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Robust Prediction of Shear Strength of SFRC Using Artificial Neural Networks

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Abstract: The assessment of shear behavior in SFRC beams is a complex problem that depends on several parameters. This research aims to develop an artificial neural network (ANN) model that has six inputs nodes that represent the fiber volume (V_f), fiber factor (F), shear span to depth ratio (a/d), reinforcement ratio (ρ), effective depth (d), and concrete compressive strength (f_c') to predict shear capacity of steel fiber-reinforced concrete beams, using 241 data test gathered from previous researchers. The proposed ANN model provides a good implementation and superior accuracy for predicting shear strength compared to previous literature, with a Root Mean Square Error (RMSE) of 0.87, the average ratio ($v_{test}/v_{predicted}$) of 1.00, and the coefficient of variation of 22%. It was shown from parametric analysis the reinforcement ratio and shear span to depth ratio contributed the most impact on the shear strength. It can also be noticed that all parameters have a nearly linear impact on the shear strength except the shear span to depth ratio has an exponential effect.

Keywords: steel fibers reinforced concrete beam; shear stress; ANN model; durability

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1. Introduction

Steel fiber-reinforced concrete (SFRC) is a structural material having a short and discrete steel fiber spread randomly through the concrete mixture to improve the mechanical properties of concrete such as the compressive strength, shear strength, and ductility [1]. The use of SFRC enhances the crack resistance by reducing crack propagation and crack width due to small spacing between fibers, resulting in bridging the diagonal tension crack and performance shear strength (Anant and Modhera 2008) [2]. SFRC also helps the concrete to change its behavior from a brittle to a ductile material.

For several years, great effort has been devoted to the study of the shear behavior of SFRC beams. The majority of the studies have shown the use of SFRC beams with no stirrups is influenced by different parameters including longitudinal reinforcement ratio (ρ), shears span to depth ratio (a/d), concrete compressive strength (f_c'), fiber factor F, and beam effective depth (d). Kwak et al. [3] studied the effect of shear span to depth ratios of 2, 3, and 4 and the fiber volume fraction (F) up to 0.75% on the shear strength. It was concluded that the ultimate shear strength increased with an increase in compressive strength, decreased with increasing span to depth ratio (a/d), and increased with fiber volume (V_f). Similarly, Sway and Bahia [4] studied the effect of longitudinal reinforcement ratio (ρ), concrete compressive strength (f_c'), and fiber volume (V_f) up to 1.2% on the shear strength of SFRC beams without stirrups. It was found that the steel fiber enhances the ultimate shear strength by increasing the fiber volume. Similar to conventional reinforced concrete beams, the shear strength of SFRC beams increases with increasing the compressive strength. Shahnewaz and Alam [5] studied the effect of compressive strength on the shear capacity of steel fiber-reinforced concrete beams. The obtained result indicated that the shear strength increased exponentially with increasing the compressive strength of concrete.

Narayanan and Darwish (1988) concluded that there is an exponential relationship between the ultimate shear strength and shear span to depth ratio where the shear strength decreases with increasing the shear span to depth ratio due to the anchorage between support and point load [6].

Researchers have proposed several models for predicting the shear strength of SFRC beams based on a calibration with experimental data. Some of these models were derived based on linear regression analysis using limited data from experimental results. Therefore, these models are not capable of predicting the average shear stress with enough precision and trustworthiness for a wide range of variables.

Sustainability in construction requires a design that focuses on durability throughout the functional life cycle. As mentioned earlier the steel fibers positively impact the concrete durability by reducing the crack propagation and crack width. The structure of steel fibers enhances the abrasion and freeze-thaw resistance. In addition, using steel fiber instead of steel reinforcement reduced the CO_2 emissions that contribute to preserving the environment. Adding the steel fiber to the marine concrete structure also delays the crack propagation and increases the flexural strength that causes reducing the corrosion of steel by reducing the growth and width of the crack, therefore, reducing the chloride penetrations.

To exploit the advantages of using steel fibers and ensure structural safety, it is essential to develop reliable models for predicting the shear capacity of steel fiber-reinforced concrete (SFRC) beams without stirrups. Artificial intelligence (AI) models have gained a lot of attention in the last two decades because of the accuracy and dependability of these data-driven approaches.

As a result, researchers used various artificial intelligence methods like artificial neural networks (ANN), Genetic algorithms (GP), and Bayesian networks to solve many complex structural engineering problems, such as estimating the compressive strength of confined concrete and determining the displacement of the reinforced concrete building. The focus of this study is to develop a reliable design model for predicting the shear stress of SFRC beams using an Artificial neural network (ANN), based on a large number of experimental data results. The study also aims to compare it with some of the models existing in the literature and to conduct a parametric study to evaluate the effect and contribution of each of the affecting variables on the shear strength of SFRC beams.

2. Background of Empirical Equation and Model

Many empirical equations have been proposed in the literature for predicting the shear strength of the SFRC beam. For instance, in 1986 Sharma [7] developed a simple empirical model to predict shear strength based on the result of his experimental, the model proposed in Equation (1)

$$v_u = k f_t' \left(\frac{d}{a}\right)^{0.25} \text{ (MPa)} \tag{1}$$

$$f_t' = 0.79 \left(f_c'\right)^{0.5} \text{ (MPa)} \tag{2}$$

where:

v_u is an average shear strength, k is a constant equal to $\frac{2}{3}$, f_t' is a tensile strength of concrete, and *a/d* is span to depth ratio. As shown in Equation (1), Sharma ignores some important parameters such as volume fiber and reinforcement ratio that are significantly influencing the shear strength.

Narayan and Darwish in 1987 [8] suggest another model for estimating the average shear stress based on the result of 33 tests on the beam without shear reinforcement and with SFRC presented in Equation (3).

Where the f_{spcf} is the computed value of split cylinder strength of fiber concrete, τ_f is the average fiber-matrix interfacial bond stress, F_{cuf} is the cube strength of fiber, F is the fiber factor, and e is the arch action factor equal to 1 if $\frac{a}{d} > 2.8$ and equal $2.8\left(\frac{d}{a}\right)$ for $\frac{a}{d} \leq 2.8$

$$v_u = e\left[0.24 f_{spfc} + 80\rho\frac{d}{a}\right] + v_b \text{ (MPa)} \tag{3}$$

$$f_{spfc} = \frac{f_{cuf}}{20 - \sqrt{F}} + 0.7 + \sqrt{F} \text{ (MPa)} \tag{4}$$

$$v_b = 0.41\tau_f \text{ (MPa)} \tag{5}$$

Another design model was also proposed by Ashour et al. (1992) [9] by testing 18 samples of high-strength SFRC beams presented in Equation (6). It was noticed that similarities between its equation with ACI building code with change in constants.

$$v_{cf} = \left(0.7\sqrt{f_c'} + 7F\right)\frac{d}{a} + 17.2\rho\frac{d}{a} \text{ (MPa)} \tag{6}$$

A later study by Kwack et al. [3] proposed another empirical formula based on 139 tests. This model presented a result with higher accuracy when compared with the previous formulas because it depended on a larger data test and included most of the parameters. This model is presented in Equation (7).

