Presumption of Shear Strength of Steel Fiber Reinforced Concrete Beam Using Artificial Neural Network Model

Namshik Ahn,[1] Hwasup Jang,[2] Do Kyong Park[3]

[1]*Department of Architectural Engineering, Sejong University, Seoul 143-747, South Korea*
[2]*Division of Civil Engineering, Wonkwang University, Chonbuk 570-749, South Korea*
[3]*Division of Architecture, Wonkwang University, Chonbuk 570-749, South Korea*

Received 22 February 2006; accepted 15 June 2006
DOI 10.1002/app.25121
Published online in Wiley InterScience (www.interscience.wiley.com).

ABSTRACT: The shear force characteristics of steel fiber reinforced concrete (SFRC) are investigated with varying shapes and mixture ratios. However, because experimental characterization of SFRC is experimentally demanding in terms of time and equipment, the characterized SFRC data are used with limitation. Therefore, for various applications, an easier approach is required to predict the shear force characteristics of unsaturated soils. In consideration of such a situation, a method to ascertain the shear force characteristics of SFRC is suggested and applied to this study as a neural network theory. The backpropagation algorithm is applied as a learning algorithm for a neural network, and learning is performed in order to converge within an error range of 0.001. In addition, a nonlinear function is used as an objective function and the problem of overfitting is resolved with a more generalized method by adopting the Bayesian regularization technique as a generalization process. To identify the reliability of this artificial neural network model, we compare values from the shear strength test of SFRC beams with the values from the model. They show correspondence between them. Therefore, it is concluded that, if many test variables and data are used as input for learning in the neural network model developed in this study, it is possible to attain a much more reliable prediction. © 2006 Wiley Periodicals, Inc. J Appl Polym Sci 103: 2351–2358, 2007

Key words: composites; fiber; network; strength

INTRODUCTION

Fiber-reinforced concrete is made by discontinuous and short fiber materials dispersed into concrete in order to improve or strengthen the mechanical characteristics of concrete, such as enhancement of the ductility and shear resistance ability of concrete and suppression of local cracks and their growth. The concept of fiber reinforcement is to enhance the strength of a material by transferring some part of the load to the fiber. The fiber delays the development of a crack by adding pinching force to the front of the crack and leads to low speed crack propagation. As a result, fiber-reinforced concrete has a much higher limit crack deformation than nonreinforced concrete. When steel fiber is mixed into concrete, the concrete has considerable ductility due to the crack bridging mechanism of equally distributed fibers in concrete.[1] To investigate such brittleness of steel fiber reinforced concrete (SFRC), many researchers have examined the shear properties through experiments with such variables as materials, shape, blend ratio, reinforcement ratio, and others. The experiments to ascertain the shear characteristics of such SFRC beams, however, require expenditures for setting up and are time consuming so that the characteristics have been applied restrictively. Therefore, a more convenient approach needs to be developed to predict shear strength.

In this study, a predictive model of the shear strength of an SFRC beam was developed by using a neural network model. Data from preceding studies[2–6] were used as input for an artificial neural network model. Parameters such as the steel fiber blend ratio, aspect ratio, reinforcement ratio, effective depth, and ratio between the shear length and depth (a/d) were used as input into the model; the shear strength was the output layer. A backpropagation algorithm was applied as the learning algorithm of the artificial neural network, and it was run to a convergence defined as an error range within 0.001. A nonlinear function was also used as an objective function and we introduced Bayesian regularization, which got rid of the overfitting problem with a more generalized method. In addition, the experimental shear strengths of the SFRC beam were compared with the shear strength predicted by the artificial neural network model and the measured shear strength to verify reliable application of the artificial neural network model.

Correspondence to: D. Park (traum927@naver.com).

TABLE I
Characteristics of Steel Fiber

Material	Diameter (μm)	Density (g cm^{-3})	Tensile strength (MPa)	Young's modulus (GPa)	Coefficient of thermal expansion (10^{-6}, K^{-1})	Melting point (°C)
Steel 0.9% C	100	7.8	4250	210	11.8	1300
Stainless steel, 18-8	50–250	8.0	700–1000	198	18.0	

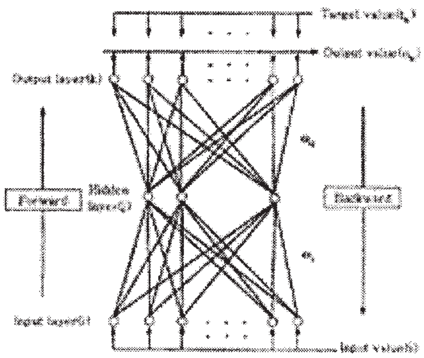

Figure 1 A diagram of backpropagation.

