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A DATA-DRIVEN APPROACH FOR INVESTIGATING SHEAR STRENGTH OF SLENDER STEEL FIBER REINFORCED CONCRETE BEAMS

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Abstract

Using a data-driven approach to study and predict the shear strength of slender steel fiber reinforced concrete beams has great applicability for the design and construction process. Based on the data-driven approach, an Artificial Neural Network (ANN) model with some hyperparameters optimized by Particle Swarm Optimization (PSO) algorithm is successfully built. The hidden two-layer ANN model with the number of neurons (5; 6) predicted shear strength with higher accuracy than the models proposed previously in the literature, with $R^2 = 0.9727$ and $RMSE = 31.9822$ kN for the control dataset. By interpreting the results of the ANN model by the values of SHAP, including the Global SHAP value and SHAP independence plot, the order of influence of the variables on the shear strength value and the predictability of the ANN model can be arranged according to effective depth of section > beam width > longitudinal reinforcement ratio > steel fiber content > concrete compressive strength > shear span/effective depth ratio > fiber tensile strength > aggregate size. Fiber tensile strength and aggregate size almost do not affect the shear strength value. An increase in the shear span-to-effective depth ratio reduces shear strength, which can be increased by increasing the value of effective depth of section, beam width, longitudinal reinforcement ratio, steel fiber content, and concrete compressive strength. The results of this paper are meaningful in the initial assessment of the shear strength of SSFRC, which helps to speed up the design process and reduce the cost of designing and testing SSFRC beams.

Keywords: concrete beam; slender steel fiber reinforced concrete; shear strength; data-driven; machine learning; data-driven approach.

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1. Introduction

The shear behavior of slender steel fiber reinforced concrete (SSFRC) beams with cracks that have formed on slanted portions is challenging to predict. This is a result of the fact that the shear behavior of SSFRC beams is influenced by a variety of variables [1–5]. Therefore, it is necessary to model the interconnectedness of these several components in order to calculate shear strength. Accurate shear capacity prediction is essential because shear failure typically occurs suddenly and without warning [4]. Shear strength tests were carried out on thin beams without girders to assess the shear strength of SSFRC beams using a number of methodologies [6–9]. Key factors affecting the shear resistance of SSFRC beams, such as the beam width, effective depth of section, longitudinal reinforcement ratio, shear span-to-effective depth ratio, aggregate size, concrete compressive strength, fiber tensile strength, and steel fiber factor, are simultaneously estimated [10]. Therefore, there are many factors affecting the shear resistance of SSFRC, and the experimental effort is time-consuming and expensive.

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Different empirical models built on regression analysis based on experimental data have been proposed to solve this problem [11–13]. Based on empirical data, actual design standards like ACI 544 [14] are all statistically supported. However, in order to get a simplification of the nonlinear relationship between shear strength and associated variables, these models are utilized in combination with specific hypotheses. There are also reliable computational methods for tackling challenging issues, including modeling fractures [15–17]. In order to forecast the shear resistance of SSFRC beams, some investigations have also looked into models based on the finite element approach [18, 19]. However, due to the difficulty of the issue in general or the complexity of SSFRC beams in particular, anticipating its shear behavior requires substantial skill and highly programmable computers.

Machine learning (ML) algorithms have acquired appeal in many areas of life due to their effectiveness in tackling a wide range of extremely complicated issues, which is attributed to the rapid development of ML techniques [20–22]. Several researchers have utilized the ANN model, one of the ML techniques, to calculate the shear strength of SSFRC beams. One hundred fifty-five data samples and five input variables were used to create the ANN model in Oreta's work [23] to predict the strength of slender beams. An ANN was used in the study of Mansour et al. [24] to predict the shear strength of RC beams using a dataset of 176 data points and nine input variables. The results show that the ANN model can accurately forecast the shear strength of SSFRC beams. Shatnawi et al. [25] used the Gradient Boosting model for predicting the shear strength of SSFRC beams based on 330 data samples and eight input variables, such as beam width, effective depth of section, longitudinal reinforcement ratio, shear span-to-effective depth ratio, aggregate size, concrete compressive strength, fiber tensile strength, and steel fiber factor. The Gradient Boosting model can predict the shear strength of SSFRC with the performance metric $R^2 = 0.963$ by Shatnawi et al. [25]. Shariati et al. [26] developed a hybrid ML model artificial neural network-particle swarm optimization (ANN-PSO) to predict the channel shear connectors embedded in normal and high-strength concrete. Therefore, the ANN algorithm is selected for investigating the shear strength of SSFRC beams in this study.

While certain ML-based strategies may successfully address regression issues, it can be challenging to understand how they work because these models are sometimes referred to as "black-box" models. In order to assist researchers in better understanding the underlying mechanisms, such as how input parameters affect outputs and increase the persuasiveness of the developed models, ML-based models should thus be better explained or interpreted. To comprehend ML models, one might use the Shapley additive explanations (SHAP) framework developed by Lundberg and Lee [27]. In SHAP, characteristics are rated according to how they affect the predictions. By examining how the features affect the outputs for a single sample, SHAP can explain the ML models locally in addition to globally.