Where $e = 1$ if $\frac{a}{d} > 3.4$ and $e = 3.4(a/d)$ for $\frac{a}{d} \leq 3.4$

$$v_{cf} = 3.7e\, f_{spfc}^{\frac{2}{3}} \left(\rho\frac{d}{a}\right)^{\frac{1}{3}} + 0.8v_b \text{ (MPa)} \tag{7}$$

Over the years, several researchers developed many new models for estimating the shear strength of SFRC beams without stirrups using Artificial intelligence models like ANN and GEP modeling. In 2005 Adhikary and Mutsuyoshi and Khuntia and Stojadinovic [10,11] proposed two models for predicting the shear capacity of steel fibers-reinforced concrete beams using ANN programming. One of the models contains four variables while the second model contains five variables. The final result obtained was that the model which contains five variables estimated the shear capacity of SFRC beams more accurately than the model with four variables.

Another design model was also developed by Alumwsawi (2018) to predict the shear strength using the hybrid ANN with particle swarm optimization (PSO) based on an 85-beam test. The result showed that the hybrid model ANN-PSO achieved good accuracy in the prediction of shear strength in SFRC beams and the model attained values of correlation coefficients and roots mean square error (RMSE) 0.82 and 0.567, respectively [12]. In 2011 Arafa et al. [13] developed the ANN model for predicting the shear strength in normal and deep beams. It was found that the developed ANN has higher accuracy in predicting shear strength when compared with the ACI code. Later studies by Ahmadi et al. proposed a new model using Gene Expression Programming (GEP) and ANN model based on 129 test results for estimating the shear strength of SFRC beams with no stirrups. It was concluded that the average shear stress can be calculated using GEP and ANN modeling with a mean absolute percentage error (MAPE) of 11.27 [14].

3. Artificial Neural Networks Programming

Artificial neural networks (ANNs) are predictive tools used to create a mathematical model for a problem in which the solution is too complex. Multi-layer perception (MLP) ANN [15] is the most known type of Artificial neural network. MLP networks consist of at least three layers: one input layer, one output layer, and one or more hidden layers. Each layer has one or more processing units (neurons) and contains a number of nodes. Each unit in the multi-layer perception (MLP) is fully connected to units in subsequent layers through weighted connections (w_{ij}) [16] Once processing units receive the information it combines with others coming from different units through a combination function then the combined data are sent to the following nodes. This process is repeated until the algorithm fits the data precisely indicated by the convergence of the error rate. The output is attained by passing the sum of the inputs and weights throughout an activation function [17].

The artificial neural network must be trained from a set of data called the training set. There are many available algorithms used to train ANN. The feed-forward back-propagation has been widely used in many studies for this purpose. During the training stage, weight vector and biases are calibrated to minimize the model error and produce the most precise prediction (lowest root mean square error RMSE). The Bayesian regularization training algorithm was used to provide generalization and prevent overfitting.

4. ANN Model and Experimental Data Collection

Developing a neural network model for predicting the shear strength of SFRC beams requires experimental data. These data were gathered from literature reviews. The data collected consists of 241 test results from 21 experimental works. The experimental data collected has been summarized in Table 1, and the data range and number of points have been illustrated in Figure 1. The detailed experimental database is listed in Appendix A.

Table 1. Collected data used for creating an ANN model.

Reference	No. of Tests	$F = V_f\ (l/d)$	ρ_t, %	d, mm	f'_c, MPa	a/d
[18]	4	0.27–0.55	0.75–1.32	202–437	19.3–21.3	3–3.1
[8]	17	0.38–1.13	0.37–4.58	215	92–101.3	1–6
[19]	43	0.10–1.1	3.09	127	33.2–40.2	1.2–5
[20]	3	0.6–1.0	1.95	261	23.8–32.9	3.45
[21]	5	0.47–0.56	3.08–4.93	255–300	110–1112	1.75–4.5
[3]	9	0.31–0.47	1.5	212	30.8–68.8	2–4
[22]	6	0.60–1.0	1.1–2.2	102–204	22.7–26.0	1.5–3
[23]	6	0.3–0.6	1.1–2.2	221	34	1.5–3.5
[24]	9	0.30–0.45	1.34–2	197	20.6–33.4	2.0–3.6
[25]	8	0.24–0.9	2.15	557	40.8–56	1.35
[26]	7	0.17–0.66	1.22	186	28.7–32.8	2–3
[10]	29	0.25–2.0	2–5.72	126–130	28.8–52.6	2–3.5
[6]	11	0.25–1.33	3.55	345	30.2–54.6	0.46–0.93
[27]	19	0.4–0.64	2.87–4.47	180–570	39.4–93.3	2.77–3.33
[28]	2	0.4–0.8	2.68	150	38.7–42.4	2–2.67
[29]	6	0.33–0.66	3.59	175	80.0	2–4.5
[30]	32	0.4–0.98	2.67	251	24.9–64.6	3.49
[4]	4	0.4–1.2	3.05–4	210	35.5–39.8	4.50
[31]	7	1	1.55–4.31	265	33.1–40.9	2–4.91
[32]	4	0.3–0.6	3.89	340	33–36	1.5–2.5
[33]	10	0.50	2.5–3.0	254–1118	29–50	3.45–3.61

Matlab Software has been utilized to develop the model. The structure of the developed ANN model consists of three layers with several nodes. One input layer consists of six neurons presented in the steel fiber factor (F), the volume fraction of steel fiber (V_f), depth of the beam (d), reinforcement ratio (ρ), shear span to depth ratio (a/d), and the compressive strength of concrete (f'_c). The output layer consists of one neuron that represents the predictive shear strength of the steel fibers reinforced concrete beam. Six hidden layers consisting of three neurons were utilized in the proposed model.

To ensure that the developed model is generalizable and to prevent overfitting, the software separates the available data into two datasets training and testing datasets. In this study, 80% of available data was randomly selected for the training set and 20% for the testing and validation set. The training sets are used in creating the ANN model whereas the training sets are used in testing the generalization of the model.

