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Artificial neural network to predict the compressive strength of high strength self-compacting concrete made of marble dust

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ABSTRACT

The construction industry is continually seeking new waste materials and techniques to enhance the sustainability and overall performance of concrete. High Strength Self-Compacting Concrete (HSSCC) is a type of concrete suitable for modern construction that offers superior mechanical properties and excellent workability. In this investigation, the compressive strength of HSSCC containing varying proportions of marble dust is predicted using an Artificial Neural Network (ANN). An exhaustive dataset collected from laboratory tests encompasses a variety of mix designs with different proportions of marble dust. The integration of marble dust, a by-product of the marble industry, into HSSCC gives a sustainable approach for overall performance of concrete. The parameters considered in the studies include the water-cement ratio, marble dust content, and quartz sand content. The results indicate that the ANN model can accurately predict the compressive strength of HSSCC. The key finding indicate architecture 3-4-1 was found to be the most effective in achieving a high regression value of 0.937.

Keywords: High Strength Self-Compacting Concrete; Artificial Neural Network; Marble dust; Mechanical properties.

1. INTRODUCTION

There is an ongoing pursuit of innovation to make materials more performant, sustainable and efficient within the construction industry. One such development in recent years is High Strength Self-Compacting Concrete (HSSCC). This specific brand of concrete possesses an inherent excellence in mechanical strength combined with a self-leveling, self-settling characteristic that occurs free of any mechanical vibration [1]. HSSCC has its own unique properties which make the construction faster and better in quality. These features are particularly advantageous in detailed formwork and heavily reinforced areas and lead to a high degree of flatness and class quality and a good material strength at the same time. HSSCC was developed in order to overcome some shortcomings such as the low workability and the time demand of vibration which previously common in the conventional concrete. These issues often result in problems such as honeycombing and inadequate structural performance [2].

In sustainable construction, much attention has been paid to the incorporation of industrial residues and wastes into concrete. This approach not only solves environmental concerns but also encourages conservation of natural resources. Marble dust, which is the residue of the marble industry, has shown potential to be an ideal material for a few specific applications [3]. The proper management of marble dust presents notable environmental difficulties owing to its small particle size, which has the potential to induce both air and water

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contamination. Incorporating marble dust in the construction of concrete not only reduces these environmental problems but also improves the performance of the concrete [4].

Several studies have shown that the addition of marble dust can enhance the microstructure and mechanical properties of concrete. Marble dust can improve the tensile strength, durability and workability of concrete when used in place of cement or fine aggregate. The denser and more refined microstructure is a result of the filler effect and pozzolanic activity of marble dust [5]. By including marble dust in HSSCC, two advantages are achieved: enhancing the performance of concrete and encouraging sustainable waste management methods [6].

Artificial Neural Networks (ANNs) are widely recognized as highly effective methods for representing intricate and nonlinear connections in diverse engineering fields, such as concrete construction. Artificial neural networks (ANNs) imitate the neural network of the human brain, allowing them to acquire knowledge from data and detect patterns that conventional statistical methods may overlook. Artificial neural networks (ANNs) are very suitable for predicting the qualities of concrete by analyzing its mix design and curing conditions [7]. The use of artificial neural networks (ANNs) has grown in the prediction of concrete qualities, including compressive strength, workability, and durability [8].

Utilizing artificial neural networks (ANNs) to forecast the compressive strength of HS-SCC including marble dust is an innovative method that merges the fields of material science and modern computational methodologies. Conventional techniques for forecasting the strength of concrete, such as empirical formulas and regression models, typically prove inadequate in accounting for the intricate interplay among different mixture constituents [9]. Artificial neural networks (ANNs), in contrast, are adept at properly managing these intricacies, yielding precise and dependable forecasts [10].

The process of creating an Artificial Neural Network (ANN) model to forecast the compressive strength of High-Strength Self-Compacting Concrete (HS-SCC) with marble dust requires multiple stages. Initially, an all-encompassing dataset is created by doing thorough laboratory tests. The dataset comprises a range of mix designs using varying proportions of marble dust, water-cement ratios, types of aggregates, and curing timeframes. The obtained data is used as the basis for training the ANN model [11]. The model utilizes a backpropagation approach, which systematically modifies the weights of the neural network in order to minimize the inaccuracy in predictions. This iterative procedure persists until the model attains a notable degree of precision [12].

The findings of this study indicate that the artificial neural network (ANN) model has the ability to accurately forecast the compressive strength of high-strength self-compacting concrete (HS-SCC), surpassing the performance of conventional regression models [13]. The model's capacity to comprehend intricate connections between mix ingredients and compressive strength underscores its promise as a forceful instrument for mix design optimization. This feature is very beneficial for engineers and researchers who aim to create advanced, environmentally friendly concrete blends [14].

Moreover, the incorporation of marble dust in HS-SCC promotes sustainable construction methods by minimizing the environmental consequences of concrete manufacturing and marble waste management. The created artificial neural network (ANN) model assists in the efficient design of high-strength self-consolidating concrete (HS-SCC) mixes by offering a dependable means of predicting concrete strength. This, in turn, encourages the use of sustainable materials in the construction sector [15, 16].

To summarize, this study highlights the practicality of utilizing marble dust in high-strength self-compacting concrete (HS-SCC) and the efficiency of artificial neural networks (ANNs) in forecasting concrete characteristics. The implemented artificial neural network (ANN) model provides a pragmatic and effective approach to enhance the optimization of concrete mix designs, hence propelling the progress of sustainable construction [17]. Subsequent research will concentrate on improving the model by utilizing more extensive datasets and investigating the impact of supplementary variables, such as temperature and humidity, to augment forecast precision. The combination of machine learning techniques and sustainable materials research shows great potential for the future of civil engineering [18].

The purpose of this methodology is to develop and validate an Artificial Neural Network (ANN) model to predict the compressive strength of High Strength Self-Compacting Concrete (HS-SCC) incorporating marble dust [19]. The methodology integrates experimental procedures based on ASTM standards and other relevant codes, along with the implementation of the ANN algorithm. This approach combines sustainable material use with advanced computational modeling, providing a novel method for optimizing concrete mix designs [20].

2. MATERIALS, METHODOLOGY AND TESTING PROCEDURE

The materials used in this work have been carefully selected to explore the potential of marble dust as a potential material in high-strength self-stabilizing concrete. By incorporating traditional cementitious materials with alternative waste materials such as marble dust, this research aims to provide durable and high-performance concrete while overcoming the environmental challenges associated with marble the management of the garbage.