In this paper, an ML-based method for forecasting the shear strength of SSFRC beams is proposed. Additionally, input variables affecting the shear strength of the SSFRC beams are quantitatively examined by interpreting the ML model using SHAP. This study has two major goals, which are to build a high-performance ML model to predict the shear strength of SSFRC beams, and this ML model used as a foundation to assess the effects of input variables on the shear strength of SSFRC beams by SHAP independence plot technique, this has not been specified in previous studies of literature. Therefore, in order to achieve reliability when analyzing the influence of input variables on shear strength, a high-performance ML model with specific parameters needs to be established and strictly controlled. In order to achieve this, 330 shear strength samples of SSFRC beams with eight input variables, including aggregate size, concrete compressive strength, fiber tensile strength, steel fiber factor, longitudinal reinforcement ratio, and shear span-to-effective depth ratio, were collected from the literature. In addition, Particle Swarm Optimization and 10-Fold Cross Validation (CV) are used to fine-tune the ideal hyperparameters of ANN. Finally, the SHAP approach, which contains the global SHAP value and SHAP independent plot, was used to understand the built-in ANN model. The effects of various factors on the predicted value "shear strength" of the ANN model are also examined.

2. Database description and analysis

In order to build a high-performance ML model for calculating the shear strength of SSFRC, a database was derived from the investigation of Lantsoght [10]. This dataset includes 330 experimental results. The database contains eight input variables: beam width (b_w), effective depth of section (d), longitudinal reinforcement ratio (ρ), shear span-to-effective depth ratio (a/d), aggregate size (d_a), concrete compressive strength (f_c), fiber tensile strength (f_t), and steel fiber factor (F_{st}).

Table 1 shows the statistical values of input variables for building the ML model. The beam width ranges from 55 mm to 610 mm (mean of 158.40 mm; standard deviation of 68.35 mm). With a mean value of 283.71 mm and a standard deviation of 178.38 mm, the effective depth of section value ranges from 85.00 mm to 1118.00 mm. The longitudinal reinforcement ratio ranges from 0.0% to 5.7% (mean of 3.0%; standard deviation of 1.0%). The shear span-to-effective depth ratio ranges from 2.5 to 6.0 in the dataset (mean of 3.35, standard deviation of 0.64). The aggregate size varies from 0.40 mm to 22.00 mm, with a mean value of 10.50 mm and a standard deviation of 5.02 mm. The concrete compressive strength ranges from 9.8 MPa to 154.5 MPa (mean of 48.51 MPa; standard deviation of 24.43 MPa). The fiber tensile strength value varies between 260.0 MPa and 4913.0 MPa, with a mean value equal to 1270.99 MPa and a standard deviation of 471.76 MPa. The percentage volume, dimension, and length of steel fibers can be represented by the steel fiber factor, which has a range of values from 0.10 to 2.86 with a mean value of 0.53 and a standard deviation of 0.34. Finally, the output variable of the shear strength of SSFRC beams ranges from 13.0 kN to 1430.0 kN, with a mean value of 150.85 kN and a standard deviation of 163.95 kN.

Table 1. Statistical value of input variables for building ML model

Variable	Abbre.	Unit	Mean	Std	Min	Max
Beam width	b_w	mm	158.40	68.35	55.00	610.00
Effective depth of section	d	mm	283.71	178.38	85.00	1118.00
Longitudinal reinforcement ratio	ρ	%	3.00	1.00	0.00	5.70
Shear span-to-effective depth ratio	a/d	-	3.35	0.64	2.50	6.00
Aggregate size	d_a	mm	10.50	5.02	0.40	22.00
Concrete compressive strength	f_c	MPa	48.51	24.43	9.80	154.50
Fiber tensile strength	f_t	MPa	1270.99	471.76	260.00	4913.00
Steel fiber factor	F_{st}	-	0.53	0.34	0.10	2.86
Shear strength	V_u	kN	150.85	163.95	13.00	1430.00

One of the main criteria for determining the importance and applicability of input variables is the correlation between input variables and shear strength. As a result, Fig. 1 shows the description of data distribution between input variables and shear strength of SSFRC beams, and each description is plotted by a linear correlation line. By the linear correlation, it is worth noting that the shear strength of SSFRC beams depends strongly on the beam width and effective depth of section, which positively affect the shear strength value. Other input variables also have influences on the shear strength of SSFRC beams. This suggests that the dataset's eight input variables should be considered independent. These eight input variables are used to determine the influences of each input variable on the beam's shear strength.

