Applied Science and Innovative Research
ISSN 2474-4972 (Print) ISSN 2474-4980 (Online)
Vol. 9, No. 1, 2025
www.scholink.org/ojs/index.php/asir

Original Paper

Intelligent Proportion Optimization of SFRC Using Ensemble Learning: A Multi-Objective Predictive Framework

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Received: January 28, 2025 Accepted: February 24, 2025 Online Published: March 4, 2025

doi:10.22158/asir.v9n1p171 URL: http://doi.org/10.22158/asir.v9n1p171

Abstract

Steel fiber-reinforced concrete (SFRC) is formulated by incorporating short, slender steel fibers into standard concrete, thereby creating a composite material. This addition significantly mitigates the brittle nature of concrete, enhancing its strength, toughness, and durability. The application of SFRC not only improves structural safety and service life but also promotes the development of green building materials and efficient construction technologies. To optimize the mix proportion design of SFRC, key parameters such as steel fiber content, water, cement, sand, natural aggregates, and water reducer were collected. A neural network model was constructed to leverage its powerful nonlinear mapping capabilities, establishing an implicit relationship between the mix proportions and compressive strength. The trained model enables rapid prediction of SFRC compressive strength, while a genetic algorithm was employed to inversely search for the optimal mix proportions that meet target performance requirements, providing a novel approach and design strategy for the intelligent design of SFRC.

Keywords

SFRC, Mix Design, Machine Learning, Artificial Neural Network, Genetic Algorithm

1. Introduction

Steel fiber reinforced concrete (SFRC), renowned for its excellent crack resistance, toughness, and energy dissipation capacity, demonstrates irreplaceable advantages in seismic, blast-resistant, and complex service environments within civil engineering applications (Carneiro, Lima, Leite, et al., 2014; Gao, Lou, & Wang, 2007; Xie, Guo, Liu, et al., 2015; Guo, Lu, Zhang, et al., 2016). Its mechanical performance is directly influenced by the intricate coupling relationships among various factors, including steel fiber dosage and matrix material proportions. Traditional mix proportion design methods often rely on empirical formulas or orthogonal experiments, which are associated with high trial-and-error costs and low parameter optimization efficiency, making it difficult to accurately capture the nonlinear mapping between multiple variables. Therefore, it is essential to explore an intelligent optimization approach for mix proportion design, aiming to establish a high-precision and scalable predictive model.

At present, research on concrete mix proportion design has become relatively mature. Fu et al. (2025) employed Gradient Boosting Decision Trees (GBDT) and XGBoost to conduct mix proportion design, verifying its feasibility under specific performance requirements. Zhou et al. (2021) constructed a prediction model based on Support Vector Machines (SVM), considering both concrete strength and slump, and utilized the Artificial Bee Colony (ABC) algorithm to identify the optimal mix proportions for various strength levels. Jiang et al. (2019) utilized the grey relational analysis model to achieve multi-objective C50 concrete mix proportion design, ultimately identifying the optimal mix proportions for C50 concrete.

To conduct a comprehensive investigation into the mix proportion design of SFRC, this study compiled key parameters, including the dosage of steel fibers, water, cement, sand, natural aggregates, and water-reducing agents. A neural network model was developed to leverage its powerful nonlinear mapping capability, establishing an implicit relationship between the mix proportions and compressive strength. The trained model enables rapid prediction of SFRC compressive strength, while the genetic algorithm was employed to inversely search for the optimal mix proportions that meet target performance requirements. This approach provides a novel pathway and design strategy for the intelligent optimization of SFRC mix proportion design.

2. Basic Principles of Artificial Neural Networks (ANN)

ANNs (Jia, 2023) are composed of multiple interconnected nodes, or neurons, with each connection assigned a specific weight that is modified throughout the learning process. The core structure of an ANN consists of an input layer, which accepts external data; Intermediate layers conduct pattern identification and nonlinear operations, while the output layer synthesizes these computations into actionable results. The architecture's mathematical framework is formalized as follows:

$$o_i = f\left(\sum_{i=1}^{n} w_{ij} x_i + b\right) \tag{1}$$

The output of an ANN is primarily determined by its connection topology, weights, and activation functions. Neural networks frequently utilize nonlinear operators such as: the Sigmoid function (logistic-type normalization), hyperbolic tangent (tanh) (gradient-preserving symmetry), ReLU (piecewise linear activation with sparsity induction),linear, threshold or step, Gaussian, and piecewise linear functions. Nonlinear activation functions, in particular, not only improve the network's ability to approximate complex nonlinear functions but also replicate neuronal behavior, enhancing the network's training efficiency.

Backpropagation Neural Network (BPNN) operates as a gradient-based optimization framework, implementing iterative refinement of network parameters through error backpropagation mechanics. Its operational cycle consists of two coupled phases:

1. Feedforward Computation: Propagates input signals through hierarchical architectures via nonlinear transformations; 2.Error Backpropagation: Constructs gradient fields of loss functions relative to weight parameters using chain rule differentiation, driving parameter space evolution along the negative gradient direction of the error hyperplane (see topological configuration in Figure 1).