2.1. Cement

Cement in concrete is the main binder, providing the necessary chemical compounds necessary for its strength and stability. The conventional portland cement (OPC) used in this study has high strength and rapid hardening, which makes it suitable for high-strength applications. The cement contributes to the overall durability of the concrete mix, strength and duration. Ordinary Portland Cement (OPC) conforming to ASTM C150.

2.2. Silica fume

Silica fume, a by-product of the manufacture of silicon and ferrosilicon alloys, is a high-performance pozzolan rich in silica in fine particles. It enhances the mechanical properties and durability of concrete by filling micropores in lifts and contributes to pozzolanic activity, improves tensile strength and reduces water permeability.

2.3. Fine aggregates (M-sand and quartz sand)

Artificial sand (M-sand) and quartz sand are used as fine aggregates. M-sand is produced by crushing hard granite boulders, providing a more consistent and cleaner alternative to natural river sand. Quartz sand is known for its high silica content and hardness, which improves the strength and durability of concrete. Natural river sand meets the requirements of ASTM C33.

2.4. Coarse aggregates

Crushed granite is used as soft aggregates in this study. The size and shape of these aggregates play an important role in determining the workability and strength of the concrete. Coarse aggregates provide the necessary bulk and structural integrity to the concrete mix. Crushed granite conforming to ASTM C33.

2.5. Superplasticizer

A superplasticizer is a high water reducing agent that improves the workability of concrete without increasing the water-cement ratio. In this study, the superplasticizer improves the flowability and shrinkage of the concrete, ensuring that it can easily fill the formwork and pass through the reinforcement without tearing. High-quality pumps conforming to ASTM C494.

2.6. Water

Water is an important component of concrete, underlies the chemical reaction required for cement hydration and contributes to the workability of the mix. The quality and quantity of water used directly influences the strength and durability of concrete. In this study, a water-cement ratio of 0.43 is maintained to achieve optimum workability and strength.

2.7. Marble sludge powder

Marble dust is a waste generated during the processing of marble stones. It contains calcium carbonate and can be used as a cement paste. The inclusion of marble dust in concrete not only solves the environmental concerns related to the disposal of marble waste but also ensures the sustainability of concrete production. The marble dust aids in filling, increasing the strength of the concrete and potentially strengthening it properly. Sources from marble processing plants, characterized by particle size distribution, specific gravity, and chemical composition per ASTM C618. Marble is a recrystallized or dolomited variable stone that can be polished to a similar appearance. Marble is used in various civil engineering applications such as flooring, interior decoration, wall decoration, ornamental finishes and the term MSP is the powder obtained during the cutting, polishing and processing of marble stones.

During the marble processing, a large volume of powder like solid waste is generated, called MSP. Figures 1 and 2 respectively show the marble production process and the types of wastes generated during the marble production, respectively. Figure 2 shows the waste generations from the marble production.

3. METHODOLOGY

The method for growing self-compacting concrete (SCC) starts by means of specifying every assets of the concrete to satisfy the necessary standards for its supposed utility. Material information, inclusive of types and sources of cement, aggregates, and admixtures, are amassed, followed by means of specifying residences of coarse aggregates, such as length, shape, and grading. The content of manufactured sand (M-Sand) and quartz

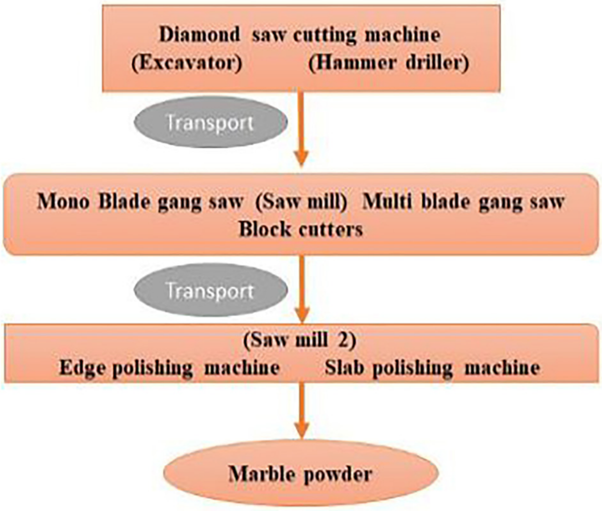

Figure 1: Marble production process.

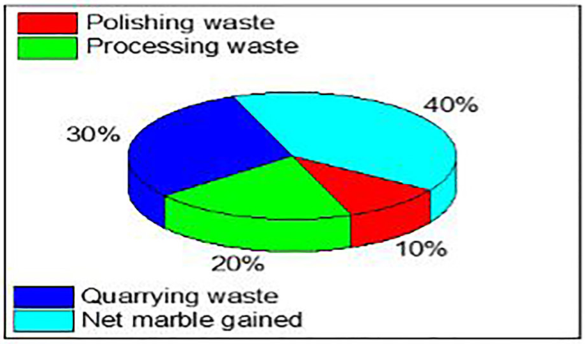

Figure 2: Waste Generations from the Marble production.

sand is finalized, and the optimum dosage of marble sludge powder is calculated to improve rheological residences. [21, 22] The quantity and composition of the concrete paste, which includes the water-to-powder ratio and the sand-to-overall mixture ratio, are then framed to obtain the favored workability. Final aggregate composition is decided, observed by using making ready trial combos and specimens to evaluate SCC properties together with workability and flowability. Fresh residences are checked to make certain consistency and ability to float without segregation. If not worthy, the mixture is reformed by way of adjusting issue proportions. Once the mixed met the requirement as per the rheological and strength parameter, the very last product is confirmed as high strength self-compacting concrete, prepared for utility. Figure 3 shows the methodology.

4. MIX DESIGN

The mix design for High Strength Self-Compacting Concrete (HSSCC) in this study is meticulously formulated to balance the various components and achieve optimal performance. The inclusion of marble dust in varying proportions is a key focus, exploring its impact on the compressive strength and overall performance of the concrete. The detailed mix proportions ensure consistency and reliability across different batches. Table 1 shows the Constituents of SCC (Acceptance Criteria).

The mix design process was guided by ACI 211.1 and EFNARC (European Federation of National Associations Representing for Concrete). The following steps were taken:

A base mix design for HSSCC without marble dust, considering target strength and workability. Developed mixes with varying proportions of m sand, quartz sand and marble sludge powder as given in table. Water-cement ratio, aggregate proportions, and superplasticizer dosage are adjusted to achieve the desired self-compacting properties. Table 2 shows the mix proposition.