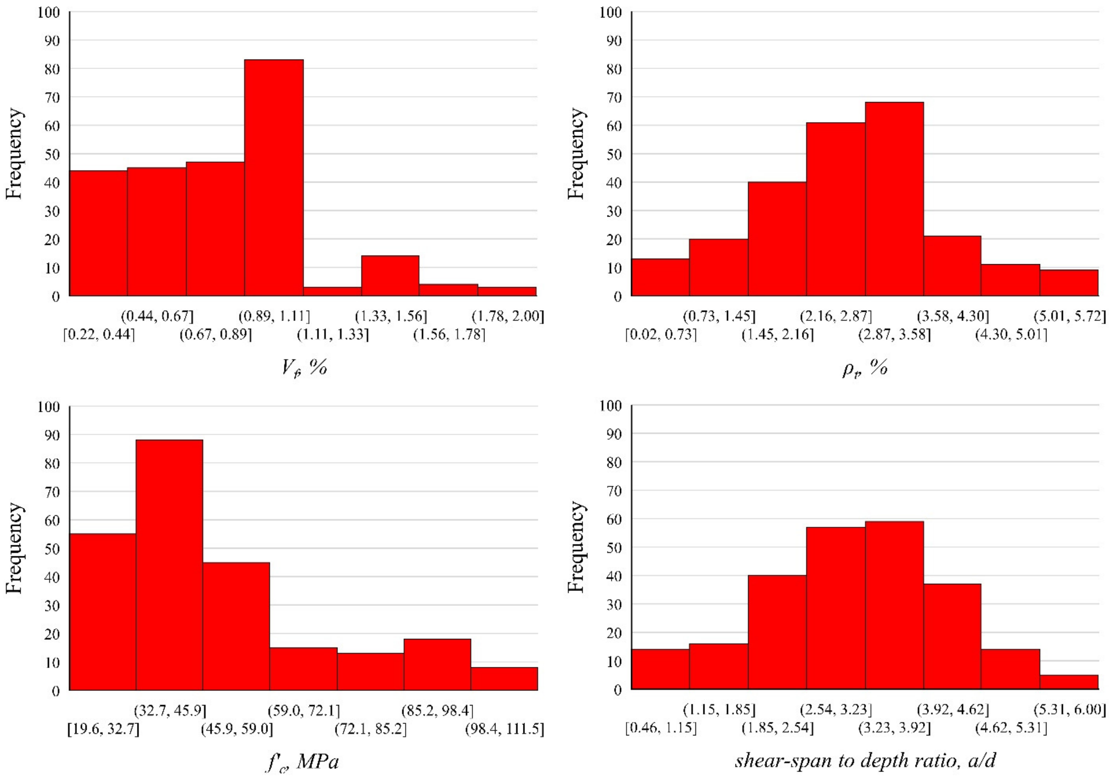

Figure 1. Experimental data range and number for each parameter.

5. Results and Discussion

The developed artificial neural network model was used to evaluate the influence of parameters like fiber volume, concrete cylinder compressive strength, longitudinal reinforcement ratio, effective depth, and shear span-to-depth ratio on the shear strength of SFRC beams. The model is fed by these input parameters to predict the shear strength.

The relation between the experimental shear strength and the prediction shear strength using the ANN model for 241 test results is shown in Figure 2, which shows a good agreement between the prediction shear strength and the experimental results.

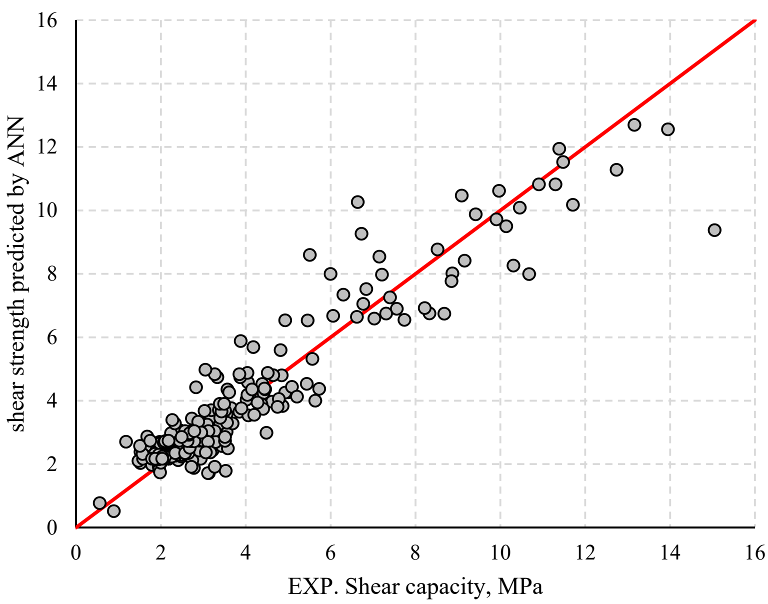

Figure 2. Experimental versus predicted shear strength using the ANN model.

Figure 3 represents a comparison between the developed ANN model and some of the previously existing models like Kwak et al. [3], Sharma [7], Narayanan and Darwish (1987) [10], and Ashour et al. [8], in terms of an average shear strength ratio of the experimental data to the predicted data ($v_{test}/v_{predicted}$), root-mean-squared error (RMSE), and coefficient of variation (COV). The root mean square error is calculated according to Equation (8). From this figure, it can be seen that the ANN model has the lowest values of RMSE and COV of (0.87, 0.22) respectively, and the average ratio of the tested shear strength to estimated shear strength ($v_{test}/v_{predicted}$) of (1.00). The developed ANN model has better accuracy than other models. According to statistical analysis, lower values of RMSE and COV indicate a higher prediction accuracy. The higher prediction accuracy for the ANN model can be attributed to the Bayesian algorithm embedded in software that minimizes the error between the input and output. In addition, ANN provides more model flexibility than conventional regression.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(v_{test} - v_{predicted}\right)^2} \tag{8}$$

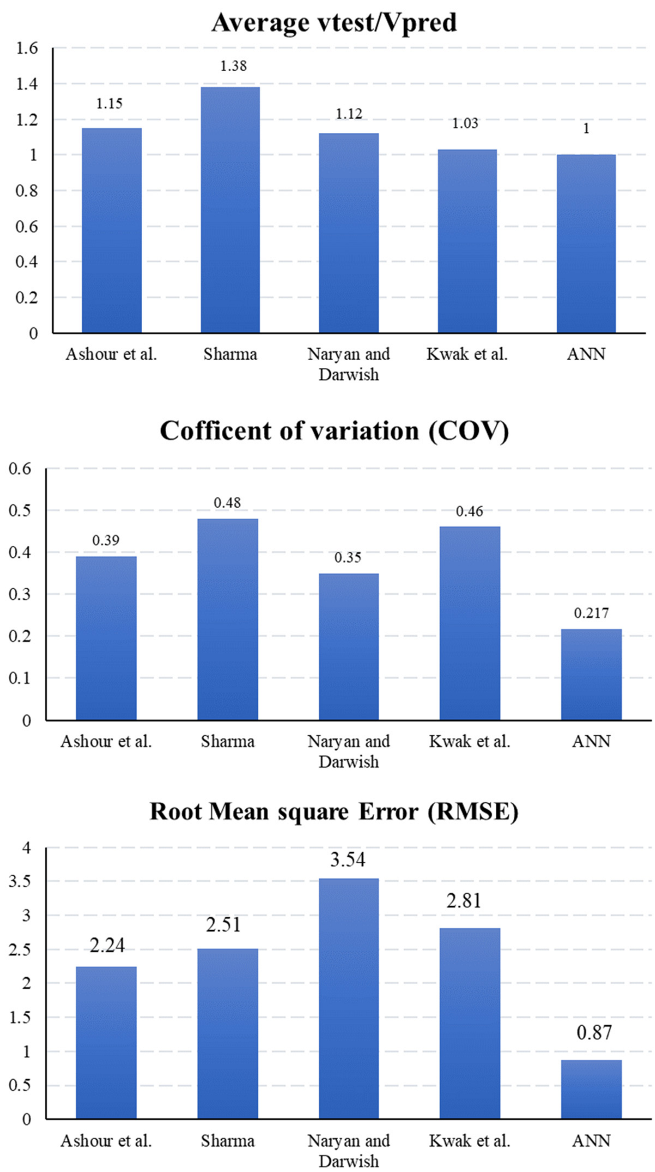

Figure 3. Comparison between proposed ANN model and other experimental models.