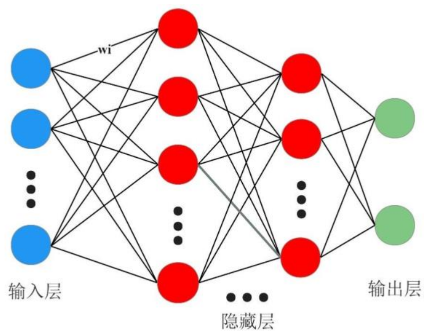

Figure 1. The Network's Architecture

Assuming the ANN consists of t layers, with each layer containing n nodes, and the training sample is represented as (x_i, y_i), the network training process typically involves the following steps, which are illustrated using the Backpropagation Neural Network (BPNN) as an example.

Step 1: Error Calculation

Error quantification initiates through comparative analysis between the network's generated outputs and target values, quantified via a loss function. This study adopts variance as its optimization metric, formalized through Equation (2).

$$E\left(w,b;x_i,y_i\right)=\frac{1}{n}\sum_{i=1}^{n}\frac{1}{2}\left\| f\left(x_i\right)-y_i\right\|^2 \tag{2}$$

In the equation, x_i and y_i represent the input and target values, respectively, while w and b correspond to the network's weights and biases. The activation function is denoted as f(x).

Step 2: Error Propagation and Weight Adjustment

The error gradient flow initiates at the output stratum, propagating retroactively across hierarchical strata via differential chaining. At each computational layer: Gradient Field Derivation: Layer-specific partial derivatives are determined through tensor contractions between error signals and activation Jacobians; Parameter Space Refinement: Stochastic gradient-based optimization schemes (e.g., Equation 3-4) iteratively adjust the weight-bias manifold along the negative gradient trajectory.

$$\frac{\partial E}{\partial w_{ij}^{(l)}}=\frac{1}{n}\sum_{i=1}^{n}\frac{\partial}{\partial w_{ij}^{(l)}}\left\| f(x_i)-y_i\right\|^2 \tag{3}$$

$$\frac{\partial E}{\partial b_{ij}^{(l)}} = \frac{1}{n}\sum_{i=1}^{n}\frac{\partial}{\partial b_{ij}^{(l)}}\| f(x_i) - y_i \|^2 \tag{4}$$

In this context, l refers to the layer index, I denotes the i-th input value in layer l, and j represents the j-th neuron in the preceding layer.

Step 3: Iterative Training Process

The steps of forward propagation, error computation, backpropagation, and weight adjustment are iteratively repeated until a predefined stopping criterion is satisfied. The stopping condition typically includes reaching a predefined number of training epochs, the error falling below a certain threshold, or no further improvement in network performance on the validation set. The updated weights and biases of each node are calculated according to Equations (5) and (6).

$$w_{ij}^{(l)} = w_{ij}^{(l)} - \alpha\frac{\partial E}{\partial w_{ij}^{(l)}} \tag{5}$$

$$b_{i}^{(l)} = b_{i}^{(l)} - \alpha\frac{\partial E}{\partial b_{i}^{(l)}} \tag{6}$$

In the equation, α is referred to as the hyperparameter learning rate, typically set within the range [0,1], and it determines the step size of the gradient descent.

3. Concrete Strength Prediction Based on ANN

3.1 Establishment of Training Sample Set

This research utilizes a subset of the data from reference (Zhang, 2017) as the training dataset, with six input parameters: natural aggregates, cement, water, fine aggregates, steel fibers, and water reducer. The output variable is the 28-day compressive strength of SFRC. The range of the input and output data is shown in Table 1. To enhance the convergence speed of the ANN model, data normalization is applied. The normalization method used in this study is the min-max normalization, which is expressed as:

$$X^{*}=(X-X_{\min})/(X_{\max}-X_{\min}) \tag{7}$$

In the equation, X^{*} represents the normalized data sample, while $X_{\max}$ and $X_{\min}$ correspond to the maximum and minimum values in the dataset, respectively.

Table 1. Range of Input and Output Data

	water (kg/m3)	cement (kg/m3)	sand (kg/m3)	natural aggregate (kg/m3)	steel fiber (kg/m3)
Min	160	342	557	0	0
max	220	550	887	1283	158
Mean Value	187	445	686	855	100
Standard Deviation	12.5	54.5	88.5	308.9	44.7

3.2 ANN Model Training

Once the ANN prediction model for the 28-day compressive SFRC is established, the data samples are inputted for multiple training iterations to identify the optimal network model. The correlation coefficient (R) for this best-performing network is 0.983, which is very close to 1, demonstrating that the ANN model has successfully learned and can accurately predict the mix proportions of SFRC. The ANN prediction results are illustrated in Figure 2.

