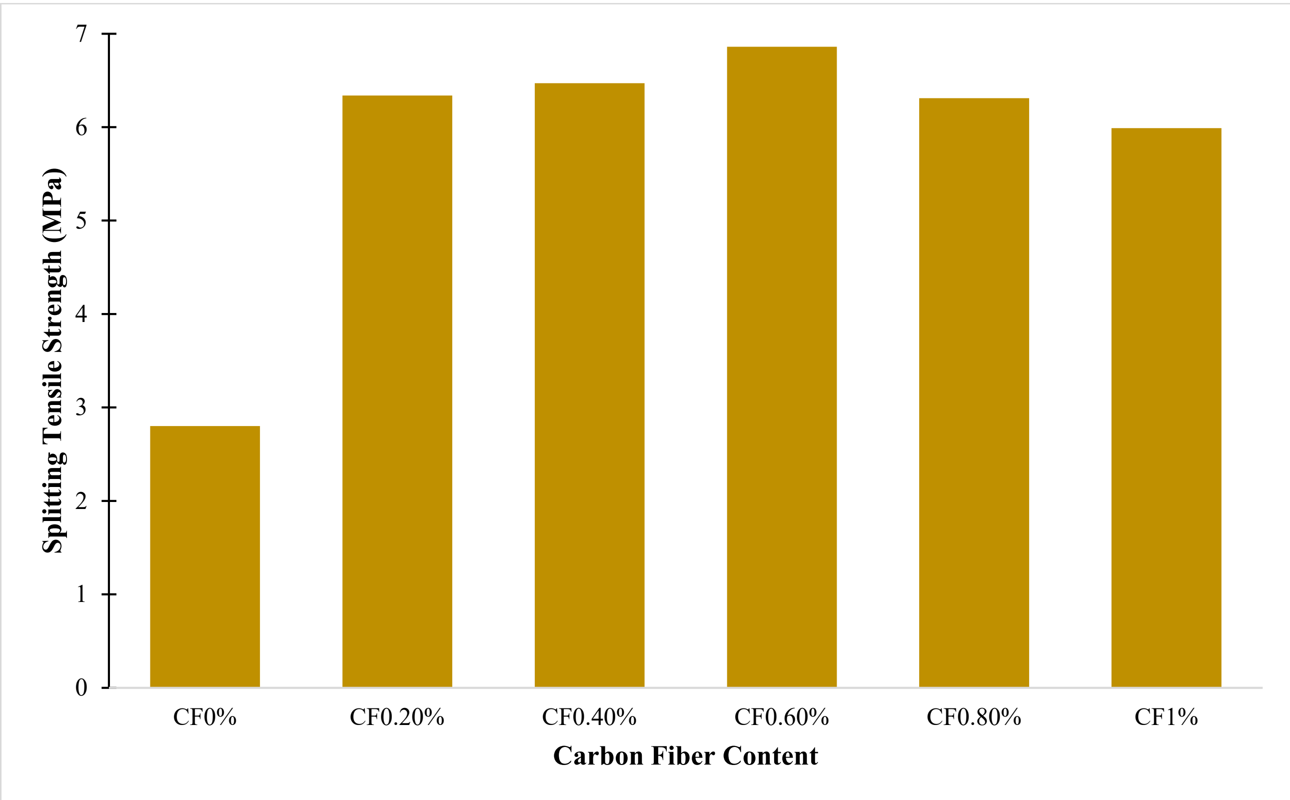

Figure 7. Split tensile strength.

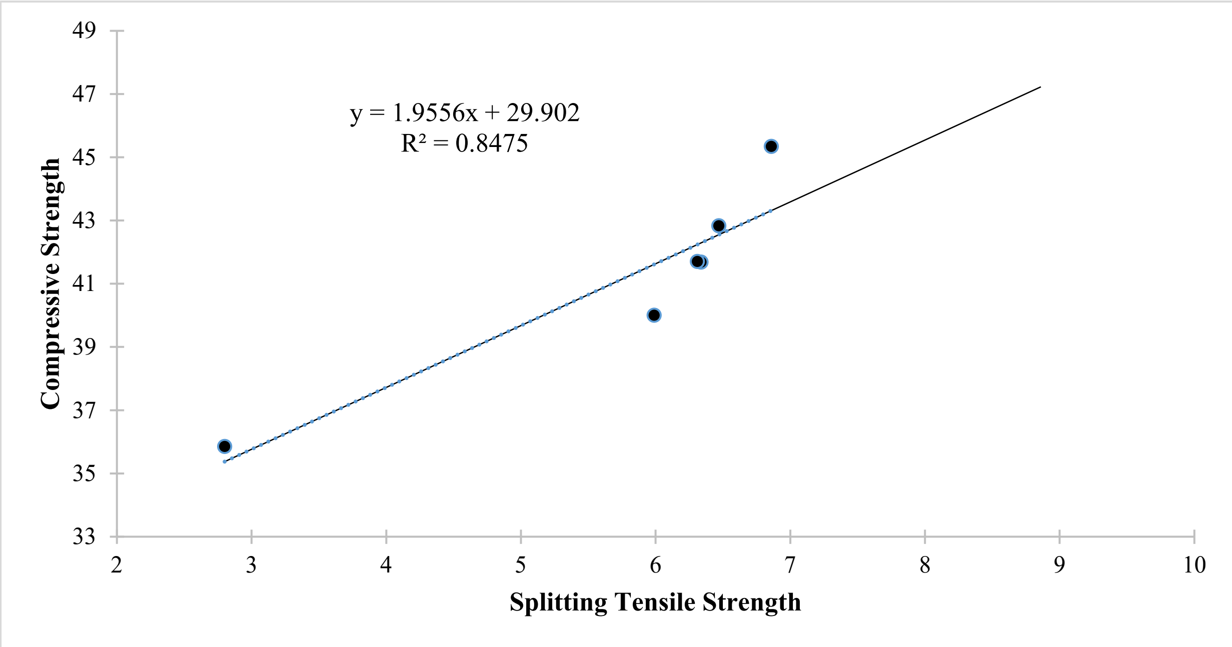

Figure 8. Relationship between concrete's split tensile and compressive strengths.

5.4. Water Absorption

Water absorption is also affected because of the addition of carbon fibers as shown in Figure 9. The control sample with zero percent of fiber has very high-water absorption of about 10.12%. It is obvious from the data that the inclusion of fiber decreases water absorption; on the addition of 0.20% (CF0.20%) of carbon fiber there is reduction of about 12.19% in water absorption. An increase in fiber content is often associated with decreased hydration needs. It indicates that the decrease in water absorption is a direct result of the buildup of fibers, and that the durability of concrete is increasing since it will absorb less water over the course of its service life. Adding 0.40% (CF0.40%) carbon fiber reduces water absorption by approximately 17.81%, CF0.60% with 0.60% fiber content reduces water absorption by 31.60%, CF0.80% with 0.8% fiber content reduces water absorption by 71.23%, and CF1% with 1% fiber content shows the greatest reduction in water absorption. Water absorption values can be reduced by the addition of fiber, particularly at higher rates; this shows that fiber helps to continue the hydration process by absorbing water at larger scale [42]. Carbon fiber has a negative impact on the absorption of water in concrete and enhances the durability of concrete [39]. When the amount of carbon fiber rises, water absorption reduces because concrete containing carbon fiber is less porous, allowing less water to permeate through the surface of the concrete.