In addition, the accuracy of the proposed model was determined by drawing the ratio of tested shear strength to estimated shear strength ($v_{test}/v_{predicted}$), with respect to each of the parameters that are illustrated in Figure 4. The flattering trend line shows accurate and consistent forecasts for the entire range of variables.

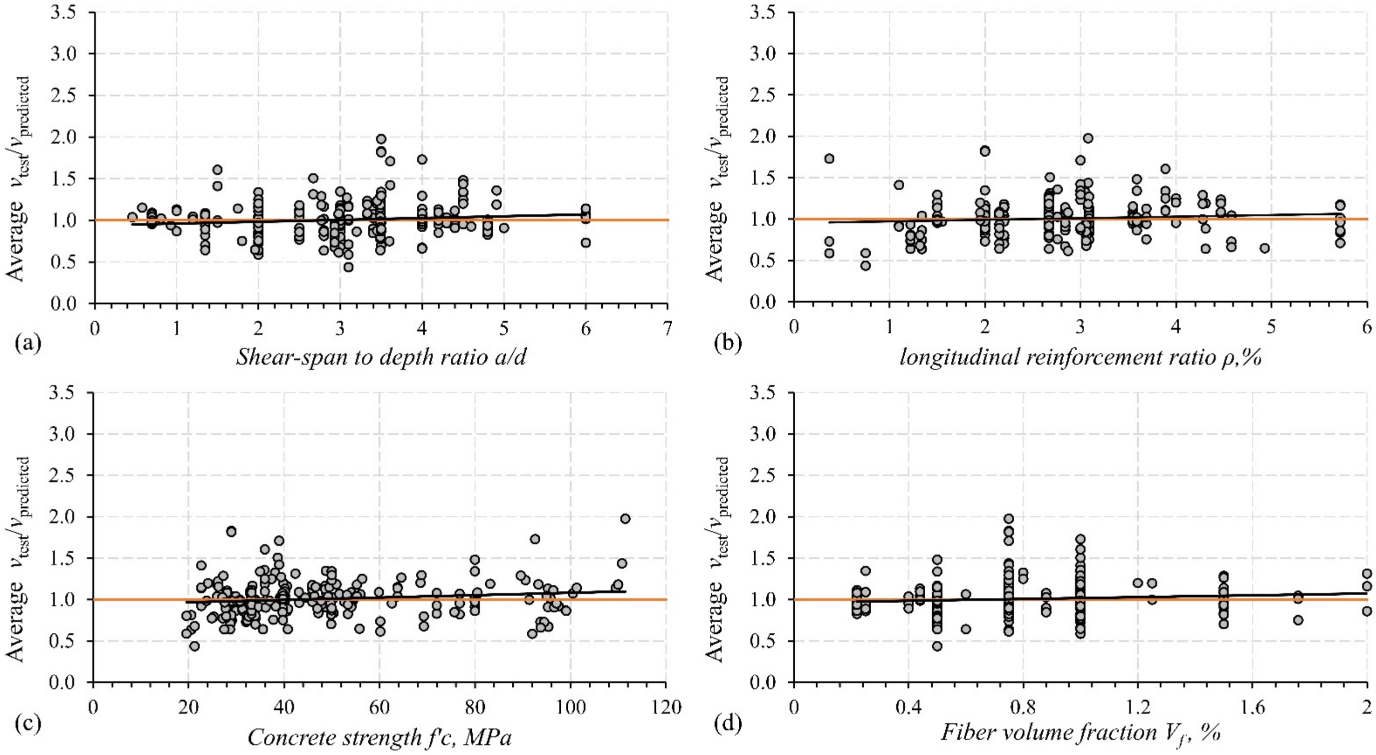

Figure 4. Ratio of ($v_{test}/v_{predicted}$) versus (**a**) shear span to depth ratio, (**b**) longitudinal reinforcement ratio, (**c**) concrete strength, and (**d**) fiber volume fraction. (Black line: trendline, Orange line: perfect fit line).

6. Parametric Analysis

The parametric analysis is performed with the developed artificial neural network to evaluate the effect of each input parameter on the shear strength. The effect was examined by varying only one parameter and fixing all other parameters.

6.1. Effect of Volume Fraction of Steel Fiber V_f %

The effect of the volume fraction of steel fibers on the shear strength is shown in Figure 5. The reinforcement ratio ρ, concrete compressive strength f_c', shear span to depth ratio (*a/d*), and the depth of the beam were kept constant. The figure shows the shear strength increase with increased volume fraction of steel fibers. It was also indicated that the effect of volume fraction on the shear strength is negligible for volume fractions larger than 1.5%.

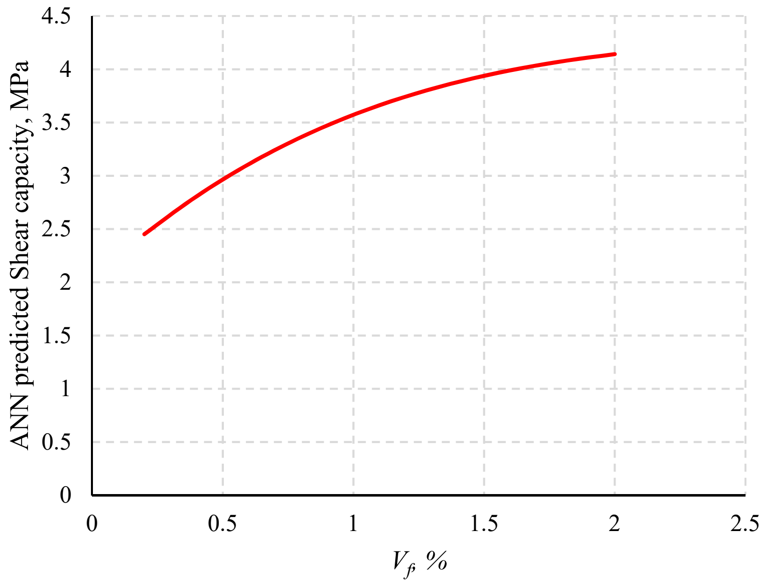

Figure 5. Effect of volume fraction of steel fibers on the predicted shear capacity.