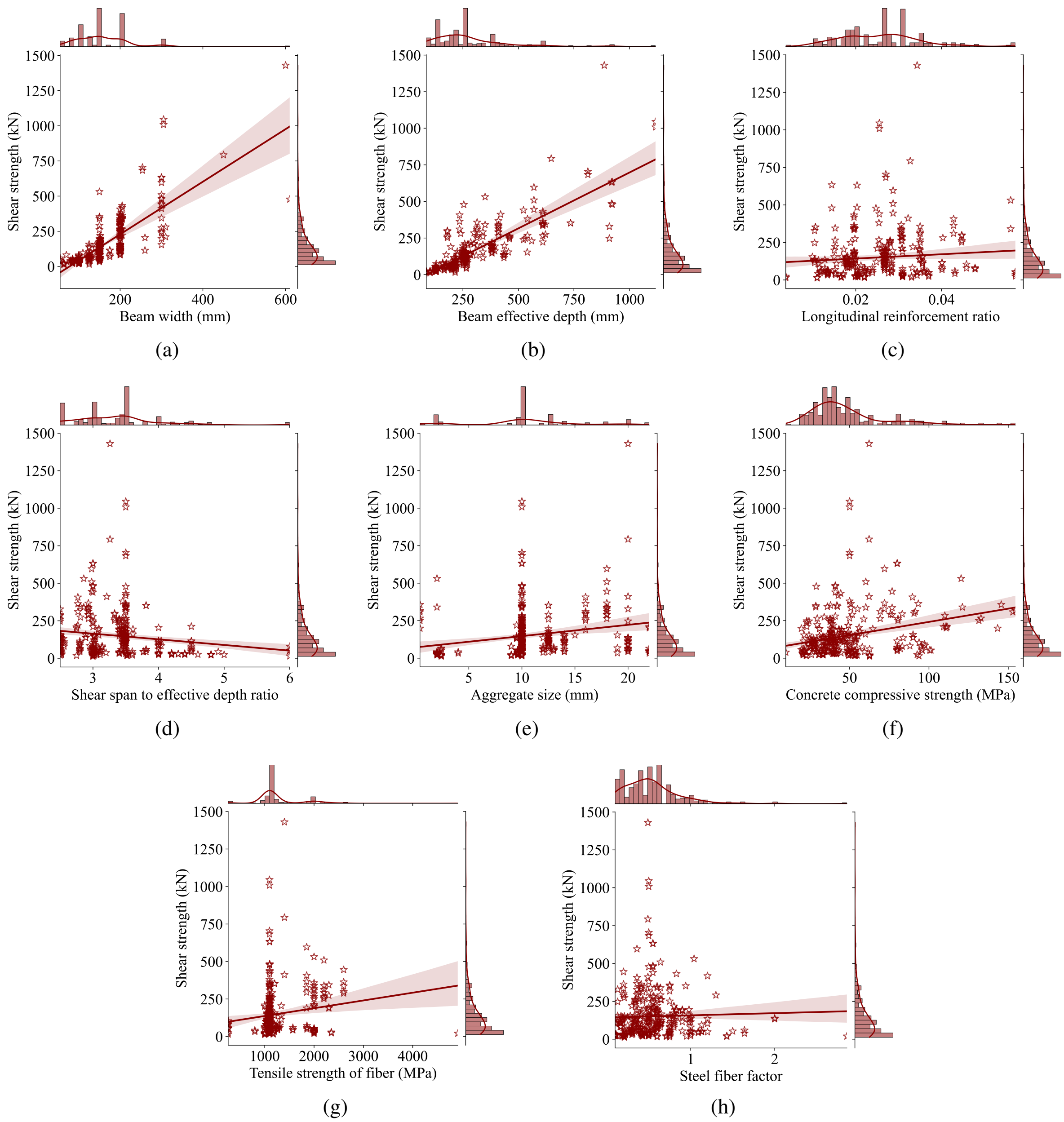


Figure 1. Distribution between input variables and shear strength of SSFRC beams

It is challenging to adequately explain the impact of the input elements on the compressive strength of steel fiber concrete using a linear correlation. Therefore, SHAP methods for further analyzing these relationships are provided in section 4.3 of this study.

Two subsets of the data used in this investigation are: the training dataset, which comprises 70% of the total experimental samples (231), is used to create ML models. The testing dataset, which comprises 30% of the total experimental samples (99 samples), is used to assess the performance of the proposed ML model.

3. Data-driven approach

3.1. Machine learning algorithms with hybrid ANN-PSO

a. Artificial Neural Network

Artificial neural networks are computational architectures inspired by the physiology of animal brains, which are made up of several parallel basic processors (neurons) coupled by a system of axons and dendrites that allows for the interchange of simple signals. In the case of an ANN, linkages become links, and neurons become units, greatly simplifying the structure of the brain. Similar to neurons, ANN nodes are interconnected with one another. The output of a node is a signal when the input crosses a threshold. A kind of ANN called a multi-layer perceptron [28] establishes many layers of neurons. Input, output, and hidden layers are the three categories that these layers fall under. The supplied database's input layers are made up of all the input parameters, while the output layers are made up of the output parameters. Between the input and output levels are processing layers known as hidden layers. The layers are linked to one another and have various weights attached to them. Artificial neural networks are taught using a learning function, which updates the ANN every time the error exceeds a certain tolerance. Fig. 2 illustrates the ANN algorithm's parts and operation. Section 4 contains comprehensive information on the ANN parameters utilized in this investigation.