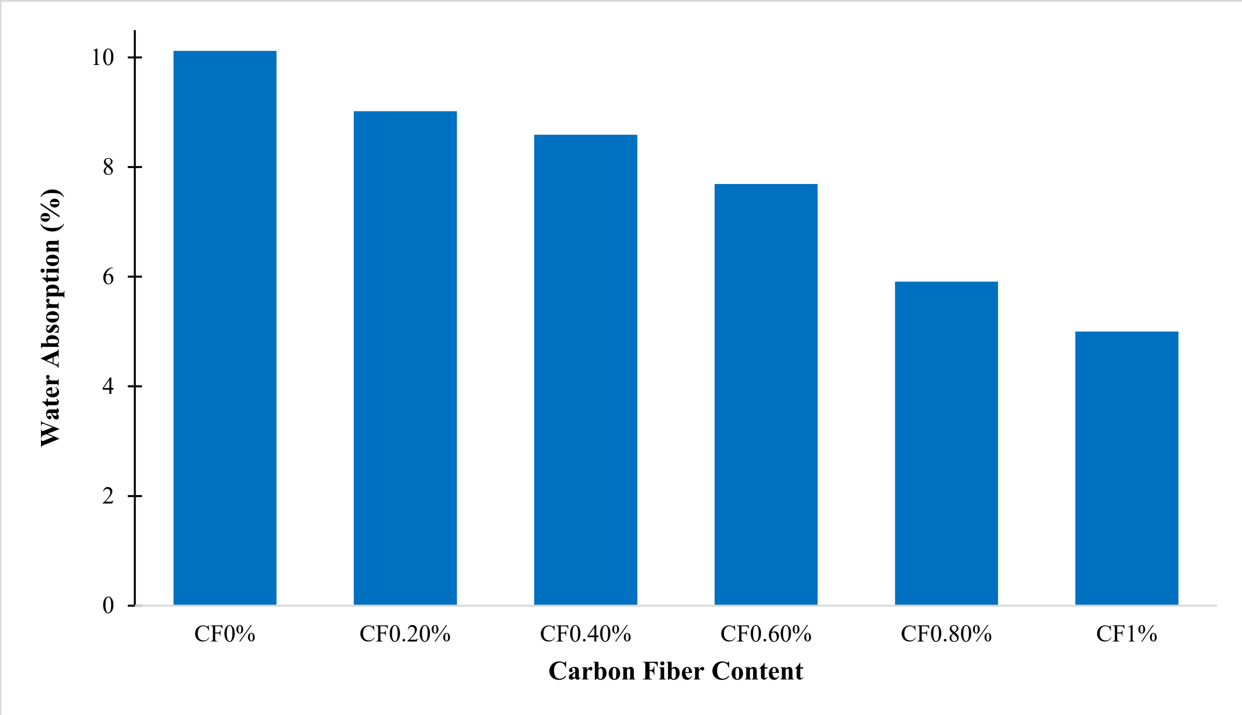

Figure 9. Water absorption.

5.5. Acid Attack Test

The results of acid attacks show that strengthening concrete with carbon fiber makes it far more resistant to damage as shown in Figure 10. At the highest ratio of carbon fiber, the mass loss due to acid attack is greatly decreased because it offers adequate strength to limit the mass loss. It also combines the constituents of concrete into one family, thereby preventing any major or minor crack progression in the concrete due to external attack. It is evident from the findings that concrete containing 1% of carbon fiber is more durable, because of a maximum reduction in the mass due to acid attack. Overall, the findings show that carbon fiber may effectively increase the durability of concrete by reducing mass loss from acid attack and enhance the concrete's rigidity and strength. It demonstrates that carbon fiber may protect concrete against acid attack for the duration of its service life and that carbon fiber is a significant ingredient in concrete for enhancing the serviceability of self-compacting concrete [39]. Low volume fractions of carbon fiber may protect concrete from extreme environmental conditions [42].

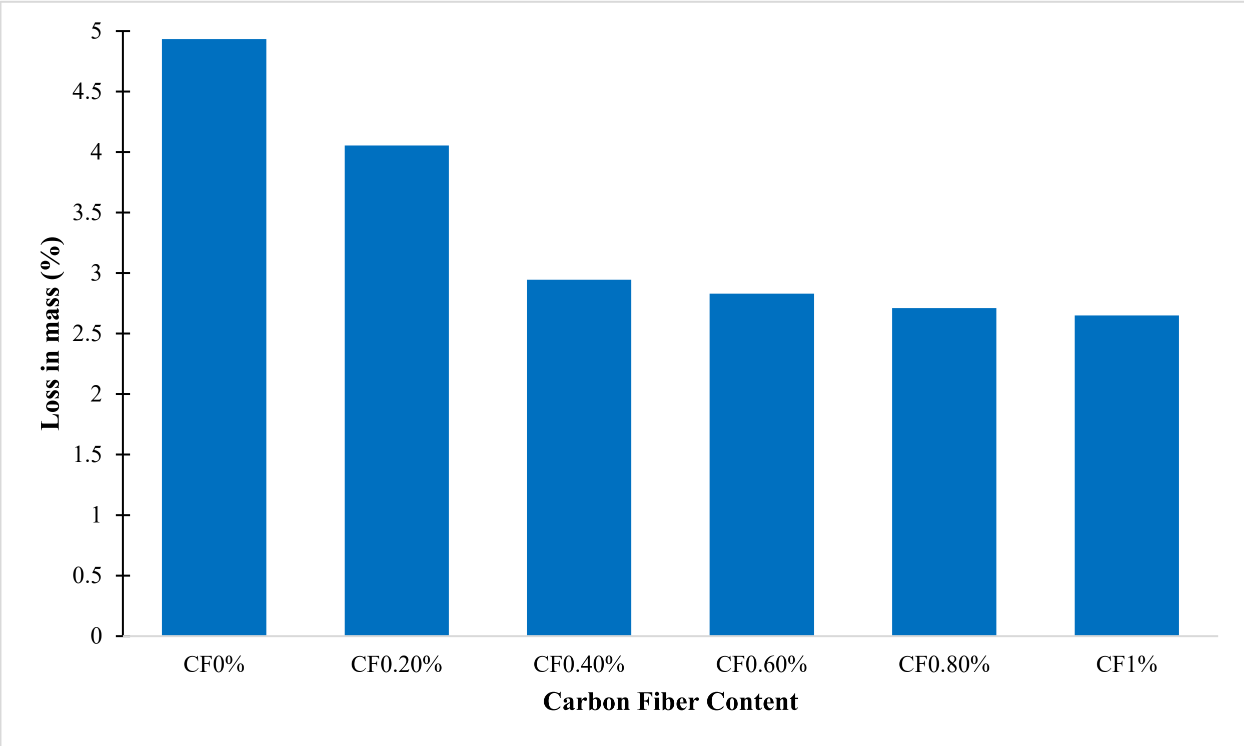

Figure 10. Acid attack test.

5.6. Sustainability Assessment

Embodied Carbon and Eco-Strength Efficiency

Embedded carbon of all mixtures combined with varying amounts of carbon fiber. The embodied carbon of each substance was determined from the accessible materials. Embodied carbon of every material is given in the Table 2 below:

Table 2. Embodied Carbon.

Embodied Carbon	CO_2 (Kg/Kg)	References
OPC	0.82	[43]
Silica fume	0.024	[44]
Carbon Fiber	33	[45]
Fine Aggregate	0.0139	[46]
Super Plasticizer	0.72	[47]
Coarse Aggregate	3.4	[45]
Water	0	[48]

Figure 11, demonstrate the embodied carbon of each mix proportion containing different percentages of carbon fiber content. Figure 7 demonstrates that the control mix containing 0% fiber has a lower embodied carbon content than other mixes incorporating fiber. CF0.20% has 6.68% more embodied carbon than the control sample, CF0.40% has 12% more embodied carbon than CF0%, CF0.6% has about 18% more embodied carbon than CF0%, and CF1% has 26% more embodied carbon than the control sample. Due to the high carbon content of carbon fiber, embodied carbon rises as carbon fiber content increases in concrete. Assessments based solely on the premise of embodied carbon concrete cannot be favored; instead, the strength of concrete, its longevity, and other features should all be taken into consideration. It is recommended that the eco-strength efficiency of concrete be estimated for better comprehension.

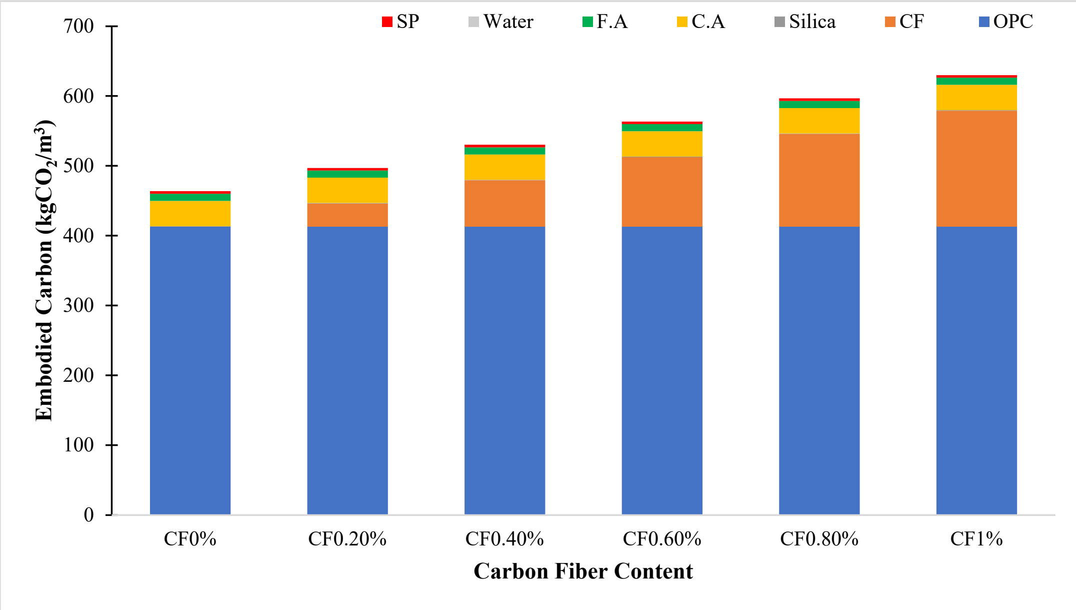

Figure 11. Embodied carbon.