6.2. Effect of Reinforcements Ratio (ρ)

Figure 6 shows the influence of varying the reinforcement ratio on the shear capacity of SFRC beams by fixing all other parameters. this figure indicates the shear capacity increase linearly with an increased reinforcement ratio (ρ) due to the dowel action can be considerably improved. It can be seen that the ANN model confirms the effect of reinforcement of steel ratio on shear strength, whereas some formulations Sharma [7], and Kuntia et al. [6] completely ignore its important role.

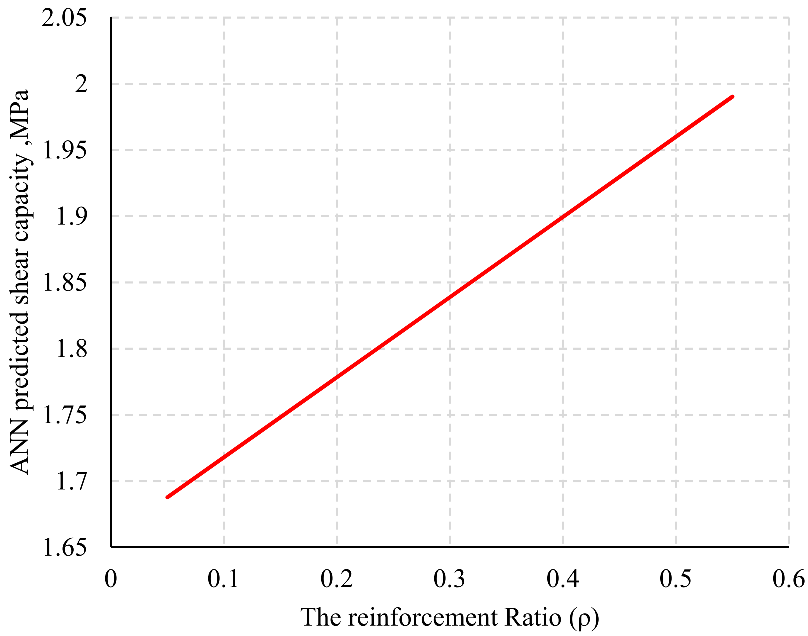

Figure 6. Effect of reinforcement ratio on the predicted shear strength.

6.3. Effect of Effective Depth (d, mm)

The influence of changing the effective depth (d, mm) on the shear strength is shown in Figure 7. The reinforcement ratio, concrete compressive strength f'_c, and all other input parameters were kept constant for this study. This figure shows the shear strength decrease with increased effective depth of the beam. This is similar to the findings of Appa Rao [33].

This figure also indicates that the decrease in shear strength converges to a constant value at a depth larger than 500 mm.

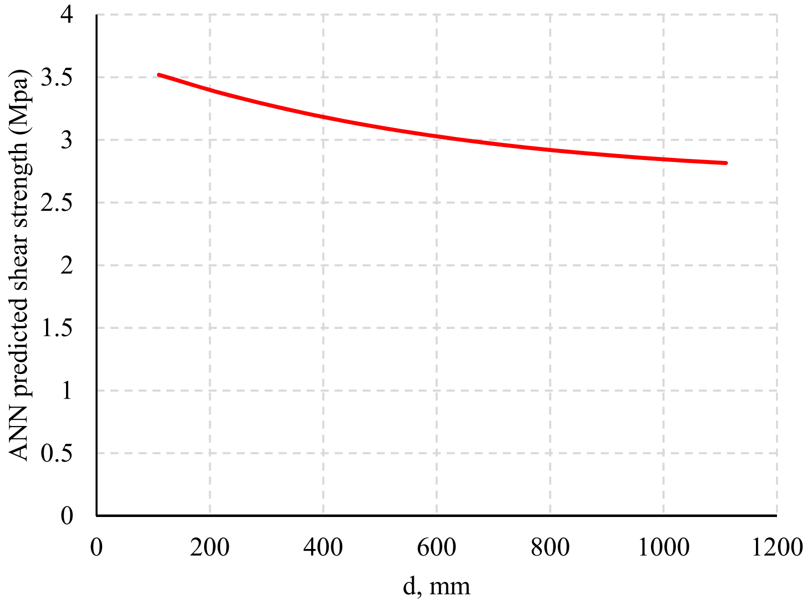

Figure 7. Effect of the effective depth on the predicted shear capacity.

6.4. Effect of Concrete Compressive Strength, f'_c

Figure 8 shows the effect of changing the concrete compressive strength on the shear strength of SFRC beams. The reinforcement ratio ρ, the depth of the beam, and fiber volume were kept fixed for purpose of analysis. It was found that the shear strength increases slightly linearly with increased compressive strength.

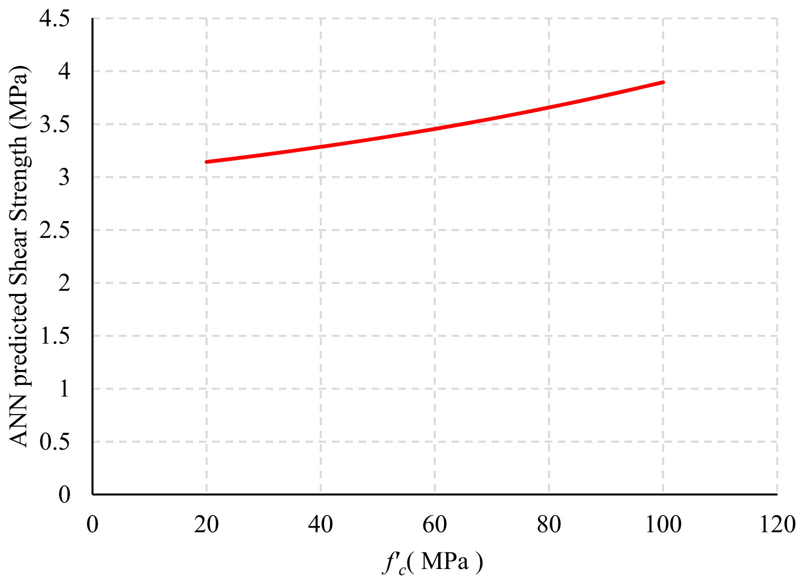

Figure 8. Effect of concrete compressive strength on the shear strength.

6.5. Effect of Shear Span to Depth Ratio (a/d)

The influence of varying shear span to depth ratio on the shear strength of SFRC beams is plotted in Figure 9. The reinforcement ratio, compressive strength of concrete, depth of the beam, and fiber volume were kept constant for this study. This figure shows that with increased (*a*/*d*) ratio, the shear strength decreased exponentially. This result is consistent with the Narayanan and Darwish [6,10]. Similarly, recent studies have also discussed similar behavior [34–40]. The adopted procedure for evaluating each of the variables has been wildly utilized in research [41–55].