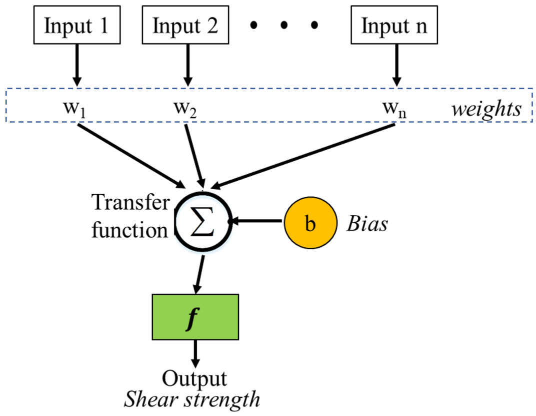


Figure 2. Simple structure of ANN algorithm

b. Particle Swarm Optimization

Particle swarm optimization is an intelligence-based metaheuristic method. It is modeled by the social behaviors of a swarm of flying birds hunting for food Considering how social animal groups behave, Kennedy and Eberhart [29] hypothesized that sharing knowledge within the group enhances the chance of survival. In order to maximize food availability and reduce the chance of encountering predators, for instance, a flock of flying birds must choose a spot to rest. This presents a difficult problem.

The objective of a swarm, which is made up of some particles moving in a high-dimensional solution space, is to discover the best (optimal) solution. A function that may have numerous local maximum values and lowest values is often maximized or minimized during optimization. Fig. 3 depicts particle movement in the PSO algorithm.

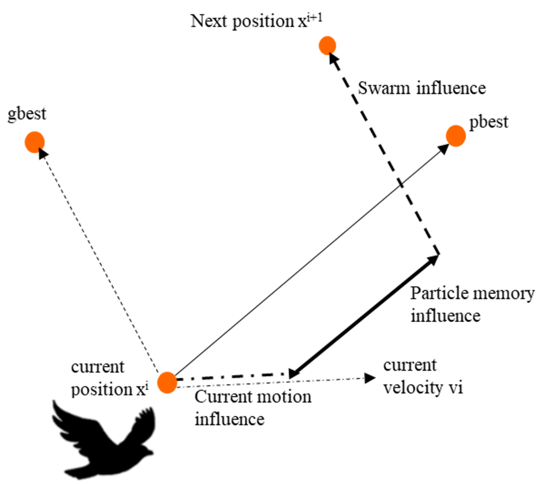


Figure 3. Simple structure of PSO algorithm

c. Hybrid ANN-PSO

The minimization problem that results from ANN training can be resolved using optimization techniques. In a hybrid ANN-PSO algorithm, the optimization algorithm is used to determine the ideal weights-biases for the ML model to increase the accuracy of the ANN. The flowchart of the hybrid ANN-PSO algorithm is briefly described in Fig. 4. As a result, the weights-biases are the variables, and the range of these variables' variations determines the issue's feasible space. The coefficient of determination may be used to define the fitness value of the particle i^{th}. These procedures can be taken to create a hybrid ANN-PSO model: Create an initial neural network with weights-biases based on the neuron number of each hidden layer. Then, updating the weights-biases may depict where a particle is located in the search space value. Finally, by predicting the output values of a specific particle in an iteration, the PSO method updates particle locations over a predetermined population number until the cost function "coefficient of determination" is maximized.

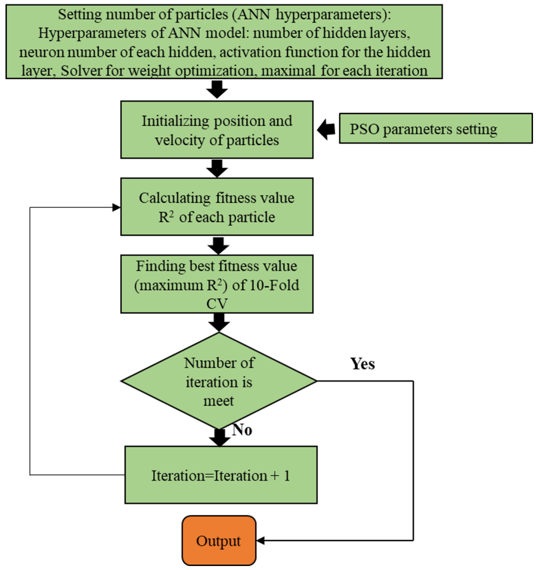


Figure 4. Flowchart of hybrid ANN-PSO algorithm

According to Blanke [30], the optimal parameters of the PSO algorithm can be considered as population size = 50, inertia = 0.4, cognitive_weight = 0.7, social_weight = 0.7, temp_weight = 0.3, rand_rest_p = 0.05. Moreover, the number of particles, such as ANN hyperparameters, consists of the number of hidden layers, neurons number of each hidden, activation function for the hidden layer, solver for weight optimization, and maximal for each iteration. Search space values of these particles will be detailed in the next section.