The following Equation (1) should be used to determine the eco-strength efficiency [49];

$$Eco - strength\ efficiency = \frac{28th\ day\ compressive\ strength}{total\ embodied\ carbon\ of\ ECC} \tag{1}$$

Concrete's eco-strength depends on the amount of incorporated carbon and its compressive strength as shown in Figure 12. The eco-strength efficiency of the CF0% control sample (containing no carbon fiber) is around 0.077 MPa/kgCO_2/m^3, whereas the sample CF0.20% has the maximum eco-strength efficiency of 0.083 MPa/kgCO_2/m^3. Due to the rise in embodied carbon of other mixes with high carbon fiber content, the eco-strength efficiency drops as the percentage of carbon fiber increases. As a result of its high carbon content, CF1% has the lowest eco-strength efficiency. Therefore, CF0.20% is the optimal figure for eco-efficiency.

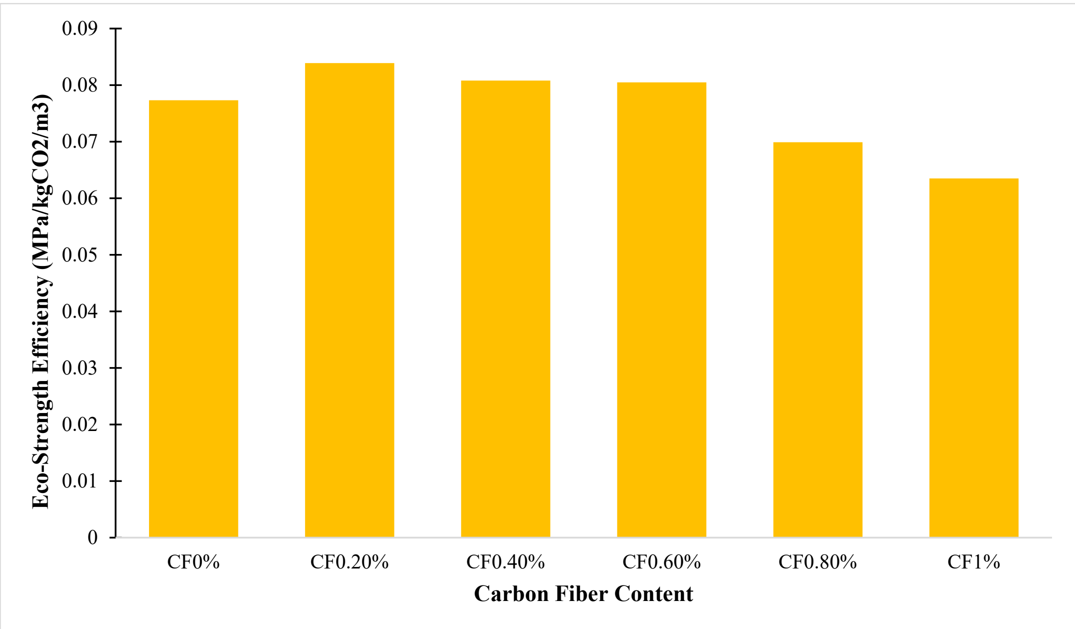

Figure 12. Eco-strength efficiency.

5.7. Modelling and Optimization Using RSM

Analysis of Variance Using RSM

The influences of carbon fiber on the fresh qualities and hardened characteristics of concrete are evaluated and projected utilizing the RSM model for precision and reliability as shown in Table 3. On the RSM experimental data set, a multiple regression analysis was conducted. Tables 4–11 presents ANOVA findings by the predicted model, based on the best design technique. Sum of squares (SS), F-value, and *p*-value are shown at a 0.05 level of significance. *p*-values of 0.05 and 0.01 are used to evaluate the importance of each component, signifying a satisfactory match between actual and predicted values [50]. The ANOVA outcomes of our investigation suggest model *p*-values 0.005 for the input factor. After 28 days of curing, F-values of the RSM model for slump, L-box test, compressive strength, splitting tensile strength test, water absorption, acid attack test, embodied carbon, and concrete's eco-strength efficiency are 1.123×10^5, 335.30, 68.65, 84.80, 5896.18, 212.74, 2.489×10^8, and 65.70, respectively, as given in Tables 4–11. It highlights the significance of the resultant models. Lack of Fits and F values are also used to evaluate the model's efficacy and validity. The lack of Fits indicates that there is some data variation near to the model fit [51]. If the *p*-value for Lack of Fit is more than 0.005, it is not statistically significant.

Table 3. Statistical checks for RSM model precision and reliability.

Model Validation Constraints	Slump Flow	L-Box Test	CS	STS	WA	Acid Attack	EC	ESE
Std. Dev.	0.268	0.8680	0.8684	0.3381	0.0405	0.1571	0.0063	0.0019
Mean	677.7	87.69	40.76	5.56	8.05	3.49	535.42	0.0761
C.V.%	0.039	0.9898	2.13	6.08	0.5039	4.50	0.0012	2.47
PRESS	1.24	12	16.02	7.09	2.08	0.5096	0.0500	0.0001
−2 Log Likelihood	0.534	29.80	29.81	3.92	−52.76	−14.65	−101.19	−129.68
R-Squared	0.999	0.9853	0.9321	0.9658	0.9997	0.9770	0.9999	0.9293
Adj R-Squared	0.999	0.9824	0.9185	0.9544	0.9995	0.9724	0.9999	0.9151
Pred R-Squared	0.999	0.9766	0.8558	0.7644	0.9465	0.9526	0.9999	0.8304
Adeq Precision	714.9	43.204	18.440	20.986	204.112	31.095	42,525.262	22.884
BIC	5.66	37.50	37.51	14.18	−39.93	−6.95	−88.37	−121.99
AICc	5.73	38.47	38.48	16.92	−34.19	−5.98	−82.62	−121.02

Table 4. ANOVA Results for the Variable Response Slump Flow.

Response	Source	Sum of Squares	Df	Mean Square	F-Value	*p*-Value > F	Significance
Slump Flow	Model	8095.51	1	8095.51	1.123×10^5	<0.0001	Significant
	A-CF	8095.51	1	8095.51	1.123×10^5	<0.0001	YES
	Residual	0.7931	11	0.0721			
	Lack of Fit	0.1264	4	0.0316	0.3319	0.8484	not significant
	Pure Error	0.6667	7	0.0952			
	Cor Total	8096.31	12				

Table 5. ANOVA Results for the Variable Response L-Box test.

Response	Source	Sum of Squares	Df	Mean Square	F-Value	*p*-Value > F	Significance
L-Box Test	Model	505.24	2	252.62	335.30	<0.0001	significant
	A-CF	467.67	1	467.67	620.74	<0.0001	YES
	A^2	6.77	1	6.77	8.98	0.0134	YES
	Residual	7.53	10	0.7534			
	Lack of Fit	7.53	3	2.51			
	Pure Error	0.0000	7	0.0000			
	Cor Total	512.77	12				

Table 6. ANOVA Results for the Variable Response 28-day Compressive Strength.

Response	Source	Sum of Squares	Df	Mean Square	F-Value	*p*-Value > F	Significance
Compressive Strength	Model	103.55	2	51.78	68.65	<0.0001	significant
	A-CF	74.92	1	74.92	99.34	<0.0001	YES
	A^2	68.11	1	68.11	90.31	<0.0001	YES
	Residual	7.54	10	0.7542			
	Lack of Fit	7.54	3	2.51			
	Pure Error	0.0000	7	0.0000			
	Cor Total	111.09	12				

Table 7. ANOVA Results for the Variable Response 28-day Splitting Tensile Strength.

Response	Source	Sum of Squares	Df	Mean Square	F-Value	*p*-Value > F	Significance
Split Tensile Strength	Model	29.09	3	9.70	84.80	<0.0001	Significant
	A-CF	0.4518	1	0.4518	3.95	0.0781	YES
	A^2	14.51	1	14.51	126.90	<0.0001	YES
	A^3	2.27	1	2.27	19.82	0.0016	
	Residual	1.03	9	0.1143			
	Lack of Fit	1.03	2	0.5145			
	Pure Error	0.0000	7	0.0000			
	Cor Total	30.12	12				

Table 8. ANOVA Results for the Variable Response 28-day Water Absorption.

