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OPTIMIZATION OF MIX DESIGN FOR SELF COMPACTING CONCRETE USING ARTIFICIAL NEURAL NETWORKS

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Abstract
Self-compacting concrete (SCC) has emerged as a revolutionary material in the construction industry, known for its high flowability and ability to consolidate under its own weight without the need for mechanical vibration. However, the complexity of SCC mix design, due to the interplay of multiple variables, poses a challenge to traditional optimization techniques. This study explores the application of Artificial Neural Networks (ANNs) for optimizing SCC mix design. A comprehensive dataset derived from experimental studies and literature was used to train and validate an ANN model. The network predicts key performance indicators such as compressive strength and flow characteristics based on input parameters including cement content, water-to-binder ratio, and admixture dosage. The ANN model achieved a high prediction accuracy ($R^2 > 0.95$), and sensitivity analysis was performed to identify critical mix components. The optimized designs were experimentally validated, showing good agreement with model predictions. The results demonstrate that ANN provides a robust and efficient tool for SCC mix design optimization, minimizing trial-and-error processes and material waste.
Keywords: Compressive strength, ANN, concrete, mix design, optimization, and Self Compacting concrete

1. INTRODUCTION

Self-compacting concrete (SCC) is a highly flowable, non-segregating concrete that can spread into place, fill formwork, and encapsulate reinforcements without mechanical consolidation. Its unique properties make it ideal for complex formwork, heavily reinforced sections, and areas requiring high surface finish. However, designing a mix that balances strength, durability, workability, and cost efficiency is challenging due to the numerous interdependent variables.

Artificial Neural Networks (ANNs), a subset of machine learning, have shown promise in modeling complex nonlinear relationships where traditional analytical methods fall short. This paper investigates the use of ANN for optimizing SCC mix designs, with a focus on improving performance prediction accuracy and reducing material experimentation.

Nowadays, performance expectations from concrete structures are more demanding. As a result, concrete is required to have properties like high fluidity, self compactability, high strength, high durability, better serviceability and long service life. In order to address these requirements, self-compacting concrete (SCC) was developed in 1980s in Japan. Self compacting concrete is a mix that can be compacted into every corner of formwork, by means of its own weight and without the need for vibrating compaction. Inspite of its high flowability, the coarse aggregate is not segregated. Thus, SCC eliminates the need of vibration either external or internal for compaction of concrete without compromising its engineering properties. Concrete is now no longer a material consisting of cement, aggregate, water and admixtures but it is an engineered material with several new constituents. The concrete today can take care of any specific requirements under most of different exposure conditions. EFNARC has published specifications and guidelines for self compacting concrete (EFNARC 2002).