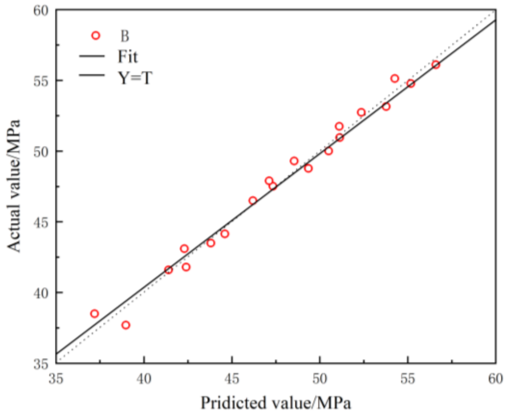

Figure 2. ANN Prediction Result

4. Target Optimization Based on Genetic Algorithm (GA)

The GA are adaptive search heuristics grounded in Darwinian evolutionary principles, leveraging population-based stochastic operators to solve high-dimensional, non-convex optimization problems. By simulating genetic inheritance mechanisms (e.g., crossover, mutation) and fitness-driven selection pressures, these algorithms iteratively evolve candidate solutions toward Pareto-efficient configurations.

The fundamental steps involved in goal optimization using a genetic algorithm can be summarized as follows:

1. Initialization of Population: Generate a set of random candidate solutions (individuals).
2. Fitness Evaluation: Score each individual to quantify its quality.
3. Selection: Retain the superior individuals and eliminate the inferior ones.
4. Crossover: Analogous to genetic recombination in biological engineering, combine the features of superior individuals to generate new individuals.
5. Mutation: Also known as random disturbance, this step introduces randomness to avoid local optima.
6. Iterative Update: The evolutionary process is repeated until the termination condition is met.

4.1 Establish Objective Function

The objective function is designed to maximize the compressive strength of SFRC. Given the intricate nonlinear relationship between the input parameters and the output, the ANN regression model is employed as the objective function for the algorithm. The mathematical representation of this function is as follows:

$$\max f_1(ANN\ (x_1, x_2 \cdots x_6)) = \left[\sum_{j=1}^{n} \left(\alpha_j - \alpha_j^* \right) \sum_{i=1}^{6} \left(1 + x_i^T x \right)^6 \right] + b$$

In the equation, x_1-x_6 represent the individual material quantities of natural aggregates, cement, water, aggregates, steel fibers, and water reducer in the steel fiber reinforced concrete, while n denotes the number of support vectors.

4.2 Constraints and Result Output

According to relevant standards and practical engineering requirements, the mix ratio parameters for each constituent material are within the following ranges: the hydration parameter (water-to-cement ratio) was systematically controlled within the range of 0.3–0.55, a critical interval for achieving target compressive strengths and workability in cementitious composites; the sand content ranges from 35% to 46%, and the steel fiber volume ratio spans from 0% to 2%.The specific constraints for each variable are as follows: $160 \le x_1$(water)≤ 220, $342 \le x_2$(cement)<550, $557 \le x_3$(sand)<887, $0 \le x_4$(natural aggregate)≤ 1283, $0 \le x_5$(steel fiber)≤ 158, $3.2 \le x_6$(water reducer)≤ 5.5.

By applying the above iterative calculations, the optimal mix ratio for steel fiber reinforced concrete based on objective optimization was determined. Additionally, the compressive strength corresponding to various mix ratios is presented in Table 2.

Table 2. Steel Fiber Mix Ratio and Corresponding Compressive Strength Based on Target Optimization

number	water	cement	sand	Natural Aggregates	Steel Fiber	Water reducing agent	Compressive strength
1	171	316	757	536	77	3.15	35.6
2	171	438	739	506	77	4.38	48.7
3	171	549	698	478	77	5.5	64.3
4	167	406	742	1121	77	4.06	47.5
5	170	422	738	739	77	4.17	48.1
6	175	472	747	0	77	4.7	49.3
7	159	405	770	556	0	4.05	47
8	165	423	752	528	40	4.2	47.7
9	178	455	754	506	117	4.53	52.4
10	183	471	726	473	156	4.73	54.3

5. Conclusion

(1) This research established an ANN framework for predictive modeling of SFRC mix designs. The model integrates six compositional predictors—natural aggregate, cement content, water dosage, coarse

aggregate, steel fiber concentration, and water-reducing admixture—with the 28-day compressive strength serving as the response variable. Following ANN architecture calibration, iterative hyperparameter optimization was applied to training datasets, yielding a top-performing architecture with a near-unity correlation coefficient (R=0.983) between predicted and experimental strength values.

(2) Based on iterative calculations using the genetic algorithm, the optimal mix ratio for steel fiber reinforced concrete was determined through objective optimization, and the compressive strength for different mix ratios was also provided.

Fund Project

Qingdao City University - Secondary College research project, project number: CE240104

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