Response	Source	Sum of Squares	Df	Mean Square	F-Value	*p*-Value > F	Significance
Water Absorption	Model	38.77	4	9.69	5896.18	<0.0001	significant
	A-CF	0.6749	1	0.6749	410.60	<0.0001	YES
	A^2	0.8525	1	0.8525	518.63	<0.0001	YES
	A^3	0.3958	1	0.3958	240.76	<0.0001	YES
	A^4	0.5822	1	0.5822	354.15	<0.0001	YES
	Residual	0.0132	8	0.0016			
	Lack of Fit	0.0132	1	0.0132			
	Pure Error	0.0000	7	0.0000			
	Cor Total	38.78	12				

Table 9. ANOVA Results for the Variable Response 28-day Acid Attack Test.

Response	Source	Sum of Squares	Df	Mean Square	F-Value	*p*-Value > F	Significance
Acid Attack Test	Model	10.50	2	5.25	212.74	<0.0001	significant
	A-CF	10.49	1	10.49	425.06	<0.0001	YES
	A^2	1.78	1	1.78	71.99	<0.0001	YES
	Residual	0.2467	10	0.0247			
	Lack of Fit	0.2467	3	0.0822			
	Pure Error	0.0000	7	0.0000			
	Cor Total	10.74	12				

Table 10. ANOVA Results for the Variable Response 28-day Embodied Carbon.

Response	Source	Sum of Squares	Df	Mean Square	F-Value	*p*-Value > F	Significance
Embodied Carbon	Model	39,448.56	4	9862.14	2.489×10^8	<0.0001	significant
	A-CF	2188.82	1	2188.82	5.525×10^7	<0.0001	YES
	A^2	0.2888	1	0.2888	7289.99	<0.0001	YES
	A^3	0.0065	1	0.0065	163.20	<0.0001	YES
	A^4	0.1032	1	0.1032	2603.77	<0.0001	YES
	Residual	0.0003	8	0.0000			
	Lack of Fit	0.0003	1	0.0003			
	Pure Error	0.0000	7	0.0000			
	Cor Total	39,448.56	12				

Table 11. ANOVA Results for the Variable Response 28-day Eco-Strength Efficiency.

Response	Source	Sum of Squares	Df	Mean Square	F-Value	*p*-Value > F	Significance
Eco-Strength Efficiency	Model	0.0005	2	0.0002	65.70	<0.0001	Significant
	A-CF	0.0001	1	0.0001	25.17	0.0005	YES
	A^2	0.0002	1	0.0002	57.87	<0.0001	YES
	Residual	0.0000	10	3.541×10^{-6}			
	Lack of Fit	0.0000	3	0.0000			
	Pure Error	0.0000	7	0.0000			
	Cor Total	0.0005	12				

Coefficient of determination (R^2) is an extra statistical parameter for assessing the performance as well as dependability of the anticipated model. The R^2 numbers represent the degree to which our data match the model. In general, the bigger the R-square value, the better the model's performance; the R-square value range is 0 to 1. In this study, the R-square values for slump, L-box test, concrete's compressive strength, concrete's split tensile strength, water absorption, acid attack test, embodied carbon, and eco-strength efficiency were 0.999, 0.985, 0.932, 0.965, 0.977, 0.999, and 0.929, respectively, on the 28th day after casting. The greater value of determination coefficients suggested that the models were an excellent match for the data. In addition, the discrepancy of 30% between the predicted and changed R square values is deemed unacceptable. Also regulated by Adeq. accuracy level, which must be more than 4, is the signal-to-noise ratio [52]. In this research, the values for Adeq. precision were 714.97, 43.204, 18.440, 20.986, 204.112, 31.095, 42,525.262, and 22.884, respectively, after 28th day of curing. These figures indicate a positive signal; hence, the models may be utilized to drive the design process.

Using actual vs. predicted graphs presented Figures 13–20, slump, L-box test, concrete's compressive strength test, concrete's split tensile strength test, water absorption, acid attack test, embodied carbon, and eco-strength efficiency were analyzed 28 days after casting. The consistency of the data points around the best-fitting line indicated that the models properly anticipated the responses in every instance. In the actual vs. predicted plots, the conformity of the data points over the line of best fit for each answer reflects how well the estimated responses corresponded to the actual replies. In addition to this, it can be deduced that the designs were successful due to the fact that the sample points were evenly dispersed around the line of best fit in the normal representations of residuals for each response. This indicates that the error terms were also normally distributed [51]. To conclude, the statistical results for each response are sufficient and fall within the permitted range.

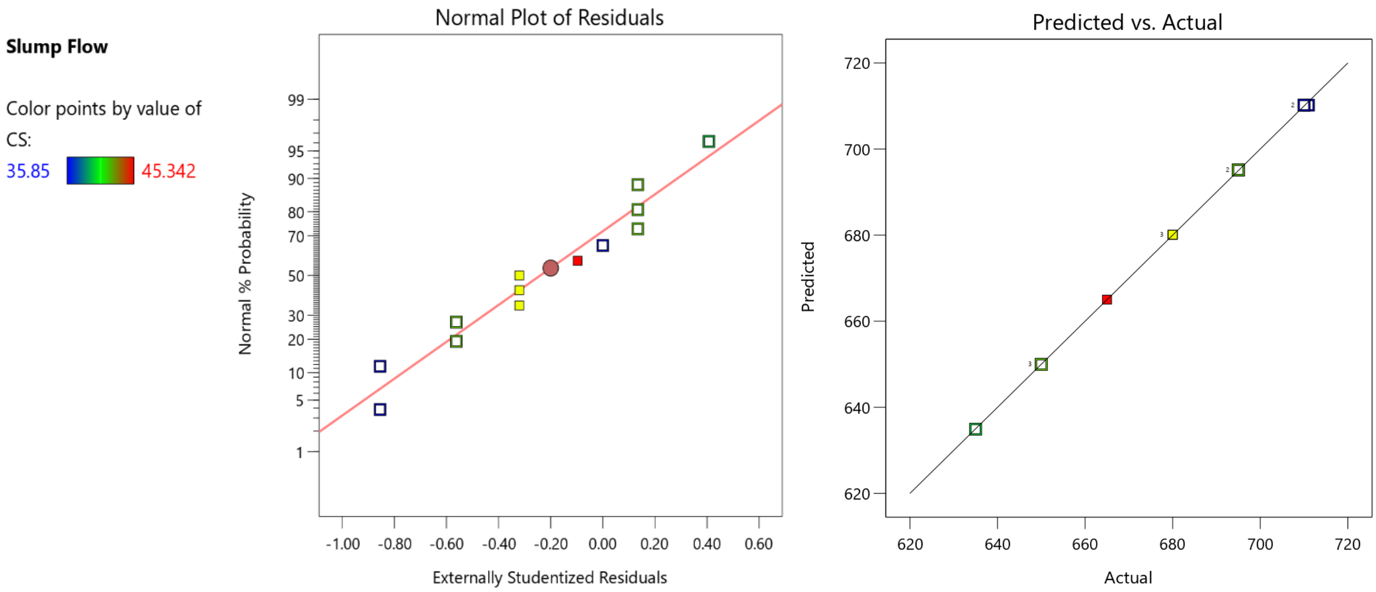

Figure 13. Normal plot for residuals, and actual vs. predicted values for slump.