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Self compacting concrete can be defined as the concrete that is able to flow in the interior of the formwork, passing through the reinforcement, filling it in a natural manner, consolidating under the action of its own weight. The filling ability, passing ability and stability can be considered as the main properties of fresh SCC. To make durable concrete structures, sufficient compaction by skilled workers is required. However, gradual reduction in the number of skilled workers in Japan„s construction industry has led to similar reduction in the quality of construction work. One solution for achievement of durable concrete is the employment of self compacting concrete.
Self compacting concrete as the name signifies should be able to compact itself without any additional vibrations or compaction. Self compacting concrete should compact itself by its self weight and under gravity. Self compacting concrete should be able to assume any complicated formwork shapes without cavities and entrapment of air. The reinforcement should be effectively covered and aggregates should be fully soaked in concrete matrix. To meet performance requirements the following three types of self compacting concretes are available i.e., powder type, viscosity agent type and combination type.
Self compacting concrete must be able to flow into all the spaces within the formwork under its own weight. This is related to workability, as measured by slump flow or orimet test. The filling ability or flowability is the property that characterizes the ability of the SCC of flowing into formwork and filling all space under its own weight, guaranteeing total covering of the reinforcement. The mechanisms that govern this property are high fluidity and cohesion of the mixture. Self compacting concrete must flow through tight openings such as spaces between steel reinforcing bars under its own weight. The mix must not block during placement. The passing ability is the property that characterizes the ability of the SCC to pass between obstacles- gaps between reinforcement, holes, and narrow sections, without blocking. The mechanisms that govern this property are moderate viscosity of the paste and mortar, and the properties of the aggregates, principally, maximum size of the coarse aggregate.
Stability or resistance to the segregation is the property that characterizes the ability of the SCC to avoid the segregation of its components, such as the coarse aggregates. Such a property provides uniformity of the mixture during transport, placement and consolidation. The mechanisms that govern this property are the viscosity and cohesion of the mixture
Concrete is now no longer a material consisting of cement, aggregate, water and admixtures but it is an engineered material with several new constituents. The concrete today can take care of any specific requirements under most critical exposure conditions. The concrete in modern days has to satisfy various performance criteria's. As a result, concrete is required to have properties like high fluidity, self compactability, high strength, high durability, better serviceability and long service life. In order to address these requirements, self-compacting concrete (SCC) was developed. Self compacting concrete is a mix that can be compacted into every corner of formwork, by means of its own weight and without the need for vibrating compaction. Inspite of its high flowability, the coarse aggregate is not segregated. At the same time there is no entrapped air. Thus, SCC eliminates the need of vibration either external or internal for compaction of
concrete without compromising its engineering properties and it saves time, labour and energy. The filling ability, passing ability and stability can be considered as the main properties of fresh SCC. Hardened mechanical properties of SCC are similar to that of normally vibrated concrete. The surface finish produced by self-compacting concrete is exceptionally good. Solution for achievement of durable concrete is the employment of self compacting concrete. In general superplasticizer and viscosity modifying agent are used in the production of SCC. Site conditions demand the use of air entraining agent, accelerator, retarder, water proofing compound and shrinkage reducing admixtures in the
production of SCC.
The main objective of this investigation is to design the optimal mix of concrete with combination of admixtures which produce self compacting concrete and to determine its strength. The different admixtures that are used in the investigation are superplasticiser, viscosity modifying admixture, air

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entertaining agent, accelerator, retarder, water proofing compound and shrinkage reducing admixture.

2. LITERATURE REVIEW

Previous studies have highlighted the sensitivity of SCC performance to mix constituents. Researchers have employed regression models, genetic algorithms, and fuzzy logic to optimize SCC mix designs. However, these methods often require simplifications and struggle with multicollinearity and nonlinearities inherent in concrete mixtures. ANNs offer a flexible modeling framework that adapts to data complexity without requiring explicit programming of the relationships. a brief review of the literature has been presented below.

Hajime Okamura in his paper entitled "Self Compacting High-Performance Concrete" has discussed about self compacting concrete as a mix that can be compacted into every corner of a formwork, purely by means of its own weight and without the need for vibrating compaction. Inspite of its high flowability, the coarse aggregate in not segregated.

A model formwork was used to observe how well self-compacting concrete can flow through obstacles. Concrete is placed into the right-hand tower, flows through the obstacles and rises in the left- hand tower. The obstacles were chosen to simulate the confined zones of an actual structure. The self-compacting concrete on the left can rise to almost the same level as on the right. It is realized that the development of self compacting concrete would be necessary to guarantee durable concrete structures in the future.

When concrete flow between reinforcing bars, the relative location of the coarse aggregate is changed. The relative displacement causes shear stress in the paste between the coarse aggregate, in addition to compressive stress. Shear force required for relative
displacement largely depends upon water cement ratio. Increasing water cement ratio leads to improved flowability of cement paste and decreases viscosity. Therefore, superplaticizer is indispensible. Coarse aggregate is limited to 50 percent of solid volume and fine aggregate content is 40 percent of mortar volume. U type test is most appropriate for evaluating self compactability.

Kamal H. Khayat in his paper entitled "Workability, Testing and Performance of Self Consolidating Concrete" has reviewed the benefits of using self- consolidating concrete to facilitate the casting of densely reinforced sections and improve productivity and onsite working conditions. Workability requirement necessary to secure self-consolidation A Study on Effect of Combination of Admixtures on the Characteristic Properties of Self Compacting Concrete Department of Civil Engineering, KLESCET, Belgaum-590 008 47 and the principles involved in proportioning such highly flowable concrete are discussed. Field oriented tests useful in evaluating the deformability, filling capacity and stability of self consolidating concrete are presented.