3.2. *Performance evaluation of machine learning model*

The ML model's predictive power is evaluated using various well-known and frequently used statistical measures, such as root mean squared error (*RMSE*), mean absolute error (*MAE*), and coefficient of determination (R^2). The R^2 values, ranging from 0 to 1, are an important consideration in regression analysis. It is determined by the square of the correlation between the predicted and actual results. A high R^2 value, therefore, denotes a good correlation between the expected and actual values. The samples' dispersion was described using *RMSE*. The lower the *RMSE*, the better the nonlinear fitting will be. The *MAE* is a more inclusive term for the mean of errors and stands for the mean of absolute errors. *RMSE* and *MAE* have the same dimension; however, the results show that *RMSE* is greater than *MAE*. This is due to the fact that *RMSE* squares the error twice, enlarging the gap between the bigger mistakes. The *MAE* accurately depicts the mistake. Because its value might represent the greatest and relatively tiny mistake in the measurement, the smaller the *RMSE* number, the higher the relevance. The values of these measures are expressed as follows:

$$R^2 = 1 - \left[\frac{\sum_{j=1}^{N} \left(a_j - b_j\right)^2}{\sum_{j=1}^{N} \left(a_j\right)^2} \right] \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(a_j - b_j\right)^2} \tag{2}$$

$$MAE = \frac{1}{N}\sum_{j=1}^{N}\left|a_j - b_j\right| \tag{3}$$

$$a_{25} = \frac{n_{25}}{N} \tag{4}$$

where: a is the output's actual value, b is the model's predicted value, and N is the number of samples in the database. Moreover, Apostolopoulou et al. [31] propose using an a-index to assess the correctness of ML models. In this study, the index is considered to be 25%. Therefore, n_{25} is the sample size with True value/Predicted value varying from 0.75 to 1.25. It displays the proportion of samples that achieve expected results with a 25% maximum deviation from experimental results.

4. Results and Discussion

4.1. Optimization of ANN hyperparameters

The ANN algorithm has many hyperparameters that need to be refined. However, in order to reduce the computation time, the selected hyperparameters and search space values for fine-tuning include the following:

(i) The activation function for the hidden layer, including identity, logistic, tanh, and relu functions.

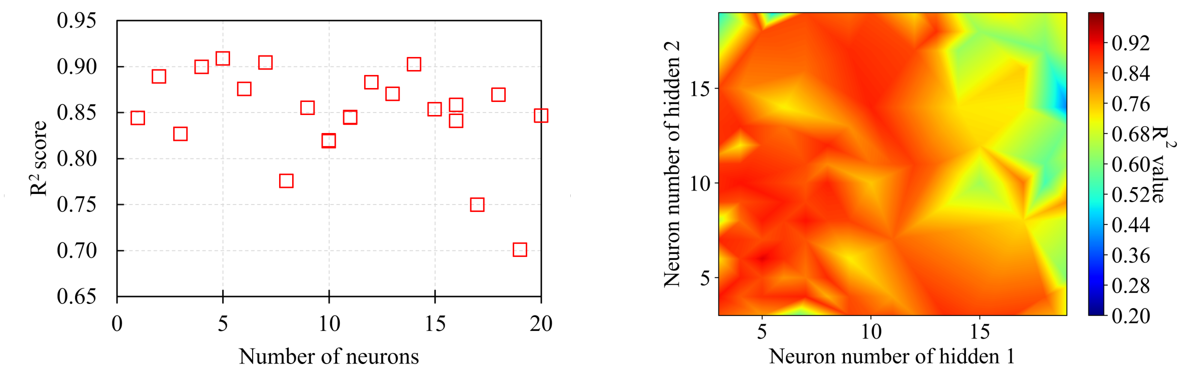
(ii) Solver for weight optimization, including L-BFGS (Limited-Memory Broyden–Fletcher–Goldfarb–Shanno), SGD (Stochastic Gradient Descent), and Adam (Adaptive moment estimation).

(iii) Maximal for each iteration varying from 1000 to 30000.

(iv) Number of hidden layers: one hidden layer, two hidden layers.

(v) Number of neurons for each hidden layer from 1 to 20.

The cost function for the PSO optimization function is the maximizer coefficient of determination, the value of the remaining hyperparameters using the default value proposed in the Sklearn library [32].