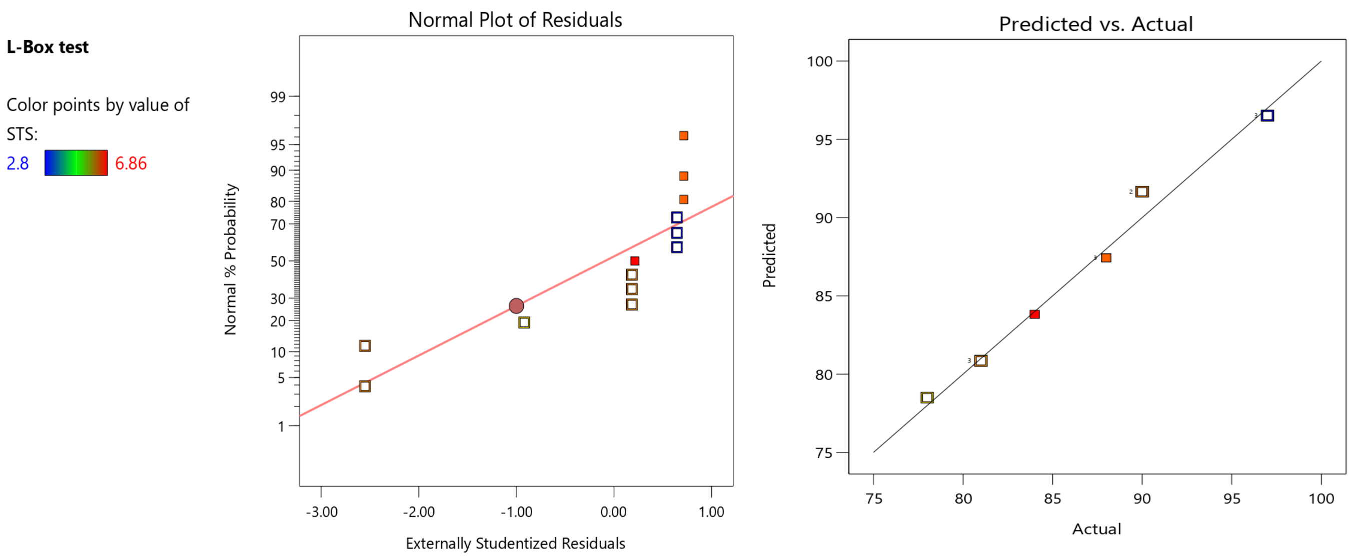

Figure 14. Normal plot for residuals, and actual vs. predicted values for L-Box test.

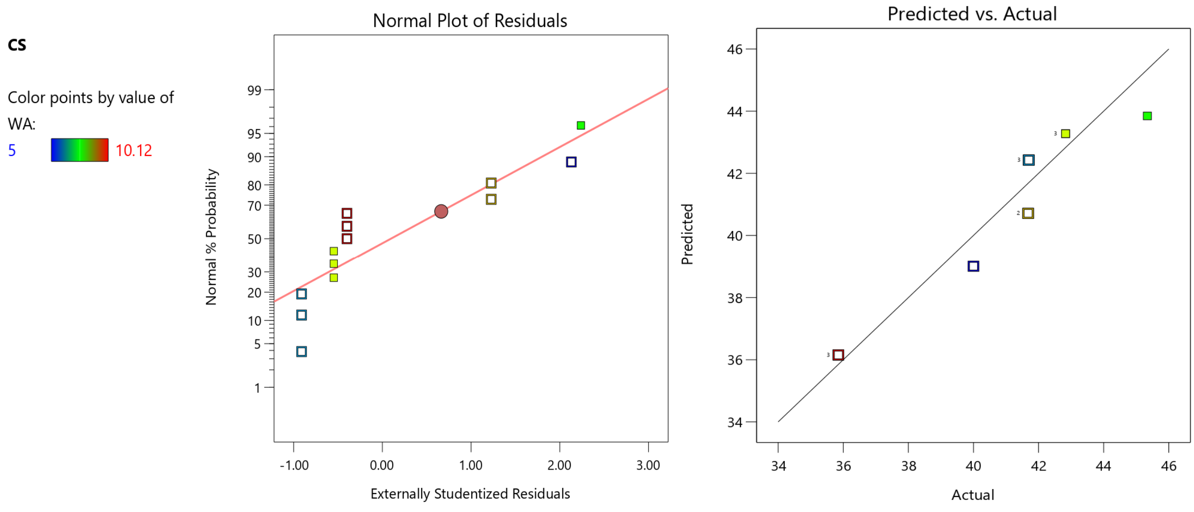

Figure 15. Normal plot for residuals, and actual vs. predicted values for compressive strength.

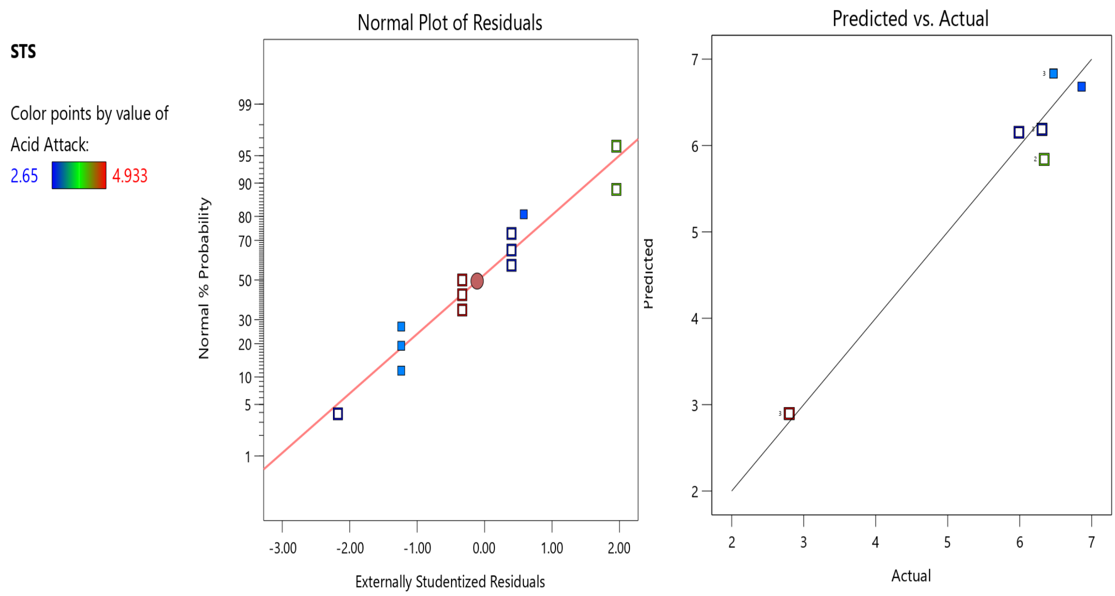

Figure 16. Normal plot for residuals, and actual vs. predicted values for splitting tensile strength.

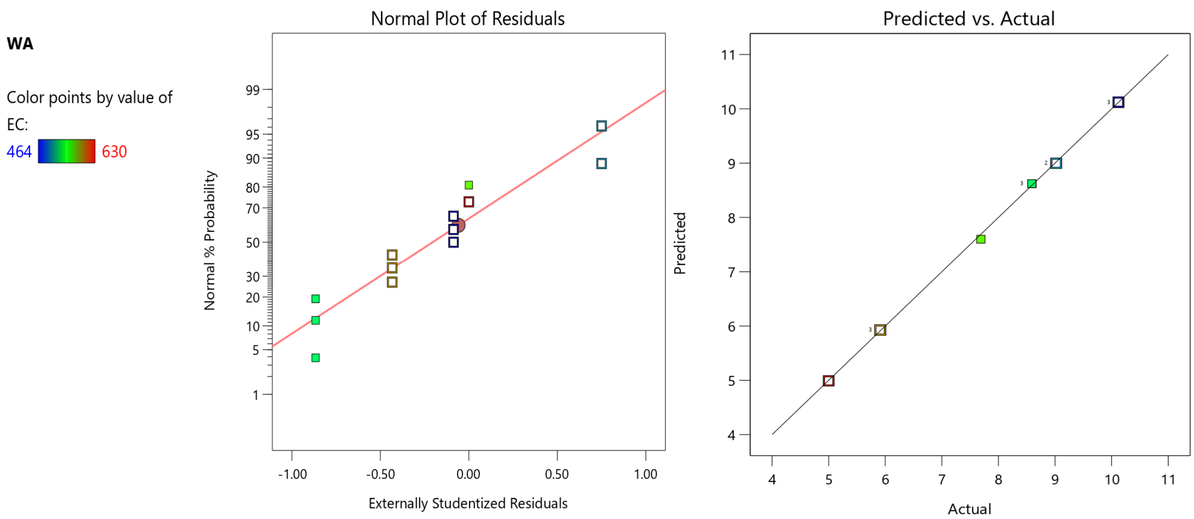

Figure 17. Normal plot for residuals, and actual vs. predicted values for water absorption.