The performance of concrete mixes proportioned according to two main approaches needed to insure high deformability, low risk of blocking during flow and proper stability are compared. Such approaches involved the proportioning of concrete with a moderate water – to- cementatious material ratio (w/cm) of 0.41 and using a viscosity enhancing admixture to increase stability, as well as mixes without any viscosity-enhancing admixtures, but with lower w/cm of 0.35 to 0.38 to reduce free water contents and provide stability. Mixes with both moderate and high contents of ternary cementatious
were evaluated. The performance of each concrete was compared to that of a flowable concrete with 250-mm slump. The conclusions drawn from the study are: An SCC with a slump flow of 650 mm containing 300 to 330 kg/m3 of 20-mm maximum size aggregate, 555 kg/m3 of cementatious materials, and 0.60 to 0.66 sand/paste volumes, can be more suitable for casting highly congested structural sections than a mix containing 375 to 400 kg/m3 of coarse aggregate, 425 kg/m3 of cementatious material and 0.70 to 0.85 sand/paste volumes. Binary or ternary binders containing high volumes of pozzolanic or nonpozzolanic fillers, such as limestone powder, can be used to reduce the cement content, heat of hydration and shrinkage in self compacting concrete. One approach to enhance viscosity is to lower the w/cm to maintain adequate cohesion friction between

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the mortar and coarse aggregate and insure uniform flow of SCC through restricted sections. Another way is to incorporate a low to moderate dosage of a VEA without lowering the w/cm. This can enable the reduction of coarse aggregate volume and reduce the risk of blockage, which is especially useful in the mixtures containing moderate content of cementations materials and fine fillers.

Kwan, A.K.H. in his paper entitled “Use of Condensed Silica Fume for Making High Strength, Self Compacting Concrete” has aimed at developing high strength, self consolidating concrete. A high strength concrete can be achieved by lowering the water/binder ratio and a high workability by adding a higher dosage of superplasticizer. However, a high performance concrete with both high strength and high workability cannot be produced by just these means because lowering water/binder ratio leads to lower workability and there is a limit to increase in workability that can be attained by adding superplasticizer. To produce high strength, high workability concrete, concrete strength need to be increased without lowering water/binder ratio. This can be done by adding silica fume. Based on the experimental data obtained, a design chart for the mix proportioning of high strength, high workability concrete is produced. This chart is applicable to concrete mixes made of the materials used in this study. Similar charts for concrete mixes can be made for other materials by using the same methodology. This study also helps to explain qualitatively the role of CSF superplasticizer concrete.

Subramanian,S. and Chattopadhyay,D in their paper entitled “Experiments for Mix Proportioning of Self-Compacting Concrete” have studied various aspects of SCC. They have described the development of mix proportion of SCC and also the procedure used for selecting the combination of viscosity modifying agent, superplasticizer and ultra fine powders. Following conclusions were drawn - Trial proportions by Okamura and Ozawa appear to be suitable for rounded gravel aggregate. When using crushed angular aggregate, the proportions are to be adjusted, incorporating more fines. Sensitivity to changes in mixture proportions requires that a viscosity modifying agent (VMA) be used. Out of four VMA’s tried, Welan gum was found to give superior performance because of its rheological characteristics. The optimum dosage of Welan gum should be arrived after considering the bleeding tendency, setting time and compatibility with the superplaticizer used. Micro silica at an appropriate dosage may be beneficial in reducing the dosage of Welan gum. This may reduce the final setting time and increase the compressive strength. Suitability of self-compacting concrete mixture proportion was verified through placement trials in a complicated mould and in a field trial. The results are Encouraging. Kamal H. Khayat and Joseph Assaad in their paper entitiled “Air-Void Stability in Self- Consolidating Concrete “have discussed about air-void stability in self compacting
concrete. Ensuring an adequate and stable air-void system in flowable concrete is essential to guarantee proper resistance to freezing and thawing. Self – consolidating concrete mixtures were prepared to evaluate the influence of mixture proportioning on the stability of the air-void system during agitation. Samples were taken at different time intervals over a period of 95 min after the initial water-cement contact to analyze the air-void system and determine its variation with agitation. Bingham rheological parameters (plastic viscosity and yield stress.) slump flow, filling capacity. V-funnel flow time and surface settlement were evaluated. The modified point-count method was employed to determine the characteristics of the corresponding air-void system.