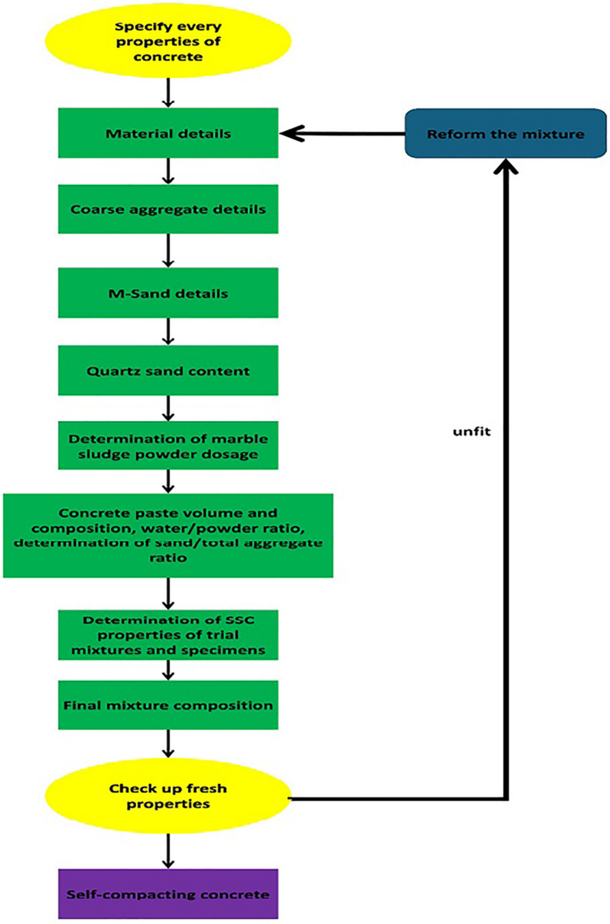

Figure 3: Shows the methodology.

The mix designs presented for High-Strength Self-Compacting Concrete (HSSCC) using different ratios of marble dust give a thorough structure for assessing the capabilities of this environmentally-friendly material in high-performance concrete. The study guarantees a systematic and precise assessment of the impact of marble dust on workability and compressive strength by maintaining consistent binder content, water-cement ratio, and superplasticizer dosage. This technique not only aids in the advancement of sustainable construction materials but also deepens the comprehension of the role of marble dust in enhancing concrete performance.

5. EXPERIMENTAL PROCEDURE

The incorporation of marble dust in high strength self-compacting concrete (HSSCC) represents a notable progress in the development of sustainable construction materials [23]. This innovation exploits the intrinsic characteristics of self-compacting concrete (SCC) and also tackles the environmental consequences linked to marble dust, a prevalent byproduct of industrial processes. The subsequent experimental technique provides a comprehensive methodology that complies with ASTM standards and other applicable rules. This methodology guarantees the generation of dependable and replicable data, which is crucial for the development of an accurate predictive model utilizing artificial neural networks (ANNs).

5.1. Sample preparation

Materials were batched by weight. Dry mixing of aggregates and marble dust for 2 minutes. Cement was added and mixed for another 2 minutes. Water and superplasticizer were gradually added while continuing to mix for 5 minutes to ensure uniform distribution.

5.2. Workability tests

Slump Flow Test (ASTM C1611) is conducted to measure the flowability of the SCC mixes. T50 Time has assessed the viscosity of the mix. V-Funnel Test has conducted to evaluate the flow time and segregation

Table 1: Constituents of SCC (Acceptance Criteria).

CONSTITUENTS	TYPICAL VALUE
Cement content	Not more than 450 kg/m^3
Powder Content (Binder + Fines)	400–600 kg/m^3
Water / powder Ratio	0.80–1.10
Fine aggregate	More than 40% of volume of the mortar More than 50% by aggregate weight
Coarse aggregate	Lesser than 50% in concrete volume 750–1000 kg/m^3
Unit water content	Lesser than 200 litre/m^3

Table 2: Mix propositions.

MIX	TOTAL BINDER CONTENT	CEMENT	SILICA FUME	M-SAND	QUARTZ SAND	MSP	CA	WATER	SUPER PLASTI-CIZER	W/C
HSSCC	550	450	100	813.54	0	0	643.5	236.5	1.925	0.43
HSSCC1	550	450	100	650.84	162.70	0	643.5	236.5	1.925	0.43
HSSCC2	550	450	100	650.84	101.69	61.01	643.5	236.5	1.925	0.43
HSSCC3	550	450	100	650.54	40.67	122.03	643.5	236.5	1.925	0.43
HSSCC4	550	450	100	488.12	325.41	0	643.5	236.5	1.925	0.43
HSSCC5	550	450	100	488.12	264.40	61.01	643.5	236.5	1.925	0.43
HSSCC6	550	450	100	488.12	203.38	122.03	643.5	236.5	1.925	0.43
HSSCC7	550	450	100	325.41	488.12	0	643.5	236.5	1.925	0.43
HSSCC8	550	450	100	325.41	427.10	61.01	643.5	236.5	1.925	0.43
HSSCC9	550	450	100	325.41	366.09	122.03	643.5	236.5	1.925	0.43
HSSCC10	550	450	100	162.70	650.83	0	643.5	236.5	1.925	0.43
HSSCC11	550	450	100	162.70	589.81	61.01	643.5	236.5	1.925	0.43
HSSCC12	550	450	100	162.70	528.80	122.03	643.5	236.5	1.925	0.43
HSSCC13	550	450	100	0	813.54	0	643.5	236.5	1.925	0.43
HSSCC14	550	450	100	0	752.52	61.01	643.5	236.5	1.925	0.43
HSSCC15	550	450	100	0	691.50	122.03	643.5	236.5	1.925	0.43

resistance. L-Box Test is conducted to determine the passing ability of the SCC through reinforcing bars. Table 3 shows the EFNARC Guidelines for SCC (Acceptance Criteria).

Concrete specimens were cast in 150 mm × 150 mm × 150 mm molds per ASTM C192. Specimens were demolded after 24 hours and cured in water at 23 ± 2°C until testing.

5.3. Compressive strength testing

Compressive strength measured at 7, 28, and 56 days using a hydraulic compression testing machine per ASTM C39.