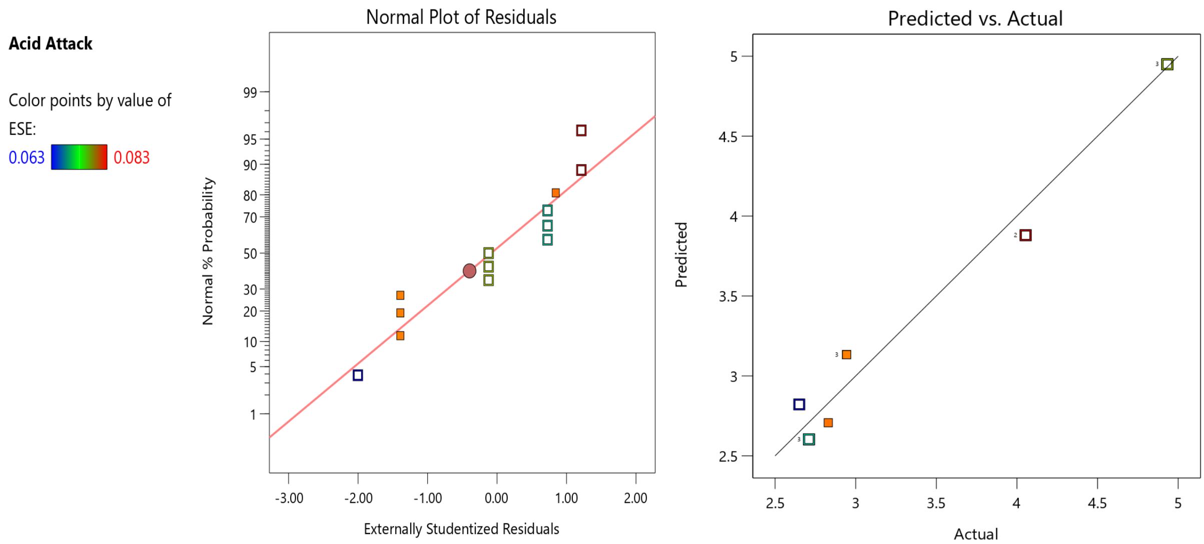

Figure 18. Normal plot for residuals, and actual vs. predicted values for acid attack test.

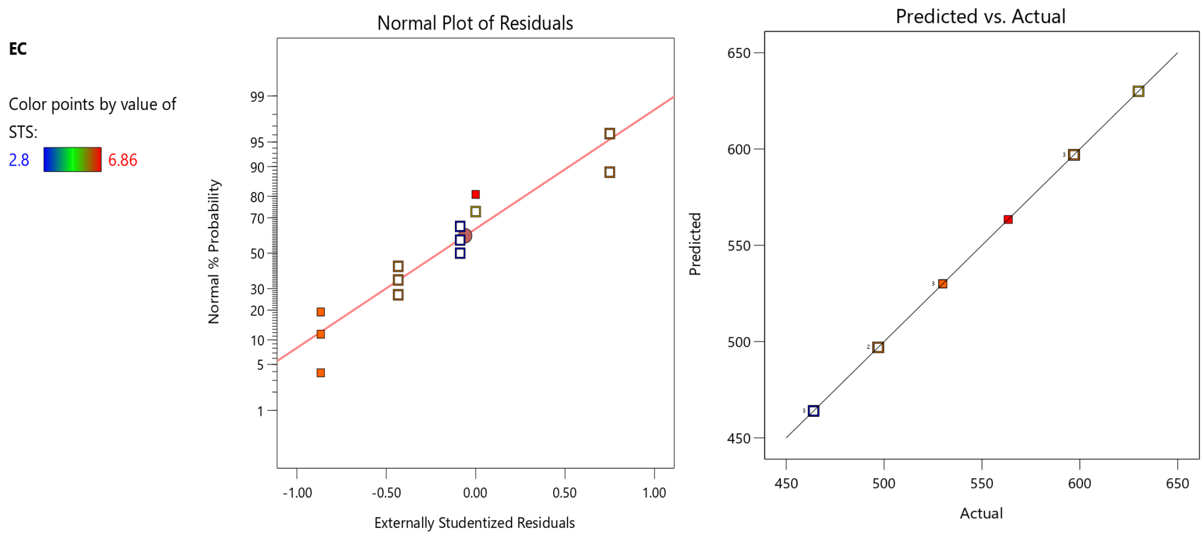

Figure 19. Normal plot for residuals, and actual vs. predicted values for embodied carbon.

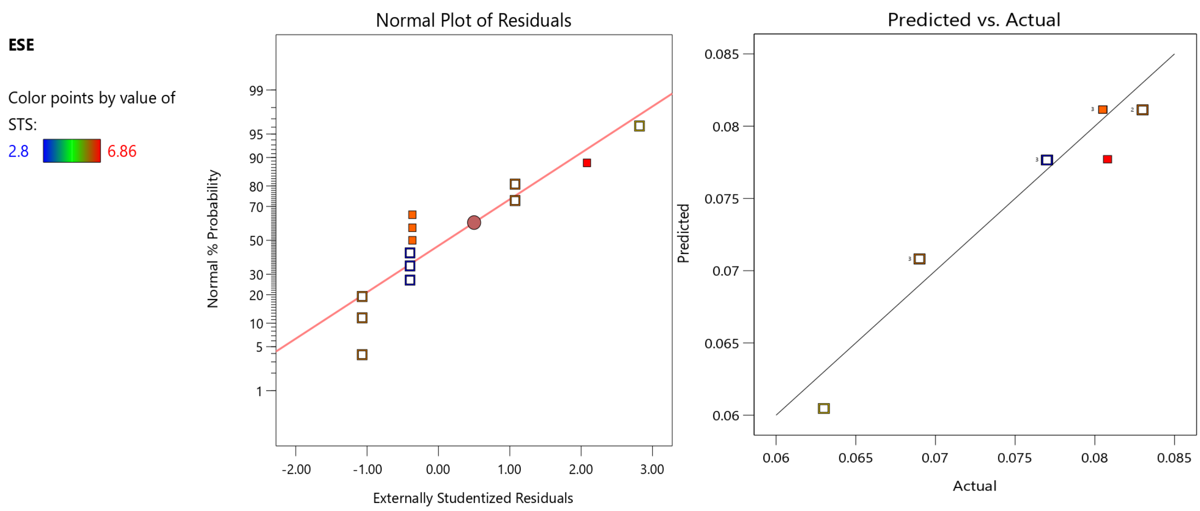

Figure 20. Normal plot for residuals, and actual vs. predicted values for eco-strength efficiency.

5.8. Effects of Carbon Fiber on Fresh Properties of Concrete

5.8.1. Slump Flow

The linear model was determined to be the most appropriate representation of the slump. The results of the ANOVA for slump values, which serve as the response variable, are shown in Table 4; these results are used to analyze the effects of carbon fiber on p value. The 1.123×10^5 F-value for the slump model illustrates its statistical significance. A significant F-value of this significance is just 0.01% likely to be due to chance. p-values for model terms below 0.050 are considered statistically significant. If the value is more than 0.100, the coefficients of regression are not significant statistically. It is advised that useless model terms be deleted if there are too many (except those needed to aid hierarchy). According to Table 4, model term A is relevant in our study. Lack of Fit is not statistically significant when compared to pure error (F-value = 0.33). This high Lack of Fit F-value is likely due to noise 84.84% of the time. Non-significant misfit is desired; the model should fit. The encoded equation may be used to calculate the factor's relative contribution. Equation (2), for the response variable contains the final model equation in the form of the coding factor A. (slump). The result for a particular level of each element may be predicted using the equation described in terms of the variables with codes. By default, component levels that are high are indicated as +1 and those that are low as −1. By comparing the factor coefficients in the encoded equation you may evaluate the relative importance of the components.

$$\text{Slump} = 680.09 - 30.12\text{A} \tag{2}$$

5.8.2. L-Box Test

The quadratic model is selected as the optimal model for the L-Box test. Table 5 presents the ANOVA results for L-box test values (response variable) to assess the effects of carbon fiber based on p-value. A model with an F-value of 335.30 for the L-box test is statistically significant. An F-value of this size has a noise component of 0.01%. If the p-value for the model terms is less than 0.05, then they are significant. In this instance, A and A^2 are important model terms. When values are above 0.1000, the model terms are not statistically relevant. If your model has multiple irrelevant words (apart from those essential to maintain hierarchy), model reduction may be able to enhance it. The result for given levels of each element may be predicted using the equation expressed in terms of variables with codes. By default, high amounts of components are indicated as +1, while low levels are portrayed as −1. By evaluating the factor coefficients, the coded equation may be used to estimate the component's relative influence. Equation (3) for the response variable contains the final model equation in the form of the coding factor A.