Test results show that the air-void characterisitics of SCC can be similar to those found for normal-slump concrete. In general, greater air-void stability can be obtained when the SCC is proportioned with a higher content of cementatious materials and a lower water – cementatious materials ratio For mixtures with a relatively low content of cementatious materials and a high w/cm, the air-void stability increases when a viscosity modifying admixtures is incorporated. To prevent coalescence of small air bubbles during agitation, the plastic viscosity and yield stress values should not exceed limiting values. Such limits are also shown to yield greater air-void stability after 95 min of occasional agitation.They have concluded that: It is possible produce highly flowable concrete with an approximate slump flow of 550 mm and SCC with a slump flow of 640 mm that exhibit an

adequate and stable air-void system As is the case with normal-slump concrete, the air content in the hardened concrete tends to be within 1% of that determined at the fresh state. Klaus Holschemacher and Yvette Klug in their paper entitled "A Database for the Evaluation of Hardened Properties of SCC" have investigated that self-compacting concrete (SCC) consists basically of the same components as normal vibrated concrete.
However, there exist clear differences regarding the concrete composition. In this context it is to verify, whether the properties of hardened self-compacting concrete and normal vibrated concrete differ significantly from each other. For clarification of this question a database with own and internationally published test results was created and evaluated regarding the relations between compressive strength, tensile strength, modulus of elasticity and bond properties. Furthermore creep and shrinkage deformations of SCC and vibrated concrete were compared.
The results of the interpretation of the database can be summarized as follows: The concrete strength of SCC and normal concrete are similar under comparable conditions, this statement includes also the time development of concrete strength. Tensile splitting strength, modulus of elasticity and shrinkage of SCC and normal concrete differ, but the differences vary within the usual scatter width, known for normal concrete. No final tendency can be given for creep of SCC.
Jianxin Ma, Jorg Dietz in their paper entitled with "Ultra High Performance Self Compacting Concrete" have discussed the experiences in the development of Ultra High Performance Concrete. Because of the high viscosity of the cement paste, compaction was necessary. To improve the compaction characteristics of the concrete the idea of adding coarse aggregate was developed. The first tests showed a good workability of the fresh concrete and a good self compacting ability. The interest in reducing costs while improving workability, shrinkage tendency and the modulus of elasticity was leading to the results in this paper.
The following conclusions were drawn from the study. The application of new superplastizicer and powders in high performance concrete give the opportunity to produce self-compacting concretes that easily reach a compressive strength of more than 150 MPa. These concretes show a very good workability in the fresh state, also the hardened concrete shows excellent quality.
Future interests will try to reduce autogenous shrinkage to minimize the crack tendency of the young concrete. Further investigations to optimize the mix proportions will aim to the applications of this concrete on site.

3. METHODOLOGY

The data required for the investigation might be obtained from a variety of sources. These sources could include published literature, established databases, industry standards and requirements, and laboratory tests carried out especially for the study. The data set for the current study comes from respectable journals and publications, guaranteeing the accuracy and legitimacy of the data.
A dataset comprising 300 SCC mix designs was compiled from published literature and laboratory experiments. Each entry included variables such as:

- Cement content (kg/m³)
- Water-to-binder ratio (w/b)
- Fine aggregate content (kg/m³)
- Coarse aggregate content (kg/m³)
- Superplasticizer dosage (% of binder)
- Viscosity modifying agent (VMA) dosage
- Fresh properties (slump flow, V-funnel time)
- 28-day compressive strength (MPa)

Observations from Statistical Analysis of the Dataset:
The dataset's statistical analysis yields significant findings on the output Compressive Strength and the input ingredients' mean, standard deviation, quartiles, and range. The range, distribution, and central tendencies of the input ingredients as well as the output Compressive Strength are clarified

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by these statistical findings, which offer a thorough picture of the dataset. They provide the foundation for more research, the creation of models, and the improvement of high-performance concrete mixes.