5.4. Artificial neural network

In this work an Artificial Neural Network (ANN) was hired to expect the compressive strength of concrete mixes incorporating various probabilities of marble dust. A complete dataset of 2 hundred mix designs are generated, such as mix proportions, workability test consequences, and compressive test values at exceptional a long time. The information preprocessing segment concerned normalizing the input and output facts to a range of 0 to 1, making sure regular scaling using the formula.

$$Xnorm = X - Xmin/Xmax - Xmin$$

The dataset was then divided into training (70%), validation (15%), and test (15%) subsets. The ANN version applied a feedforward backpropagation network architecture, with the enter layer which includes

Table 3: EFNARC Guidelines for SCC (Acceptance Criteria).

CHARACTERISTICS	TEST	ACCEPTABLE VALUES	
		FROM	TO
Flowability	Slump Flow	650 mm	800 mm
	T50 Slump Flow	2 sec	5 sec
	V-Funnel	6 sec	12 sec
	Orimet	0 sec	5 sec
Passability	J-Ring	0 mm	10 mm
	L-Box (h2/h1)	0.8	1.0
	U-Box (h2 – h1)	0 mm	30 mm
	Fill-Box	90%	100%
Resistance to segregation	GTM Screen Test	0%	15%
	V-Funnel T5minutes	0 sec	3 sec

6 neurons similar to the enter functions (water-cement ratio, percentage of marble dirt, first-rate combination, coarse aggregate, superplasticizer dosage, and curing time). The network featured two hidden layers with 10 and six neurons respectively, employing the ReLU (Rectified Linear Unit) activation function, and an output layer with one neuron corresponding to the compressive strength, the use of a linear activation function.

Initial loading during the loading is Xavier's loading procedure were used during the training phase. It contains the forward propagation step to calculate the weighted sum of input and apply the activation function, backpropagation to compute the error or mean squared error (MSE) loss function and update the weights by the gradient descent algorithms with 0.01 learning rate with measure. The trained ANN model was evaluated using the test set performance metrics: mean squared error (MSE), mean absolute error (MAE), coefficient of determination (R2).

6. RESULTS AND DISCUSSION

6.1. Fresh properties of HSSCC

This test was conducted to assess the inherent characteristics of the SCC, such as its capacity to flow freely, its unconfined flowability, and its resistance to segregation. The J-ring and L-box tests verified the ability to pass. The unconfined flowability of the SCC mixes was evaluated using slump flow and V-funnel (Tv) measurements. Segregation resistance was evaluated by measuring the slump flow at T50 and the V-funnel flow time at T5minutes. Table 4 shows the workability test results.

6.1.1. Slump flow test

The Slump Flow test quantifies the lateral expansion of concrete within a slump cone, providing an indication of the fluidity of the mixture. The values span from 665 mm to 740 mm across the various mixtures. The HSSCC (control mix) exhibited the highest slump flow measurement of 740 mm, suggesting exceptional flowability. As the amount of marble dust rose, there was a consistent drop in the slump flow. The HSSCC11 sample had the lowest value of 665 mm. This indicates that increasing the amount of marble dust may have a little negative impact on the flowability.

6.1.2. The T50 slump flow time

The T50 Slump Flow test quantifies the duration required for the concrete to expand to a diameter of 500 mm during the Slump Flow test, which serves as an indicator of the mix's viscosity. The T50 values varied between 2.5 seconds and 3.9 seconds. The control mix, also known as HSSCC, had a T50 time of 2.6 seconds, whereas HSSCC6 had the longest T50 time of 3.9 seconds. Increased durations correspond to increased viscosity and reduced flow rate.

6.1.3. L-Box test

The L-Box test evaluates the permeability of concrete when subjected to reinforcement. The measure of passing ability is determined by the ratio of heights (h2/h1), where values closer to 1 indicate higher passing ability. The values varied from 0.75 to 0.93, with HSSCC8 achieving the highest ratio of 0.93, which indicates exceptional passing ability. Smaller ratios (such as 0.75 for HSSCC5) indicate possible challenges in navigating dense reinforcement structures.

Table 4: Workability test results.

MIX	SLUMP FLOW (mm)	T 50 SLUMP FLOW VALUE (sec)	L BOX (h2/h1)	V FUNNEL (sec)	J RING STEP HEIGHT (mm)	J RING SLUMP FLOW (mm)
HSSCC	740	2.6	0.9	8	6	640
HSSCC1	730	2.7	0.87	9	8	660
HSSCC2	715	3.1	0.85	7.5	7	650
HSSCC3	722	3.3	0.9	8.5	5	630
HSSCC4	735	3.5	0.78	8	8.5	620
HSSCC5	715	3.6	0.75	9.5	7	605
HSSCC6	703	3.9	0.82	10	3.5	615
HSSCC7	680	3.2	0.88	11.5	4	625
HSSCC8	690	2.5	0.93	8	5.5	635
HSSCC9	685	2.8	0.89	7	4.5	620
HSSCC10	692	3.1	0.87	8.5	6	610
HSSCC11	665	2.8	0.86	9	6.5	615
HSSCC12	675	3	0.9	10	5.5	603
HSSCC13	680	3.6	0.88	10.5	7	610
HSSCC14	685	3.4	0.92	11	7.5	620
HSSCC15	690	3.8	0.88	10	6	625

6.1.4. V-Funnel test

The V-Funnel test quantifies the duration required for concrete to pass through a constricted aperture, providing an indication of its viscosity and resistance to segregation. The recorded times varied from 7 seconds to 11.5 seconds. The HSSCC7 sample exhibited the longest duration of 11.5 seconds, suggesting a higher viscosity and potentially reduced flowability. In contrast, HSSCC9 demonstrated the shortest duration of 7 seconds, indicating superior flowability.

6.1.5. J-Ring test

The J-Ring test evaluates the passing ability and possible segregation by measuring the step height and modified slump flow. The step heights varied between 3.5 mm and 8.5 mm, with larger numbers suggesting more challenging hurdles to overcome. The slump flow values observed in the J-Ring test varied between 603 mm and 660 mm. The control mix, also known as HSSCC (High-Strength Self-Compacting Concrete), exhibited a slump flow measurement of 640 mm. In contrast, HSSCC1 demonstrated the maximum value of 660 mm. Smaller step heights (e.g., 3.5 mm for HSSCC6) imply less obstruction to flow, whereas larger step heights (e.g., 8.5 mm for HSSCC4) signal greater resistance to passage.