$$\text{L-Box test} = 87.43 - 7.83\text{A} + 1.26A^2 \tag{3}$$

5.9. Effects of Carbon Fiber on Concrete's Mechanical Properties

5.9.1. Compressive Strength

The quadratic model is selected as the best match for compressive strength. After 28 days, on the compressive strength values (response variable), an ANOVA was done to explore the impacts of carbon fiber on the p-values, shown in Table 6. The fact that the F-value for the compressive strength test model is 68.65 indicates that the model has some degree of statistical significance. A noise source might be the cause of an F-value of this size in around 0.01% of all cases. p-values that are lower than 0.05 indicate that the model terms being considered are significant. A and A^2 are important model terms in this instance. If the value is more than 0.1000, the model terms are not statistically significant. Model reduction may be able to enhance your model if it has several irrelevant words (aside from those that are needed for hierarchy). The equation expressed in terms of factor codes may be used to anticipate the response for varied values of each variable. By default, the component's high values are encoded as +1 and its low values as −1. The encoded equation helps determine the relative influence of the components by comparing the factor coefficients. The response variable Equation (4) includes the final model equation in the form of coding factor A.

$$\text{Compressive Strength} = 43.28 + 3.14\text{A} - 3.99A^2 \quad (4)$$

5.9.2. Split Tensile Strength

The cubic model is selected as the optimal model for the splitting tensile strength test. After 28 days, carbon fiber's impacts on the compressive strength values (response variable) were analyzed using *p*-values obtained from ANOVA analysis shown in Table 7. The fact that the model has a statistical significance is shown by the fact that the split tensile strength F-value is 84.80. An F-value of this size may be the consequence of noise; although, there is only a 0.01% probability of this happening. *p*-values that are less than 0.05 are considered to be statistically significant, which suggests that the model terms are important. In this instance, A^2 and A^3 are important model terms. If you are looking at the model terms, values that are larger than 0.1000 suggest that they do not have statistical significance. Model reduction may be able to assist or enhance your model if it has a lot of terms that aren't significant (apart from those that are essential to maintain the hierarchy intact). It is possible to utilize the equation that is specified in terms of variables with codes in order to make predictions about the result for various levels of each element. By default, high levels of components are denoted with a value of +1, whereas low levels are denoted with a value of −1. By contrasting the various factor coefficients, one may utilize the encoded equation to ascertain the degree to which each component contributes to the whole. The final model equation is encoded in the response variable Equation (5) as coding factor A.

$$\text{Split Tensile Strength} = 6.83 + 0.5745\text{A} - 2.29A^2 + 1.07A^3 \quad (5)$$

5.10. Water Absorption

The quartic model provides the most accurate representation of water absorption. After 28 days, an analysis of variance (ANOVA) was performed on the values of compressive strength (the response variable) in order to explore the impacts of carbon fiber using *p*-values. The results of this study are shown in the following table, listed in Table 8. It may be deduced from the fact that the water absorption model has an F-value of 5896.18 that the model is significant statistically. An F-value of this magnitude has a 0.01% probability of being caused by noise, which is a very tiny likelihood indeed. This indicates that the chances of noise being the cause is very low. *p*-values that are lower than 0.05 are considered to indicate that the regression coefficients are significant. In this instance, the model terms A, A^2, A^3, and A^4 are relevant. When values exceed 0.1000, model terms are not statistically significant. If your model has a number of irrelevant terms (other than those essential to maintain hierarchy), it may be improved by simplification. The answer for given values of each element may be predicted using the equation expressed in terms of variables with codes. By default, high levels of components are represented with the number +1 and low levels with the number −1. Using the coded equation and comparing the factor coefficients associated with each component, it is possible to ascertain the relative impact of the constituents. The final model equation is encoded as coding factor A in the response variable Equation (6).

$$\text{Water Absorption} = 8.62 - 1.17\text{A} - 1.52A^2 - 0.9332A^3 + 0.9281A^4 \quad (6)$$

5.11. Acid Attack Test

It was concluded that the quadratic model had the greatest fit for the acid attack test. Following a period of 28 days, in order to study the impacts of carbon fiber using the *p*-values, an analysis of variance (ANOVA) was carried out on the values of compressive strength (the response variable) presented in Table 9. The model's statistical significance was shown by an F-value of 212.74. There is a 0.01% chance that a noise level of this magnitude would produce an F-value of this magnitude. *p*-values that are lower than

0.0500 are indicative of significant model terms. In this particular instance, A and A^2 are important model terms. Values that are greater than 0.1000 indicate that the model terms do not have a substantial impact on the results. If your model has a significant number of terms, that are not relevant, it is possible that it might be enhanced via the use of model reduction (not counting those that are necessary to support hierarchy). Using the equation that is defined in terms of the coded factors, you are able to produce predictions about the response based on specified levels of each element. These predictions are based on the coded factors. The values +1 and −1 are given as the defaults to the high and low levels of the components, respectively. The encoded equation is a useful tool for identifying the relative significance of the individual components since it compares the various factor coefficients. The final model equation is encoded in the response variable as coding factor A in Equation (7).

$$\text{Acid Attack Test} = 3.13 - 1.17\text{A} + 0.6437A^2 \tag{7}$$

5.12. Effects of Carbon Fiber on Environmental Sustainability of Concrete

5.12.1. Embodied Carbon

It has been determined that the quartic model is the most accurate representation of embodied carbon. ANOVA was also performed on the carbon emission of the concrete blended with carbon fiber in order to investigate the effect of concrete on environmental sustainability using *p*-values. This was done to determine whether or not concrete has a positive or negative impact on environmental sustainability, presented in Table 10. Given that the model being examined has an F-value of 2.489×10^8, there is reason to believe that it is significant. An F-value of this magnitude would only have a 0.01% chance of being produced by a noise level of this magnitude, given the probabilities involved. When analyzing the significance of the model terms, *p*-values that are lower than 0.0500 are considered to be significant. In this particular scenario, the model variables A, A^2, A^3, and A^4 are relevant. Values that are greater than 0.1000 indicate that the model terms do not have a substantial impact on the results. If your model has a significant number of terms that are not relevant, it is possible that it might be enhanced via the use of model reduction (not counting those that are necessary to support hierarchy). Using the equation that is stated in terms of the coded factors enables us to produce predictions about the response based on certain levels of each element. These levels are based on the coded factors. The values +1 and −1 are given as the defaults to the high and low levels of the components, respectively. By contrasting the various factor coefficients, the encoded equation is a helpful tool for determining the relative importance of the various elements.

$$\text{Embodied carbon} = 530 + 66.38\text{A} + 0.8873A^2 + 0.1193A^3 - 0.3907A^4 \tag{8}$$

5.12.2. Eco-Strength Efficiency

The quadratic model was chosen because it provided the most accurate representation of eco-efficiency. Analysis of variance (ANOVA) was performed on the Eco-strength efficiency of the concrete mixed with carbon fiber in order to investigate the impact that concrete has on the environmental sustainability of a structure. The *p*-values that were provided were used for this purpose. With a score of 65.70 for the Model F-value, we may conclude that the model has statistical significance. An F-value of this size has a 0.01% chance of being caused by noise, which is a very small likelihood indeed. *p*-values that are lower than 0.05 suggest that the model terms are significant. In this instance, A and A2 are important model terms. When looking at the model terms, values greater than 0.1000 indicate that they are not statistically significant. Model reduction might be beneficial for your model if it contains a significant number of superfluous terms (with the exception of those that are required to preserve hierarchy). Using the equation expressed in terms of the components, one is able to make a prediction about the response based on a certain amount of each coded ingredient. By default, the highest level of a factor receives the value 1, while the level with the lowest value receives the value −1. By comparing the factor coefficients, the encoded Equation (9) may be used to determine the relative importance of the components.

$$\text{Eco-Strength Efficiency} = 0.0811 - 0.0034\text{A} - 0.0069A^2 \quad (9)$$

5.12.3. Optimization and Model Validation

Obtaining the greatest value for numerous replies at the same time is tricky. As a consequence, multiobjective optimization approaches are used to optimize a variety of answers. For eight multiple replies, a compromise method of optimization was adopted in this study. As previously indicated, just one element, carbon fiber content, was employed as an independent factor. As a dependent variable, eight responses were used: Slump (mm), L-Box test, concrete's compressive strength, split tensile strength test, absorption of water, acid attack test, embodied carbon, and eco-strength efficiency. Figure 21 is presenting the correlation analysis matrix indicating acceptable trend and correlation among fresh and hardened properties. This equality qualifies the results to be suitable in terms of RSM validation. RSM was used to calculate the optimal factor content in order to optimize the eight parameters. In order to optimize the design process, the 13 edition of the Design Expert software was used in this investigation. A significance level has been assigned to each variable and response. A multiobjective optimization method yields a reasonably near solution that meets the set upper and lower boundaries as shown in Table 12. The degree of similarity between the proposed solution and the actual result sets the bar for desirability. For best results, it is recommended to have a desirability that is closer to one. The value of desirability was 0.809, suggesting that response optimization is feasible. With a desirability value of 0.809, the best eight response values for the slump, L-box test, concrete's compressive strength, split tensile strength test, absorption of water, acid attack test, embodied carbon, and eco-strength efficiency were 666.025, 84.041, 43.870, 6.711, 7.693, 2.725, 561.18, and 0.0780, respectively as shown in Figure 22.