Table 1. Statistical Analysis of the Dataset

Variables	Mean	Maximum	Std
C (kg/m³)	396.5	540	103.4
FA (kg/m³)	770.49	992.6	79.37
CA (kg/m³)	964.83	1445.2	82.79
W (kg/m³)	182.98	247.25	21.71
VMA (kg/m³)	2.3	5.8	1.68
SP (kg/m³)	6.42	32.2	5.80
Age (Days)	44.92	365.85	60.44
Slump value (mm)	480	510	92.55
Compressive Strength (MPa)	35.84	82.60	16.10

3.1. Data Preprocessing

The raw data in the database was prepared for analysis and model building using a series of steps known as data preparation in machine learning (ML), which includes data cleaning, feature selection, and data normalization when required. The predictors considered for the model included amounts of Cement content (kg/m³) Water, Fine and coarse aggregate content (kg/m³), Superplasticizer dosage (% of binder), Viscosity modifying agent (VMA) dosage, Fresh properties (slump flow, V-funnel time), 28-day compressive strength (MPa) It should be noted that sophisticated machine learning approaches have the ability to capture intricate, non-linear correlations between the CS and the chosen inputs, which could result in predictions that are more accurate. To enhance ANN performance, the data was adjusted to a [0, 1] range. In order to handle missing variables, we employed k-nearest neighbors (k-NN) imputation. Seventy percent of the dataset was then used for training, fifteen percent for validation, and fifteen percent for testing.

3.2. ANN Model Development

There are several varieties of deep learning neural networks, and the ANN is a popular method that has been used extensively to create prediction models across a range of industries. Because ANN is widely used and simple to use, it is used in this study. In particular, a modified and optimized version of ANN that is frequently used in practice is the Backpropagation Neural Network (BPNN). The Tensor Flow framework in Python was used to create a feed forward back propagation neural network. The structure was made up of:

- Input layer: 7 neurons (input variables)
- Two hidden layers: 20 and 10 neurons respectively, with ReLU activation
- Output layer: 1 neuron (compressive strength), with linear activation

The network was trained using the Adam optimizer with a mean squared error loss function. In the initial phase, every input neuron receives an input that indicates the percentage of ingredients and

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sends a prediction to the buried layer neurons based on Eq. (3.1).

$$yj = \sum_{i=1}^{n} (wij.xi) + bj \qquad 3.1$$

The input and output of the jth neuron are denoted by xi and yj, the weight (connection) between the ith and jth neuron by wij, the bias parameter for the jth neuron by u is the number of neurons. To provide non-linearity to the fitting process, an activation function is applied at the output neuron and each hidden layer. Differentiability is crucial for this activation function. The input for the activation function is thought to be the output of the input neurons. The output is calculated and sent forward as input to either the output layer neurons or the subsequent hidden layer neurons, depending on the selected activation function, following Eq. (3.2).

$$Aj=(yj) \qquad 3.2$$

In this case, yj represents the activation function's input that was obtained from Eq. 3.1. The error is computed by comparing the output neuron's prediction with the actual value after it has been generated. This calculation of error aids in evaluating the model's correctness.To reduce the error, the estimated error is transmitted backward in the second stage. Each neuron's weight and bias are tuned during this procedure. The MSE provided in Eq. 3.3 is used to assess the error in BPNN.

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n} (yi - \hat{y}i)^2 \qquad 3.3$$

The mean squared error is represented by MSE, the total number of samples is represented by n, the actual output is represented by yi, and the predicted output of the model is represented by $\hat{y}i$.

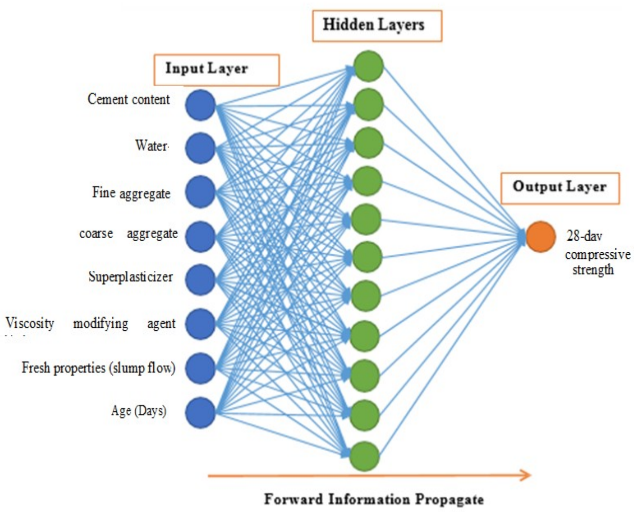

FIGURE 1. Architecture of ANN adopted

3.3. Optimization Algorithm

After training, combinations of input variables were investigated using a grid search method under realistic limitations. Reducing the cement content while keeping the compressive strength over 40 MPa was the aim. The method of Artificial Neural Networks (ANN) Artificial neural networks (ANNs) are made up of interconnected neurons arranged in layers, such as input, hidden, and output layers. Data is received by the input layer, processed by hidden layers, and predictions are made by the output layer. Through forward and backward operations (forward propagation and backpropagation), the network modifies its weights and biases throughout training in order to identify patterns in the data (Hong, 2023).