6.1.6. Notable observations

Consistency: The HSSCC mixes exhibit consistent performance throughout various tests, showcasing their capacity to maintain self-compaction even when the amount of marble dust varies. The addition of marble dust typically led to a little decrease in flowability and an increase in viscosity, as seen by lower slump flow values and higher T50 times. Nevertheless, the concrete retained sufficient workability within acceptable parameters or self-compacting concrete. Passing Ability: The inclusion of more marble dust in the mixes resulted in a modest decrease in passing abilities, as seen by the L-Box and J-Ring tests. However, the ratios and step heights remained within acceptable limits, indicating that the concrete can still pass through reinforcement without any serious problems.

6.2. Compressive strength test

Figure shows the compressive strength test results. The M70 grade concrete with 7, 28 and 90 days' test results are assessed in this trial. At seven days, the M70 grade concrete with normal concrete with crushed dust delivers higher compressive strength. For all grades of concrete, the 28 and 90 days achieved higher compressive strength because of MSP and Quartz Sand. At last, the concrete strength is improved, and the MSP denotes the

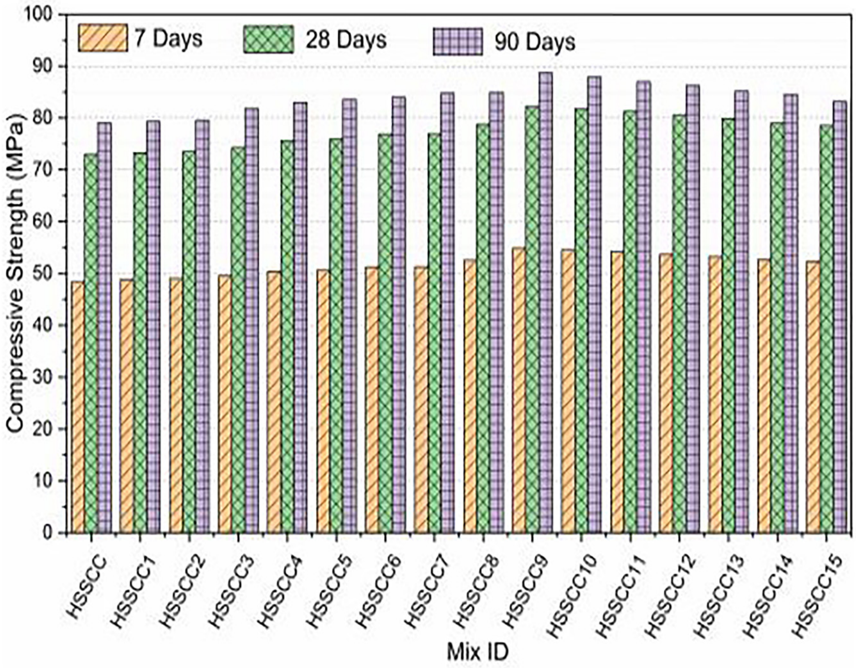

Figure 4: Compressive strength of HSSCC.

cement with a slowly concrete effect. The maximum compressive strength was found as 88.71 MPa for 90 days' specimen, as shown in Figure 4.

The maximum percentage strength increase in specimens was achieved in HSSCC9, which has increased to 13.5%, 12.6%, and 12.2% for 7, 28 and 90 days, respectively. The compressive strength is found to be linearly increasing until 60% replacement of M-sand after that the curve starts to decline linearly. In that 60% replacement, higher strength was found in 15% MSP and 45% Quartz Sand combination replaced concrete specimen.

The compressive strength increased by 51.13% from 7 to 28 days for the control specimen and 8% from 28 days to 90 days for the control specimens. It is found to be almost the same percentage increase as the day increases for all the specimens. Consequently, the concrete strength is improved the MSP limiting cement pore structures. Specific reactivity of MSP and Silica Fumefillers reacts forming very less transition zone development among cement paste and filler, change in the CSH, accelerating impact on the hydration of C2S, C3S, and the spending of calcite. The satisfactory compressive strength is analyzed at the end of this test.

The synergistic impact of combining Silica fume, MSP, and Quartz Sand is responsible for augmenting the compressive strength. The MSP contained in the concrete undergoes a slow reaction with the cement, hence enhancing the overall strength of the concrete mix design. Moreover, MSP assists in diminishing the pore structure of concrete, hence boosting the material's strength. By adding filler to freshly mixed concrete can significantly alter its rheological properties. This is because the filler part of the aggregate has a huge surface area. This is a result of the expansive surface area of the aggregate's filler part. MSP fillers can be distinguished from other types of fillers based on several characteristics, such as calcite consumption, carbo-aluminate formation, accelerated hydration of C3A and C3S, alterations in cement paste hydration, and the creation of a transition zone between the filler and the cement paste, among other factors. This can be achieved optimally by using MSP as a filler, which is a valid option.

6.2.1. Prediction of 28-days compressive strength of trial mixes

In this study, the optimal ANN model was applied from among many different trained networks and tested. The architecture has six input parameters and one output parameter for the compressive strength measured after 28 days of testing. Twenty various networks were trained and tested for compressive strength until the optimal architecture was discovered. High strength self-compacting concrete was influenced by three factors that were varied for different quantities of sand, MSP, and quartz sand, among other things. The following parameters were chosen for the input: sand, MSP, and quartz sand; the output is the compressive strength after 28 days. Figures 5 to 10 depicts the regression values for tested and trained data for network 3-1-1, 3-4-1, 3-1-1-1, 3-1-2-1, 3-4-2-1, 3-2-3-1.

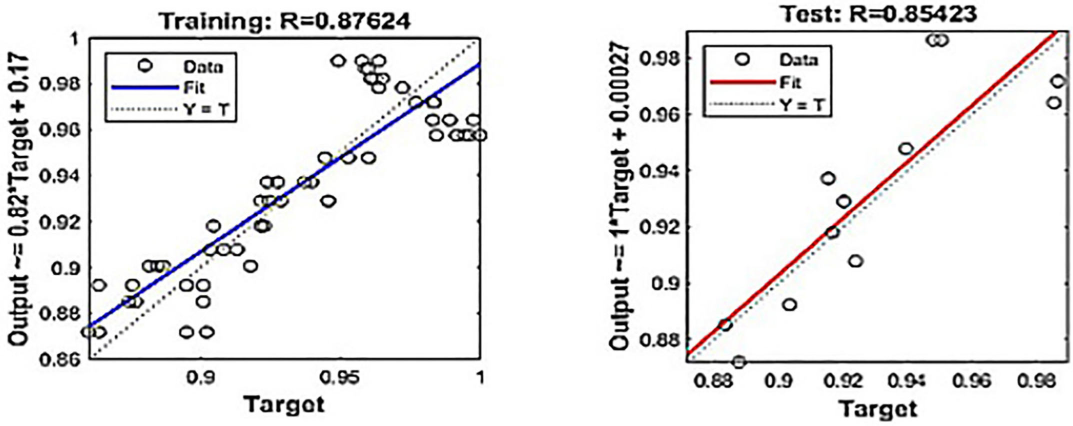

Figure 5: R2 values for tested and trained data for network 3-1-1.