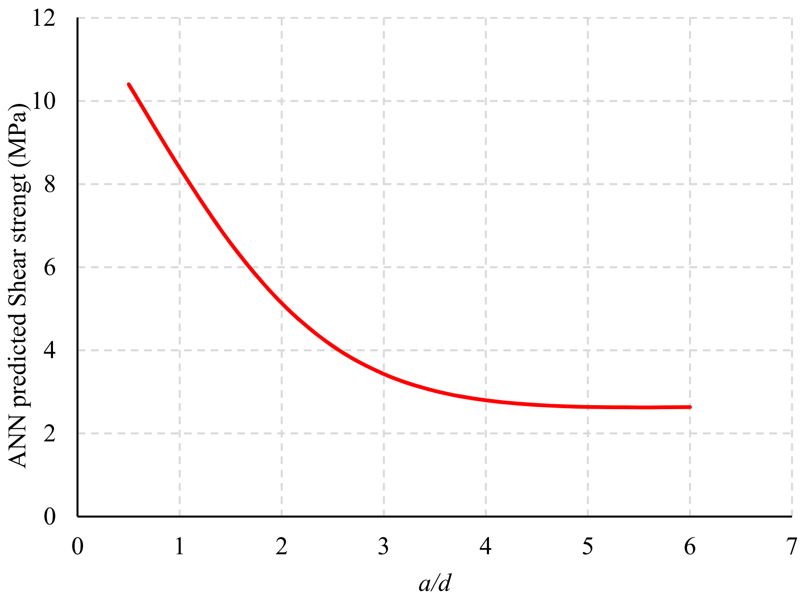

Figure 9. Effect of span to depth ratio on the predicted shear strength.

7. Conclusions

The artificial neural network is improved and used to forecast the shear capacity of steel fiber-reinforced concrete beams based on 241 datasets gathered from previous researchers. The ANN model's parameters were reinforcement ratio (ρ), fiber volume fraction V_f, concrete compressive strength, effective depth, shear span to depth ratio (*a/d*), and fiber factor. The proposed ANN model provides a good implementation and superior accuracy for predicting shear strength compared to previous literature, with Root Mean Square Error (RMSE) of 0.87, the average ratio of the tested shear strength to estimated shear strength ($v_{test}/v_{predicted}$) of (1.00), and the Coefficient of Variation of 22%.

The parametric analysis shows the predicted shear capacity of steel fiber-reinforced concrete beams increase with increased reinforcement ratio (ρ), concrete cylinder compressive strength (f_c'), and volume fraction of steel fibers. However, it was noticed that the shear strength of SFRC beams decreased with an increase in the effective depth and span to depth ratio. In addition, it can be noticed that all parameters have a nearly linear impact on the shear strength except for shear span to depth ratio has an exponential effect.

It can also be concluded that adding the fibers to reinforcing concrete enhances the improvement of some characteristics of concrete, such that the tensile strength, post-peak behavior, ductility, and abrasion resistance.

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Informed Consent Statement: Not applicable.

Data Availability Statement: Experimental database is included in Appendix A. Model data is available from authors upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Collected Database

Table A1. Collected Experimental Database.

Reference	V_f, %	$F = V_f\ l/d$	ρ_t, %	d, mm	f'_c,MPa	a/d	EXP Shear Capacity, MPa
[22]	1.00	0.60	2.20	102	22.70	3.00	3.16
	1.00	0.60	1.10	102	22.70	3.00	2.43
	1.00	0.60	1.10	102	22.70	1.50	5.64
	1.00	1.00	2.20	102	26.00	3.00	3.55
	1.00	0.60	2.20	204	22.70	3.00	3.05
	1.00	1.00	2.20	204	26.00	3.00	3.05
[24]	0.50	0.30	1.34	197	29.10	2.00	2.54
	0.50	0.30	1.34	197	29.10	2.80	1.78
	0.50	0.30	1.34	197	29.10	3.60	1.52
	0.75	0.45	2.00	197	29.90	2.80	2.20
	0.75	0.45	2.00	197	20.60	2.80	2.03
	0.75	0.45	2.00	197	33.40	2.80	2.91
	0.75	0.45	1.34	197	29.90	2.00	2.88
	0.75	0.45	1.34	197	29.90	2.80	2.03
	0.75	0.45	1.34	197	20.60	2.80	1.52
[23]	0.50	0.30	1.10	221	34.00	2.50	1.79
	0.50	0.30	2.20	221	34.00	1.50	4.02
	0.50	0.30	2.20	221	34.00	2.50	1.90
	0.50	0.30	2.20	221	34.00	3.50	1.47
	1.00	0.60	2.20	221	34.00	1.50	4.39
	1.00	0.60	2.20	221	34.00	2.50	2.46
[10]	0.25	0.25	2.00	130	48.80	2.00	2.96
	0.25	0.25	2.00	130	48.80	2.50	2.67
	0.25	0.25	2.00	130	48.80	3.00	2.77
	0.25	0.25	2.00	130	31.36	2.00	2.71
	0.25	0.25	2.00	130	31.36	2.50	2.07
	0.25	0.25	2.00	130	31.36	3.00	1.94
	0.50	0.67	2.00	130	48.64	3.00	3.23
	1.00	1.33	2.00	130	52.64	3.00	3.66
	0.50	0.67	2.00	130	28.80	3.00	1.97
	1.00	1.00	2.00	130	29.20	3.00	2.97
	0.50	0.67	2.00	130	48.64	2.00	4.62
	0.50	0.67	2.00	130	48.64	2.50	3.69
	0.50	0.67	2.00	130	39.20	3.50	2.61
	1.00	1.33	2.00	130	45.84	2.00	5.57
	1.00	1.33	2.00	130	45.84	2.50	4.42
	1.00	1.33	2.00	130	45.92	3.50	2.97
	0.50	0.67	3.69	128	39.20	3.00	2.96
	0.50	0.67	5.72	126	39.20	3.10	3.55
	0.50	0.67	3.69	128	28.80	3.00	2.24
	0.50	0.67	5.72	126	28.80	3.10	2.33
	1.00	1.33	3.69	128	45.92	3.00	4.37
	1.00	1.33	5.72	126	45.92	3.10	5.00
	1.50	1.50	5.72	126	50.40	3.10	4.85
	2.00	2.00	5.72	126	40.64	3.10	4.93
	1.50	1.50	3.69	128	50.40	3.00	4.46
	0.50	0.50	5.72	126	47.20	2.00	5.46
	1.00	1.00	5.72	126	43.20	2.00	6.77
	1.50	1.50	5.72	126	50.40	2.00	7.15
	2.00	2.00	5.72	126	40.64	2.00	6.30