(a) ANN one hidden layer (b) ANN two hidden layers

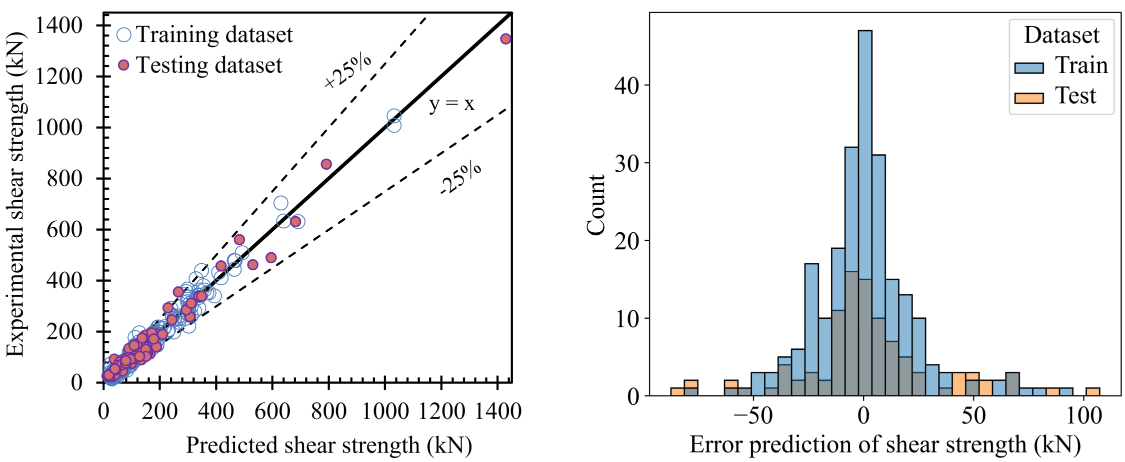
Figure 5. Cost function R^2 depending on the number of neurons

R^2 is aggregated as the value of a 10-Fold CV. The hyperparameters of ANN models are tuned in 2000 iterations, and the hyperparameters are defined as activation function ='relu', solver = 'L-BFGS' for both cases of using one and two hidden layers. Fig. 5 shows the cost function R^2 depending on the number of neurons: (a) one hidden layer and (b) two hidden layers. Fig. 5(a) shows the number of neurons varying from 1 to 20 in a single hidden layer. It can be seen that a neuron count of 5 gives a maximum R^2 value of 0.9085 for a hidden layer and a maximum of 5000 iterations, respectively. Fig. 5(b) shows that the R^2 value changes when the number of neurons in the two hidden layers changes from 1 to 20. When both hidden layers use up to 20 neurons, the R^2 value domain is lower when the number of neurons in the two hidden layers is small (less than 15 neurons). For two hidden layers, maximal iteration equals 14000, hidden layer 1 using 5 neurons, and hidden layer 2 using 6 neurons ANN (5; 6), the R^2 value of the largest ANN model is equal to 0.9287 higher than that of ANN containing 5 neurons for only 1 hidden layer. Therefore, an ANN model with a hidden layer structure consisting of 5 neurons for hidden layer 1 and 6 neurons for hidden layer 2, with activation function 'relu', solver for weight optimization 'L-BFGS', and maximal iteration = 14000 are proposed in predicting the shear strength of SSFRC beams.

4.2. Predicting Shear strength of SSFRC using the ANN model

Use the ANN model with the structure and fine-tuned hyperparameters proposed in section 4.1 to predict the shear strength of SSFRC beams. The shear strength prediction results using the proposed ANN model are compared with the actual shear strength results. The comparison is shown through the correlation data in Fig. 6(a) and the prediction error in Fig. 6(b). This comparison is performed simultaneously for both the training and testing datasets.

Fig. 6(a) shows the correlation between the shear strength value predicted by the ANN model and the actual shear strength value within the range of values bounded by the ±25% error line, with many points lying asymptotically on the perfect line $y = x$. This is true for both training and testing data sets. Therefore, the prediction error of the ANN model, as shown in Fig. 6(b), shows that the error is mainly concentrated in the ±50 kN region. Minimal error approaching 0 kN has the largest number. The predictive accuracy of the ANN model is quantified through the values $R^2 = 0.9767$, $RMSE$ = 22.752 kN, MAE = 15.5608 kN, and $a_{25} = 0.8448$ for the training dataset, while $R^2 = 0.9727$, $RMSE$ = 31.9822 kN, MAE = 21.5267 kN, and $a_{25} = 0.7677$ for the testing dataset. This accuracy is higher than the Gradient Boosting model proposed by Shatnawi et al. [25], in which $R^2 = 0.9630$, despite using the same database and input variables.