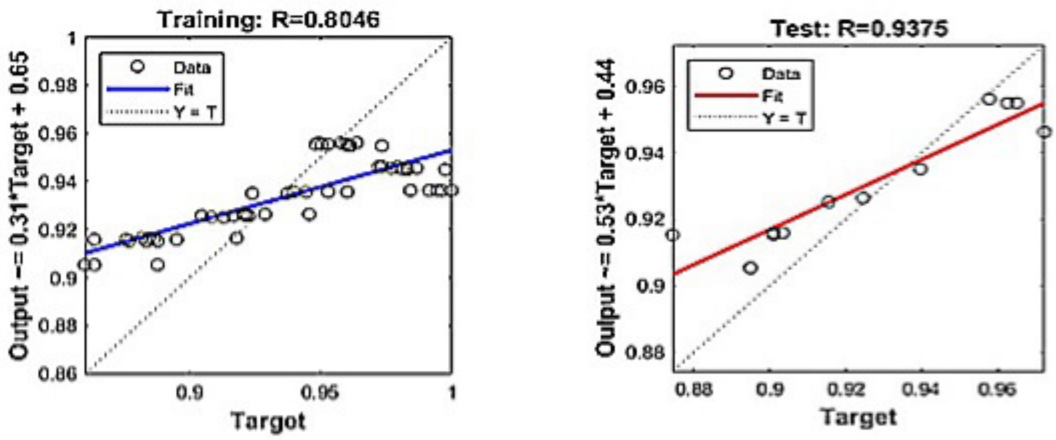

Figure 6: R2 values for tested and trained data for network 3-4-1.

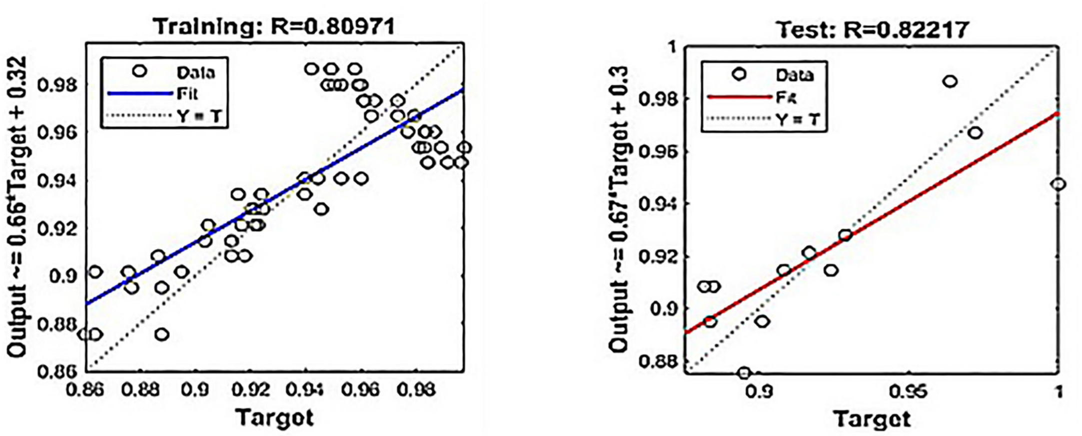

Figure 7: R2 values for tested and trained data for network 3-1-1-1.

Among the networks examined, Network 3-1-1 had the highest level of compressive strength. The neural network is composed of three neurons in the input layer, one neuron in the hidden layer, and one neuron in the second layer, all interconnected [24]. Ultimately, the 28-day compressive strength was forecasted by employing a solitary neuron in the output layer. To determine the correlation coefficient R2 between the experimental and

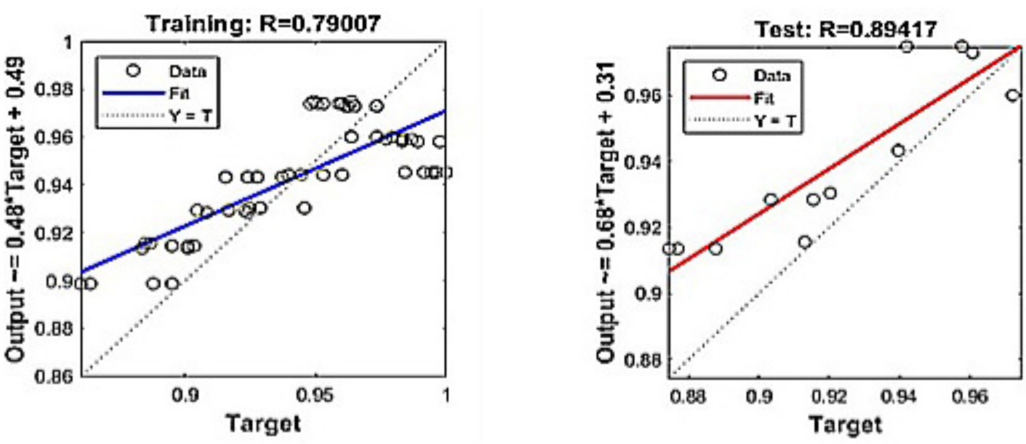

Figure 8: R2 values for tested and trained data for network 3-1-2-1.