Table A1. *Cont.*

Reference	V_f, %	$F = V_f\ l/d$	ρ_t, %	d, mm	f'_c, MPa	a/d	EXP Shear Capacity, MPa
[8]	1.00	0.00	0.37	215	92.00	2.00	1.68
	1.00	0.00	0.37	215	92.60	4.00	0.89
	1.00	0.00	0.37	215	93.70	6.00	0.56
	0.50	0.00	2.84	215	99.00	1.00	9.09
	0.50	0.00	2.84	215	99.10	2.00	4.82
	0.50	0.00	2.84	215	95.40	4.00	2.27
	0.50	0.00	2.84	215	95.83	6.00	1.95
	1.00	0.00	2.84	215	95.30	1.00	12.74
	1.00	0.00	2.84	215	95.30	2.00	6.06
	1.00	0.00	2.84	215	97.53	4.00	3.17
	1.00	0.00	2.84	215	100.50	6.00	1.96
	1.50	0.00	2.84	215	96.40	1.00	13.95
	1.50	0.00	2.84	215	96.60	2.00	7.21
	1.50	0.00	2.84	215	97.10	4.00	3.51
	1.50	0.00	2.84	215	101.32	6.00	1.98
	1.00	0.00	4.58	215	94.50	2.00	6.73
	1.00	0.00	4.58	215	93.80	4.00	3.88
	1.00	0.00	4.58	215	95.00	6.00	2.93
[4]	0.80	0.80	3.05	210	38.16	4.50	3.22
	0.40	0.40	4.00	210	35.52	4.50	2.16
	0.80	0.80	4.00	210	37.44	4.50	3.10
	1.20	1.20	4.00	210	39.84	4.50	3.13
[6]	0.25	0.50	3.55	345	43.12	0.70	9.16
	0.50	1.00	3.55	345	51.60	0.70	10.14
	0.75	1.00	3.55	345	49.76	0.70	9.42
	1.00	1.00	3.55	345	46.40	0.70	10.46
	1.25	1.00	3.55	345	54.56	0.70	11.48
	1.00	1.25	3.55	345	53.60	0.70	11.39
	1.00	0.25	3.55	345	49.28	0.46	13.16
	1.00	0.00	3.55	345	46.64	0.58	11.71
	1.00	0.00	3.55	345	44.48	0.81	9.91
	1.00	0.25	3.55	345	47.92	0.93	9.97
	1.00	1.33	3.55	345	30.24	0.70	8.52
[29]	0.50	0.33	3.59	175	80.00	2.00	6.84
	0.50	0.33	3.59	175	80.00	3.00	3.19
	0.50	0.33	3.59	175	80.00	4.50	2.78
	1.00	0.66	3.59	175	80.00	2.00	7.40
	1.00	0.66	3.59	175	80.00	3.00	4.10
	1.00	0.66	3.59	175	80.00	4.50	3.44
[26]	0.50	0.17	1.22	186	28.70	2.00	1.64
	0.50	0.33	1.22	186	32.20	2.00	1.94
	1.00	0.33	1.22	186	29.00	2.00	2.18
	1.00	0.33	1.22	186	32.10	3.00	1.58
	1.00	0.66	1.22	186	32.30	3.00	1.98
	1.50	0.50	1.22	186	32.80	3.00	2.42
	1.00	0.66	1.22	186	32.60	2.00	2.73
[28]	1.00	0.40	2.68	150	38.70	2.67	4.49
	2.00	0.80	2.68	150	42.40	2.67	5.73
[31]	1.00	0.00	4.31	265	35.60	2.00	5.51
	1.00	0.00	4.31	265	40.88	3.43	4.05
	1.00	0.00	4.31	265	36.00	4.91	2.92
	1.00	0.00	2.76	265	37.76	2.00	4.93
	1.00	0.00	2.76	265	33.12	3.43	3.13
	1.00	0.00	2.76	265	35.92	4.91	2.94
	1.00	0.00	1.55	265	35.68	2.00	4.65

Table A1. *Cont.*

Reference	V_f, %	$F = V_f\ l/d$	ρ_t, %	d, mm	f'_c,MPa	a/d	EXP Shear Capacity, MPa
[25]	0.75	0.00	2.15	557	54.10	1.35	3.30
	1.50	0.00	2.15	557	49.90	1.35	3.87
	0.40	0.00	2.15	557	55.00	1.35	2.44
	0.60	0.00	2.15	557	56.00	1.35	2.77
	0.75	0.00	2.15	557	54.10	1.35	2.84
	1.50	0.00	2.15	557	49.90	1.35	3.33
	0.60	0.00	2.15	557	40.80	1.35	2.83
	0.40	0.00	2.15	557	47.00	1.35	2.95
[32]	0.50	0.00	3.89	340	35.00	2.00	10.68
	0.75	0.00	3.89	340	33.00	2.00	8.87
	1.00	0.00	3.89	340	36.00	2.00	10.31
	1.00	0.00	3.89	340	36.00	2.50	7.56
	1.00	0.00	3.89	340	36.00	1.50	15.05
[3]	0.50	0.00	1.50	212	63.80	2.00	5.09
	0.75	0.00	1.50	212	68.60	2.00	5.44
	0.50	0.00	1.50	212	62.60	3.00	3.09
	0.75	0.00	1.50	212	63.80	3.00	3.40
	0.50	0.00	1.50	212	63.80	4.00	2.41
	0.75	0.00	1.50	212	68.80	4.00	2.74
	0.50	0.00	1.50	212	30.80	2.00	4.04
	0.50	0.00	1.50	212	30.80	3.00	2.55
	0.50	0.00	1.50	212	30.80	4.00	2.00
[18]	0.50	0.00	1.32	202	21.30	3.00	1.57
	1.00	0.00	1.32	202	19.60	3.00	1.86
	0.50	0.00	0.75	437	21.30	3.10	1.18
	1.00	0.00	0.75	437	19.60	3.10	1.51
[20]	0.75	0.00	1.95	261	32.90	3.45	2.77
	1.00	0.00	1.95	261	23.80	3.45	2.38
	1.25	0.00	1.95	261	24.10	3.45	2.90
[19]	0.22	0.00	3.09	127	33.22	4.80	2.18
	0.22	0.00	3.09	127	33.22	4.80	2.18
	0.22	0.00	3.09	127	33.22	4.80	2.10
	0.22	0.00	3.09	127	33.22	4.80	2.18
	0.22	0.00	3.09	127	33.22	4.80	2.18
	0.22	0.00	3.09	127	33.22	4.80	2.10
	0.22	0.00	3.09	127	33.22	4.80	2.10
	0.22	0.00	3.09	127	33.22	4.40	2.49
	0.22	0.00	3.09	127	33.22	4.20	2.49
	0.22	0.00	3.09	127	33.22	4.20	2.18
	0.22	0.00	3.09	127	33.22	4.20	1.95
	0.22	0.00	3.09	127	33.22	4.30	2.34
	0.22	0.00	3.09	127	33.22	4.30	2.18
	0.44	0.00	3.09	127	40.21	4.20	2.57
	0.44	0.00	3.09	127	40.21	4.00	2.57
	0.44	0.00	3.09	127	40.21	4.00	2.42
	0.44	0.00	3.09	127	40.21	4.00	2.57
	0.22	0.00	3.09	127	33.22	4.40	2.26
	0.22	0.00	3.09	127	33.22	4.40	2.10
	0.22	0.00	3.09	127	33.22	4.00	2.34
	0.22	0.00	3.09	127	33.22	4.00	2.42
	0.22	0.00	3.09	127	33.22	4.00	2.57
	0.22	0.00	3.09	127	33.22	4.60	2.03
	0.22	0.00	3.09	127	33.22	4.40	2.10
	0.22	0.00	3.09	127	33.22	4.40	2.03
	0.22	0.00	3.09	127	33.22	5.00	1.95