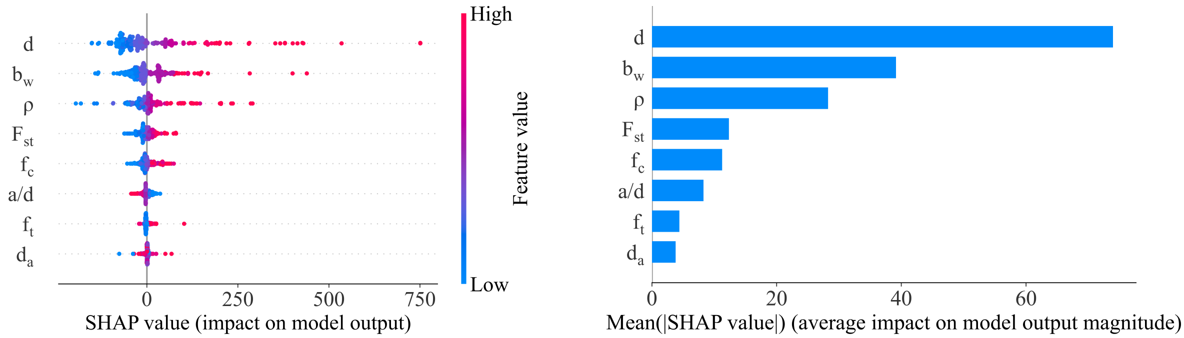
(a) Correlation data

(b) Error prediction of ANN model

Figure 6. Comparison between experimental and predicted compressive strength of steel fiber concrete

4.3. Investigation of factors affecting the shear strength of SSFRC beams

To better explain the predictive principle and predictive power of the ANN model, as well as to evaluate the factors affecting in general, specifically each factor to the shear strength of SSFRC beams, the SHAP global and SHAP independent plot values are shown in Figs. 7 and 8, respectively.



(a) (b)

Figure 7. Global SHAP value for interpreting input effect on the predicted shear strength

Specifically, Fig. 7(a) allows determining the relative quantification of the influence of eight input variables on the shear strength value through the colors showing the magnitude of each variable. The *y*-axis in Figs. 7(a) and 7(b) indicates the importance of each input variable to the model's predictive accuracy. The higher the position of the input variable, the higher the importance. The larger the size, the stronger the influence on the accuracy of the model and the shear strength value. Figs. 7(a) and 7(b) show that the order of influence of the variables on the shear strength value and the predictability of the ANN model can be arranged in descending order as follows: effective depth of section > beam width > longitudinal reinforcement ratio > steel fiber content > concrete compressive strength> shear span-to-effective depth ratio > fiber tensile strength > aggregate size.

The aggregate size and the fiber tensile strength have a negligible and obvious effect on the shear strength of SSFRC beams, as indicated in Fig. 7(a), Fig. 8(g), and Fig. 8(h). Meanwhile, the effective depth of section, beam width, longitudinal reinforcement ratio, steel fiber content, and compressive strength of concrete have a positive effect on the shear strength of SSFRC beams. This means that when the values of these input variables increase, the shear strength will increase (cf. Fig. 7(a)). Conversely, among the input variables, the a/d ratio has a negative effect on the shear strength as its value increases.

Fig. 8(a) shows that when the effective depth of section increased from 100 mm to 900 mm, shear strength increased by about 600 kN. Similarly, with beam width increased from 50 mm to 450 mm, shear strength increased by about 400 kN, as indicated in Fig. 8(b). When the global SHAP value is zero, the actual shear strength equals the mean shear strength shown in Table 1. The upward trend in the influence of d and b_w on the shear strength tends to be relatively linear. If we exclude the outlier domain of longitudinal reinforcement ratio (values greater than 5%), the upward trend in shear strength by longitudinal reinforcement ratio is relatively linear with a 120 kN SHAP value variation, as shown in Fig. 8(c). The steel fiber factor value is from 0.1 to 1.5, and the shear strength value can be increased by 100 kN, as indicated in Fig. 8(d). The increase in concrete compressive strength from 25 MPa to 150 MPa causes a linear increase in the shear strength in the range of 85 kN, as shown in Fig. 8(e). The a/d ratio seems to have a nonlinear effect on the shear strength when its values range from 2.5 to 5. However, if observed over the whole range studied $2.5 < a/d < 6$, the rule shear strength decline is relatively linear with a variation of about 50 kN, as can be seen in Fig. 8(f).

It can be seen that, based on the value of the SHAP independence plot (Fig. 8), it is possible to investigate the influence of each variable on the ability to contribute the value of the shear strength of SSFRC beams in the design process.