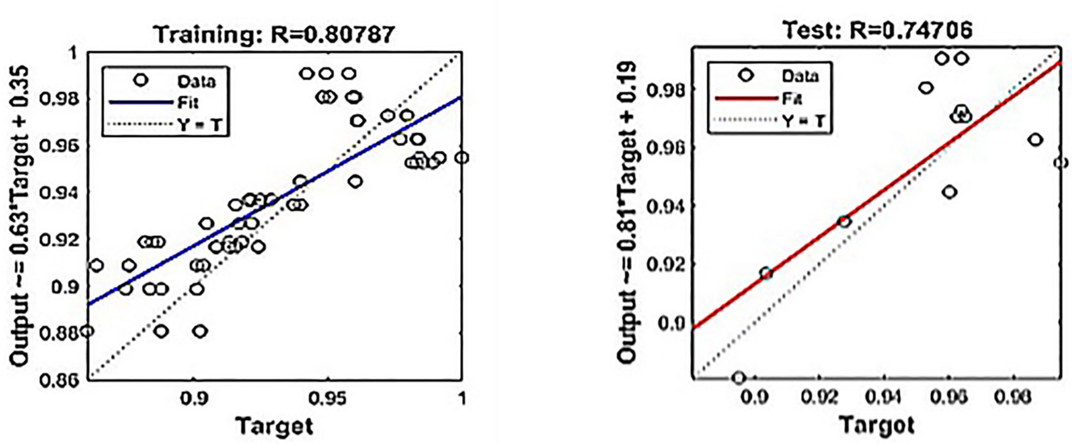

Figure 9: R2 values for tested and trained data for network 3-4-2-1.

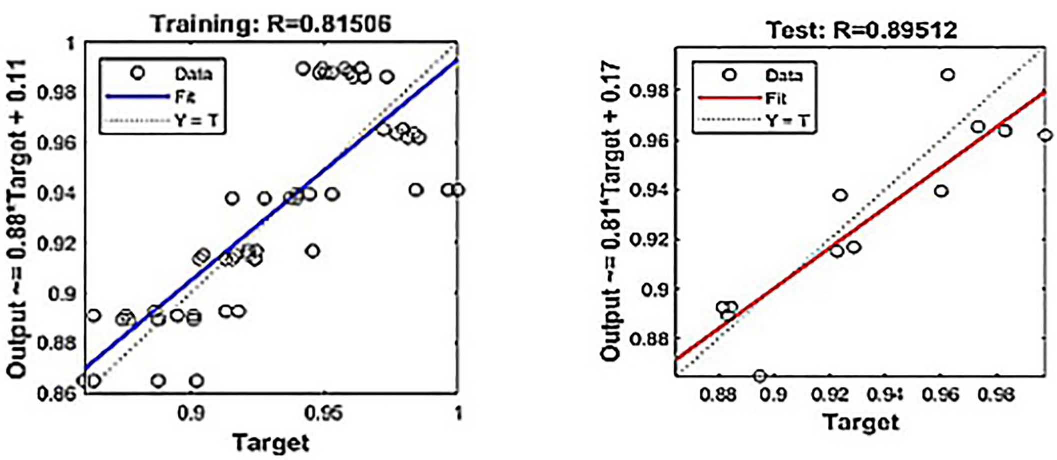

Figure 10: R2 values for tested and trained data for network 3-2-3-1.

predicted values, we utilized the regression plot after completing the training process. Figure 11 displays the comparison between the mean square error and the number of epochs, namely 13 epochs. Enhancing the quantity of neurons and layers typically enhances the model's capacity to acquire intricate patterns, as evidenced by ANN 4, ANN 7, and ANN 10. Excessive complexity can result in overfitting, a situation where the model

Table 5: Statistical Analysis using Artificial Neural Network.

SL. NO.	ARCHITECTURE	ID	R2 FOR 28 DAYS COMPRESSIVE STRENGTH	
			TRAINING	TESTING
1	3-1-1	ANN 1	0.876	0.854
2	3-2-1	ANN2	0.846	0.824
3	3-3-1	ANN 3	0.798	0.818
4	3-4-1	ANN 4	0.804	0.937
5	3-1-1-1	ANN 5	0.881	0.828
6	3-2-1-1	ANN 6	0.855	0.791
7	3-3-1-1	ANN 7	0.809	0.902
8	3-4-1-1	ANN 8	0.827	0.845
9	3-1-2-1	ANN 9	0.790	0.894
10	3-2-2-1	ANN 10	0.801	0.924
11	3-3-2-1	ANN 11	0.837	0.692
12	3-4-2-1	ANN 12	0.807	0.747
13	3-1-3-1	ANN 13	0.815	0.834
14	3-2-3-1	ANN 14	0.815	0.895
15	3-3-3-1	ANN 15	0.835	0.480
16	3-4-3-1	ANN 16	0.856	0.729
17	3-1-4-1	ANN 17	0.833	0.810
18	3-2-4-1	ANN 18	0.826	0.852
19	3-3-4-1	ANN 19	0.805	0.864
20	3-4-4-1	ANN 20	0.835	0.802

performs well on the training data but poorly on unseen data (e.g., ANN 15). The architecture that performs the best in terms of testing R^2 is ANN 4 (3-4-1), which has a value of 0.937. Table 5 shows the statistical analysis using artificial neutral networks.

Enhancing the quantity of neurons and layers typically enhances the model's capacity to acquire intricate patterns, as evidenced by ANN 4, ANN 7, and ANN 10. Excessive complexity can result in overfitting, a situation where the model performs well on the training data but poorly on unseen data (e.g., ANN 15). The architecture that performs the best in terms of testing R^2 is ANN 4 (3-4-1), which has a value of 0.937. This indicates that the simpler architecture, consisting of four neurons in a single hidden layer, successfully reflects the relationship between the inputs and the compressive strength.

The ANN 10 (3-2-2-1) model similarly has a high testing R^2 value of 0.924, indicating that this moderately more intricate model is capable of generalizing effectively without suffering from overfitting.

The models ANN 4, ANN 10, and ANN 14 have robust generalizability, as indicated by their elevated testing R^2 values. This suggests that these models are resilient and proficient in producing precise forecasts on unfamiliar data. Overfitting is observed in certain architectures, especially those with a higher number of neurons and layers, such as ANN 11 and ANN 15. This emphasizes the significance of choosing the appropriate level of complexity in order to strike a balance between the ability to learn and the ability to apply knowledge to different situations. One notable pattern is that certain models may have high R^2 values during training, but their R^2 values during testing can be considerably lower, suggesting overfitting. The objective is to attain elevated and evenly distributed R^2 values for both the training and testing phases, as observed in ANN 4 and ANN 10.

The results of the ANN models provide valuable insights into the effectiveness of different architectures for predicting the compressive strength of HSSCC with marble dust. While simpler models like ANN 4 (3-4-1) exhibit exceptional performance and generalizability, more complex models require careful tuning to avoid overfitting. These findings emphasize the importance of selecting appropriate network complexity to achieve reliable and accurate predictions in practical applications. Future work should focus on further refining these models and exploring additional factors that could influence the compressive strength predictions.