3.4. Training and Validation

The model was trained using the Adam optimizer with a mean squared error (MSE) loss function. Hyperparameter tuning was performed through grid search and cross-validation. Early stopping was used to prevent overfitting.

4. RESULTS AND DISCUSSION

4.1. Model Performance

The ANN model employed in this study was found to predict compressive strength with a high degree of accuracy:

- Slump flow prediction: $R^2 = 0.96$,
- RMSE = 13.2 mm
- Compressive strength prediction: $R^2 = 0.95$,
- RMSE = 2.8 MPa

This demonstrates a robust relationship between expected and actual strengths, confirming the efficacy of the ANN.

4.2. Sensitivity Analysis

Sensitivity analysis revealed the following variables had the greatest impact:

- Superplasticizer dosage on slump flow
- Water-to-binder ratio on compressive strength

4.3. Optimization

Using the trained ANN model, an optimization algorithm (e.g., genetic algorithm) was integrated to identify optimal mix proportions satisfying both flowability and strength criteria. Several mix designs produced compressive strengths > 35 MPa with 20–30% less cement were found throughout the optimization phase. In keeping with environmental goals, these blends also decreased heat of hydration and enhanced workability.

The output optimized mix is given below:

- Cement content: 390(kg/m³)
- Water : 185(kg/m³)
- Fine aggregate content: 700 (kg/m³)
- Coarse aggregate content : 980 (kg/m³)
- Superplasticizer: 9 (kg/m³)
- Viscosity modifying agent :3.2(kg/m³)
- Slump flow: 490 mm
- 28-day compressive strength: 38(MPa)

These results were within ±5% of the predicted values.

4.4. Discussion

The performance of the Artificial Neural Network (ANN) model developed in this study was evaluated based on its ability to predict two critical performance parameters of Self-Compacting Concrete (SCC): slump flow (a measure of flowability) and 28-day compressive strength (a key strength indicator). The ANN demonstrated high accuracy with R^2 values of 0.96 for slump flow and 0.95 for compressive strength, indicating a very strong correlation between predicted and experimental values. These results validate the ANN's ability to capture the complex, nonlinear interactions among SCC mix parameters such as cement content, water-to-binder ratio, and admixture dosages. The Root Mean Square Error (RMSE) of 13.2 mm for slump flow and 2.8 MPa for compressive strength are within acceptable engineering limits and suggest that the model is reliable for practical use in predicting SCC performance. The relatively low error margins and high R^2 values further emphasize that ANN can act as a surrogate model, potentially replacing the need for repetitive laboratory trials in the mix design phase.

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5. CONCLUSION

The invention of SCC is a major boom to the concrete industry as well as to the precast industry. The use of SCC in construction can bring down the construction time by 25%. Superior finishing quality, faster rate of construction, saving in the electricity, etc have made SCC a popular material.In this research programme around 1900 specimens were cast and tested. Based on the present investigations, it is noticed that the use of combination of admixtures in the production of SCC can enhance the flow characteristics and strength characteristics of SCC. Even it is found that the durability properties of SCC can be enhanced with the use of combination of admixtures. The use of combination of admixtures in the production of SCC can help the construction industry in the special situations where the early strength and early setting is to be achieved or where delayed setting is required or where water proofing becomes an essential criteria or where the shrinkage has to be controlled because of durability problems. The combination of admixtures will help the construction industry in any of the above situations. The feasibility of using artificial neural networks to optimize sustainable concrete mix designs is demonstrated in this study. ANN models can lessen the need for trial-and-error techniques and greatly aid in achieving environmental goals in construction by precisely forecasting compressive strength and investigating different binder combinations. In order to maximize compressive strength while reducing environmental effect, this research explores how artificial neural networks (ANNs) might be used to optimize mix designs for SCC.

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