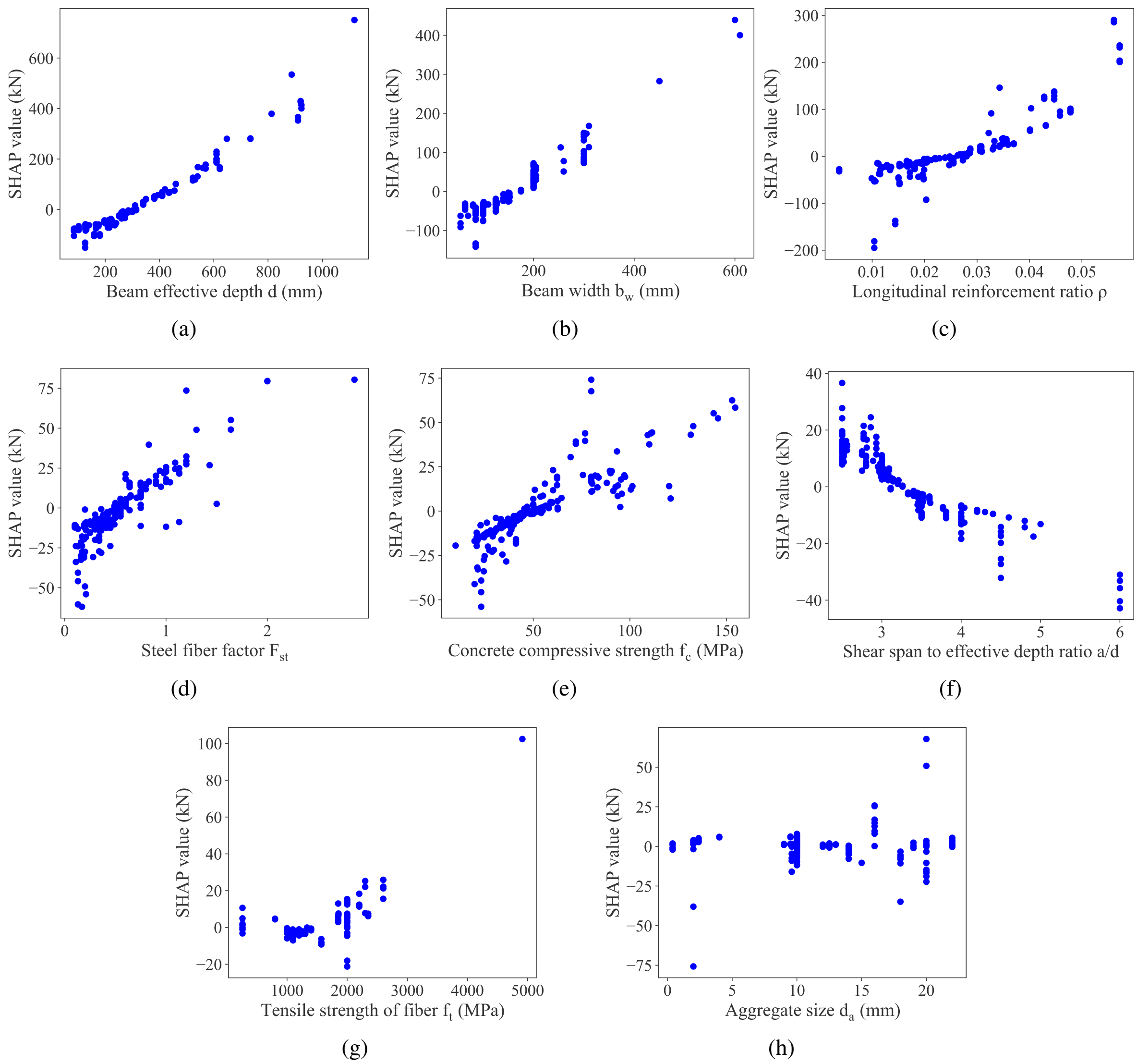


Figure 8. Partial dependence plot in analyzing the influencing factors

5. Conclusions and Perspectives

The study has successfully developed an approach of data-driven to studying the shear strength of SSFRC beams. Based on a database of 330 data samples and eight input variables (beam width, effective depth of section, longitudinal reinforcement ratio, shear span-to-effective depth ratio, aggregate size, concrete compressive strength, fiber tensile strength, steel fiber factor), a hybrid machine learning model between ANN and PSO algorithms have been successfully established to select hyper-parameters for the model. The ANN includes activation function 'relu', solver of weight optimization 'L-BGFS', two hidden layers with the number of neurons (5; 6), and maximal iteration 14000.

A 10-Fold CV is used to validate the reliability of the ANN-PSO machine learning model. With the proposed hyperparameters, the shear strength of SSFRC beam prediction accuracy is higher than in previous studies, with $R^2 = 0.9727$, $RMSE = 31.9822$ kN, $MAE = 21.5267$ kN, and $a_{25} = 0.7677$ for the control dataset.

By interpreting the results of the ANN model by the values of SHAP, including Global SHAP value and SHAP independence plot, the order of influence of the variables on the shear strength value and the predictability of the ANN model can be arranged according to the effective depth of section > beam width > longitudinal reinforcement ratio > steel fiber content > concrete compressive strength > shear span-to-effective depth ratio > fiber tensile strength > aggregate size. In which fiber tensile strength and aggregate size have almost no effect on the shear strength value. An increase in the shear span-to-effective depth ratio reduces shear strength, which can be increased by increasing the value of effective depth of section, beam width, longitudinal reinforcement ratio, steel fiber factor, and concrete compressive strength.

The results of this paper are meaningful in the initial assessment of the shear strength of SSFRC, which helps to speed up the design process and reduce the cost of designing and testing SSFRC beams.

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