Table A1. *Cont.*

Reference	V_f, %	$F = V_f\, l/d$	ρ_t, %	d, mm	f'_c,MPa	a/d	EXP Shear Capacity, MPa
[19]	0.22	0.00	3.09	127	33.22	4.80	1.79
	0.44	0.00	3.09	127	40.21	4.00	2.49
	0.44	0.00	3.09	127	40.21	4.20	2.65
	0.44	0.00	3.09	127	40.21	4.20	2.34
	0.44	0.00	3.09	127	40.21	4.20	2.57
	0.88	0.00	3.09	127	39.72	3.20	2.88
	0.88	0.00	3.09	127	39.72	3.40	2.73
	0.88	0.00	3.09	127	39.72	3.40	2.57
	0.88	0.00	3.09	127	39.72	3.40	3.27
	0.88	0.00	3.09	127	39.72	3.40	3.12
	1.76	0.00	3.09	127	39.79	2.80	4.44
	1.76	0.00	3.09	127	39.79	1.80	6.00
	1.76	0.00	3.09	127	39.79	1.20	11.30
	1.76	0.00	3.09	127	39.79	1.20	10.91
	0.22	0.00	3.09	127	33.22	4.80	1.95
	0.22	0.00	3.09	127	33.22	4.80	1.87
	0.22	0.00	3.09	127	33.22	4.80	2.03
[27]	1.00	0.00	4.47	180	90.60	3.33	8.33
	1.00	0.00	4.47	180	83.20	3.33	8.22
	0.50	0.00	4.47	180	80.50	3.33	7.03
	0.75	0.00	4.47	180	80.50	3.33	7.31
	1.00	0.00	3.09	195	39.40	3.08	4.87
	1.00	0.00	4.28	235	91.40	2.77	6.62
	1.00	0.00	4.28	235	93.30	2.77	7.74
	1.00	0.00	4.28	235	89.60	2.77	8.68
	1.00	0.00	3.06	410	76.80	2.93	3.57
	1.00	0.00	3.06	410	76.80	2.93	4.15
	1.00	0.00	3.06	410	72.00	2.93	4.52
	1.00	0.00	3.06	410	72.00	2.93	4.04
	0.50	0.00	3.06	410	69.30	2.93	3.27
	0.50	0.00	3.06	410	69.30	2.93	3.85
	0.75	0.00	3.06	410	60.20	2.93	4.18
	0.75	0.00	3.06	410	75.70	2.93	3.61
	1.00	0.00	2.87	570	76.80	2.98	2.68
	1.00	0.00	2.87	570	72.00	2.98	3.56
	0.75	0.00	2.87	570	60.20	2.98	3.05
[21]	0.75	0.00	3.08	300	109.50	1.75	8.85
	0.75	0.00	3.08	300	110.00	2.50	4.78
	0.75	0.00	3.08	300	111.50	3.50	3.53
	0.75	0.00	3.08	300	110.80	4.50	3.58
	1.00	0.00	4.93	255	55.84	1.96	6.64
[30]	0.75	0.00	2.67	251	28.10	3.49	3.03
	0.75	0.00	2.67	251	25.30	3.49	2.12
	1.00	0.00	2.67	251	27.90	3.49	2.92
	1.00	0.00	2.67	251	26.20	3.49	3.29
	1.50	0.00	2.67	251	28.10	3.49	2.97
	1.50	0.00	2.67	251	27.30	3.49	3.51
	0.50	0.00	2.67	251	27.50	3.49	1.75
	0.50	0.00	2.67	251	24.90	3.49	2.07
	0.75	0.00	2.67	251	27.80	3.49	2.44
	0.75	0.00	2.67	251	27.30	3.49	2.71
	1.00	0.00	2.67	251	26.30	3.49	3.11
	1.00	0.00	2.67	251	27.10	3.49	2.79
	0.75	0.00	2.67	251	53.40	3.49	3.03
	0.75	0.00	2.67	251	54.10	3.49	3.37
	1.00	0.00	2.67	251	53.20	3.49	3.85

Table A1. *Cont.*

Reference	V_f, %	$F = V_f\ l/d$	ρ_t, %	d, mm	f'_c,MPa	a/d	EXP Shear Capacity, MPa
[30]	1.00	0.00	2.67	251	55.30	3.49	4.41
	1.50	0.00	2.67	251	64.60	3.49	5.21
	1.50	0.00	2.67	251	59.90	3.49	4.28
	0.50	0.00	2.67	251	47.80	3.49	3.40
	0.50	0.00	2.67	251	49.50	3.49	4.06
	0.75	0.00	2.67	251	55.30	3.49	3.90
	0.75	0.00	2.67	251	56.40	3.49	4.75
	1.00	0.00	2.67	251	53.40	3.49	3.43
	1.00	0.00	2.67	251	51.00	3.49	4.20
	1.00	0.00	2.67	251	27.80	3.49	2.12
	1.00	0.00	2.67	251	27.20	3.49	2.10
	1.00	0.00	2.67	251	27.60	3.49	2.63
	1.00	0.00	2.67	251	27.90	3.49	2.18
	1.00	0.00	2.67	251	34.70	3.49	2.66
	1.00	0.00	2.67	251	36.20	3.49	2.68
	1.00	0.00	2.67	251	37.00	3.49	2.95
	1.00	0.00	2.67	251	38.30	3.49	2.79
[33]	0.75	0.00	0.02	254	29.00	3.50	3.13
	0.75	0.00	0.02	254	29.00	3.50	3.11
	0.75	0.00	0.03	394	39.00	3.61	2.72
	0.75	0.00	0.03	394	39.00	3.61	3.27
	0.75	0.00	0.03	541	50.00	3.45	2.49
	0.75	0.00	0.03	541	50.00	3.45	3.51
	0.75	0.00	0.03	813	50.00	3.50	3.39
	0.75	0.00	0.03	813	50.00	3.50	3.49
	0.75	0.00	0.03	1118	50.00	3.50	3.17
	0.75	0.00	0.03	1118	50.00	3.50	3.06

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