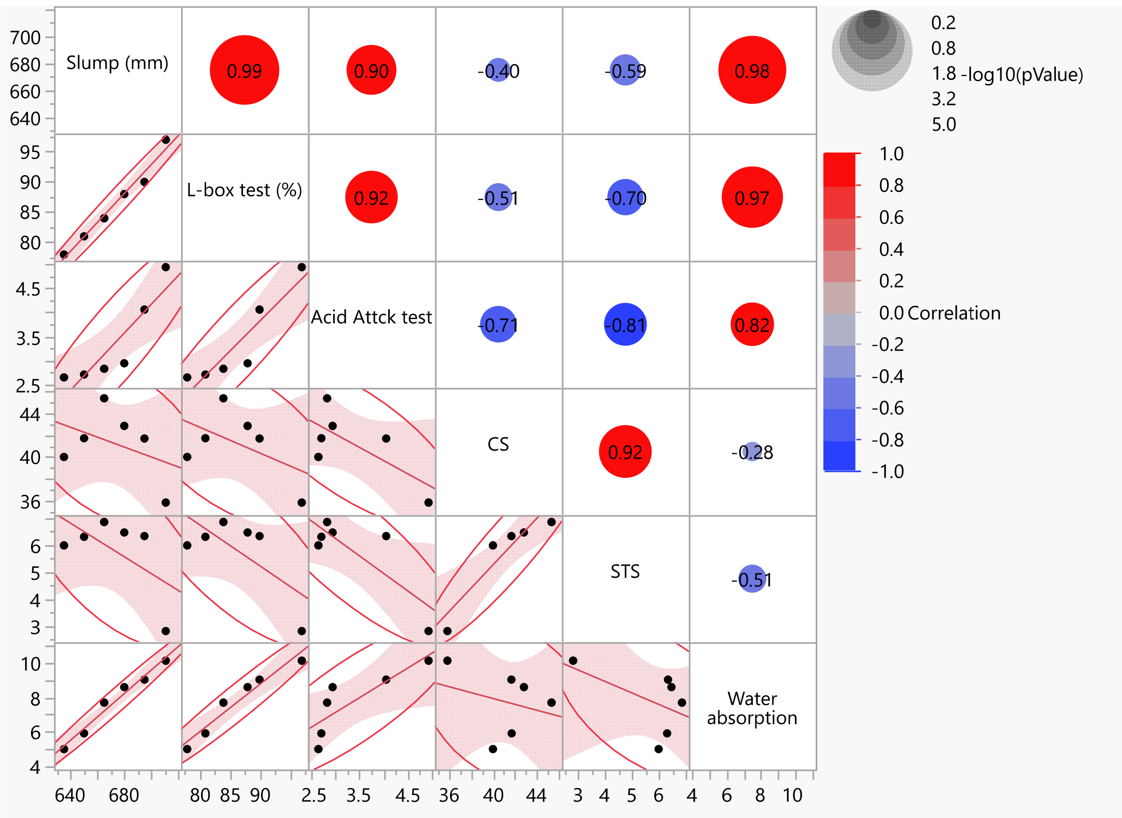

Figure 21. Correlation analysis of fresh and hardened concrete properties.

Table 12. Multiobjective Optimization.

Factors		Variable (Input Factors)	Response (Output Factors)							
		Carbon Fiber	Slump	L-Box Test	Compressive Strength	Split Tensile Strength	Water Absorption	Acid Attack Test	Embodied Carbon	Eco-Strength Efficiency
Value	Minimum	0%	635	78	35.85	2.8	5	2.65	464	0.063
	Maximum	1%	711	97	45.342	6.86	10.12	4.933	630	0.083
Goal			In range	In range	Maximize	Maximize	In range	Minimize	Maximize	Maximize
Optimization results		0.586	666.025	84.041	43.870	6.711	7.693	2.725	561.18	0.0780
Desirability		0.809								

Table 13 below represents differences between experimental and predicted values, which are obtained by the optimization of responses. To create the samples optimum outcomes were followed, and to differentiate between both predicted and experimental values error is defined in percentage; it can be seen that the value of error for all the responses is less than 5%. This shows that model accuracy is very high.

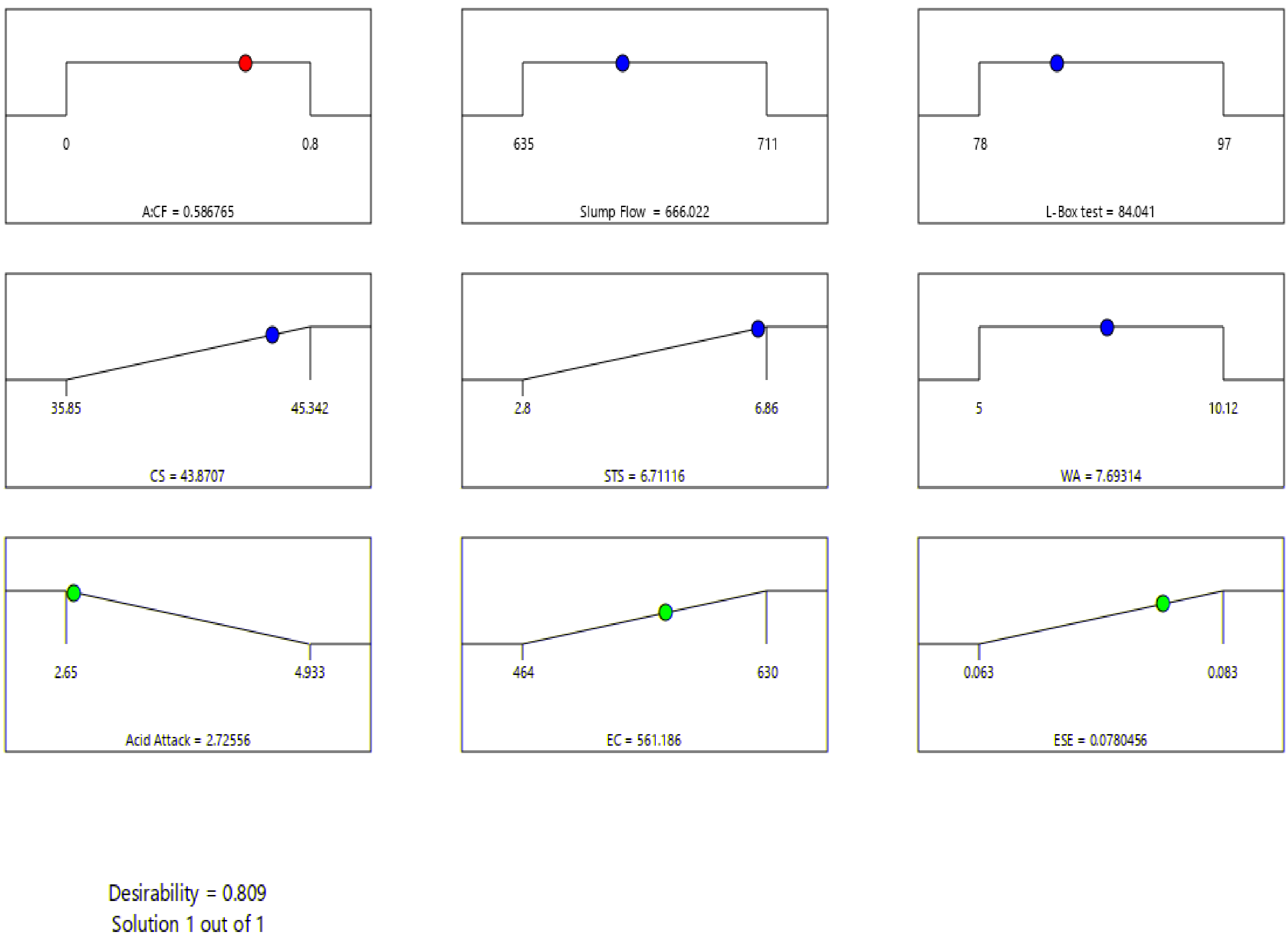

Figure 22. Multiobjective optimization ramp diagram.

Table 13. Model Validation.

Responses	Predicted	Experimental	Error (%)
Slump Flow	666.025	661	0.75%
L-box test	84.041	83	1.23%
Compressive Strength	43.870	45	2.57%
Split Tensile Strength	6.711	6.5	3.10%
Water Absorption	7.6933	7.5	2.50%
Acid Attack	2.725	2.67	2.01%

6. Conclusions

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