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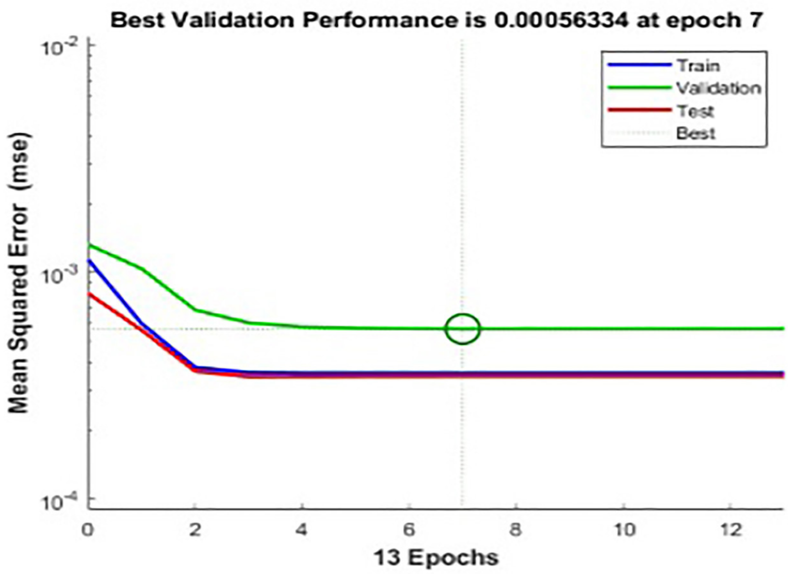

Figure 11: Mean square error vs 13 epochs.

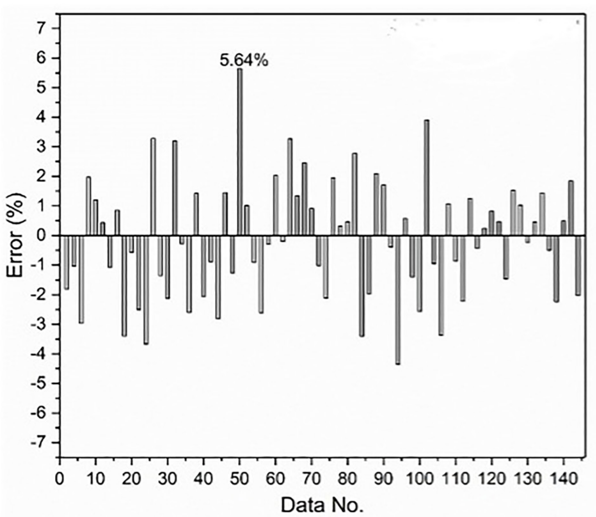

Figure 12: Showing sample error plot for data set of HSSCC.

ANN 4 (3-4-1) exhibit exceptional performance and generalizability, more complex models require careful tuning to avoid overfitting [25]. These findings emphasize the importance of selecting appropriate network complexity to achieve reliable and accurate predictions in practical applications. Future work should focus on further refining these models and exploring additional factors that could influence the compressive strength predictions [26]. Figure 12 shows the sample Error plot for data set of HSSCC.

The trained ANN model was evaluated using the test set performance metrics: mean squared error (MSE) as shown in figure 11. This study's focus on specific materials and controlled laboratory conditions limits its applicability to other sources and environments. The study only examined 200 mix designs and did not evaluate long-term performance after 90 days. The ANN models worked, but they need more validation to be widely used. Practical testing is needed to address potential segregation in larger applications and laboratory-to-field translation [27].

7. CONCLUSION

The tremendous research of High Strength Self-Compacting Concrete (HSSCC) that includes the use of marble dust as a further material become conducted to assess the practicality, effectiveness, and environmental friendliness of those concrete mixes. Multiple High-Strength Self-Compacting Concrete (HSSCC) mixtures have been created and examined to be able to determine the impact of marble dust at the mechanical characteristics, particularly the compressive energy and workability, of the concrete.

Performance of marble dust in High Strength Self Compacting Concrete (HSSCC) is evaluated primarily based on its compressive strength. The incorporation of marble dust along with quartz sand into HSSCC mixes shown a sizeable impact on the compressive strength after 28 days. Various blends, along with HSSCC4 and HSSCC10, exhibited improved compressive strength in comparison to the usual mixture, suggesting that marble dust can be successfully increase the strength of concrete. The mixes that showed the high-quality performance have been the ones wherein marble dust was used to replace a certain percentage of aggregates. This demonstrates the ability of marble sludge to have a positive effect on the concrete without affecting its structural integrity.

Performance tests, such as slump flow, T50 slump flow, L-box, V-funnel, J-ring tests, proved that the addition of marble dust tends to preserve the self-compacting characteristics of HSSCC Exceptional in admixtures such as high strength self-consolidating concrete (HSSCC) and HSSCC1 Water and buoyancy were determined in narrow areas Although the addition of more marble dust slightly reduced the flow rate, but the mixture retained acceptable levels for shrinkage concrete.

Artificial neural network (ANN) models developed to predict the compressive strength of high-strength self-compressed concrete (HSSCC) mixes revealed an accurate Neural network architecture with four neurons in one hidden layer (ANN 4) with the highest prediction-accuracy was shown, where the R2 value for the test-set was 0.937 This indicates a high correlation between expected and actual compressive strength.

These findings highlight the potential of ANNs to identify specific attributes, contribute to the development of optimized concrete mixes, and reduce the need for extensive physical testing. Incorporating marble dust into HSSCC aligns with sustainable construction principles by repurposing industrial waste, thus mitigating the environmental impact of marble waste disposal. This approach not only enhances the sustainability of concrete production but also offers a cost-effective alternative to specific micro-aggregates, thereby improving material efficiency in the construction industry.

The study's findings indicate that marble dust can be efficiently utilized in HSSCC to attain concrete mixes that are both high-performing and sustainable. The mix proportions established in this research are excellent and can be directly applied in the construction industry. Subsequent investigations could prioritize further examinations of the long-term durability of marble dust-incorporated HSSCC, the impacts of different curing procedures, and the efficacy of this material in various environmental situations. Furthermore, investigating the utilization of alternative waste materials in conjunction with marble dust has the potential to significantly improve the eco-friendliness and effectiveness of concrete. Ultimately, the study effectively confirmed the use of marble dust as a valuable ingredient in High Strength Self-Compacting Concrete.

This study confirms the viability of marble dust as a valuable component in High Strength Self-Compacting Concrete. The positive outcomes in terms of compressive strength, workability, and sustainability underscore the potential of this innovative method to advance sustainable and resilient construction practices.

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