EXPERIMENTAL

Steel fiber

The utility of steel fibers lies in enhancing the tensile strength, flexural rigidity, crack resistance, toughness, shear strength, and shock resistance of concrete by dispersion of a discontinuous filament made of metals or synthetic resins into concrete. There are polymer fibers such as alkali-resistant glass fiber, carbon fiber aramid, vinylon, and high strength and superelastic polyethylene included in steel fibers used for reinforcing concrete.[7–10] Steel fiber is produced by cold drawing of low carbon steels. Its aver-

TABLE II
Properties of Former Studies

Research	Fiber type	V_f (%)	l_f/d_f	ρ	d (mm)	f_{ck}(MPa)	a/d	V_0
Mansur et al.[2]	Hooked	0.5	60	1.34	197	29.1	2	2.54
		0.5	60	1.34	197	29.1	2.8	1.78
		0.5	60	1.34	197	29.1	3.6	1.52
		0.75	60	2	197	29.9	2.8	2.2
		0.75	60	2	197	20.6	2.8	2.03
		0.75	60	2	197	33.4	2.8	2.91
Lim et al.[3]	Hooked	0.5	60	1.1	221	34	2.5	1.73
		0.5	60	2.2	221	34	1.5	4.02
		0.5	60	2.2	221	34	2.5	1.9
		0.5	60	2.2	221	34	3.5	1.47
		1.0	60	2.2	221	34	1.5	4.39
		1.0	60	2.2	221	34	2.5	2.46
Ashor et al.[4]	Hooked	0.5	75	2.84	215	99	1	9.09
		0.5	75	2.84	215	99	2	4.82
		1.0	75	2.84	215	95	1	12.74
		1.5	75	2.84	215	96	1	13.95
		1.5	75	2.84	215	96	2	7.21
		1.0	75	4.58	215	94	2	4.89
		1.0	75	4.58	215	94	4	3.88
Adebar et al.[5]	Hooked	0.75	60	2.15	557	54	1.35	3.3
		1.5	60	2.15	557	50	1.35	3.87
		0.4	60	2.15	557	55	1.35	2.44
		0.6	60	2.15	557	56	1.35	2.77
		0.4	100	2.15	557	47	1.35	2.95
Tan et al.[6]	Hooked	0.5	60	3.89	340	35	2	10.68
		0.75	60	3.89	340	35	2	8.87
		1.0	60	3.89	340	35	2	10.31
		1.0	60	3.89	340	35	2.5	7.56
		1.0	60	3.89	340	35	1.5	15.05
Li et al.[12]	Hooked	1.0	60	2.2	102	22.7	3	3.16
		1.0	60	1.1	102	22.7	3	2.43
		1.0	60	1.1	102	22.7	1.5	5.64
		1.0	100	2.2	102	26	3	3.55
		1.0	60	2.2	204	22.7	3	3.05

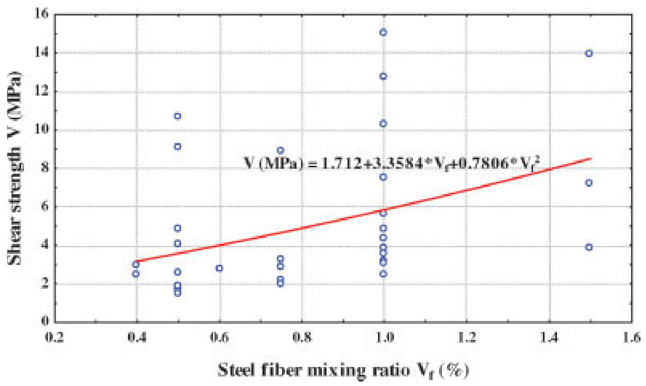

Figure 2 A comparison of the shear strength and steel fiber mixing ratio. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

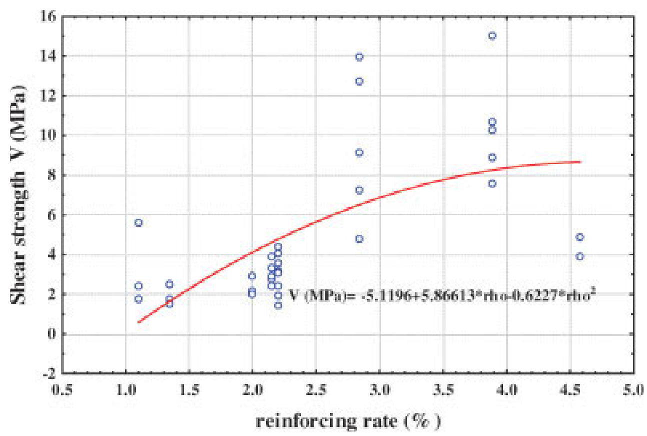

Figure 4 A comparison of the shear strength and reinforcement ratio. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

age tensile strength is 1240 MPa. Generally, it has a length of 25–60 mm, a diameter of 0.3–0.6 mm, and a cross section of 0.06–0.3 mm^2. A steel fiber with a length/diameter ratio of 50–100 is widely used. The characteristics of steel fiber are provided in Table I.

In addition, because concrete-reinforcing products are made of steel wire that has a short length and small cross section, this type of bundle is made for the purpose of enhancing the physical features of the existing concrete. This is done by introducing and dispersing 0.25–2% steel fiber into hydrophilic concrete and fine aggregate per unit capacity to improve the toughness, tensile strength, flexural strength, and crack resistance.

SFRC, which was developed to compensate for the physical weaknesses of the existing concrete in the 1960s, was first used for a truck terminal in Ohio in 1971. It has been widely used in construction, engineering, and other concrete-related sectors because of its superior physical features. SFRC is a synthetic material that improves physical characteristics such as the mechanical behavior and strength of concrete through input and dispersion of discontinuous and short steel fibers (25–80 mm) into a compound of hydrophilic cement and fine aggregate.

Model of artificial neural network

Artificial neural network theory

Biologically, the brain comprises a complex connection of neurons, which have three main components: dendrite, cell body, and axon. Their contact points are called synapses, which play a role in delivering a reaction produced by a stimulus to other neurons. Thus, a neural network is made up of the strength of each synapse and the arrangements of neurons determined by complicated chemical reactions. An artificial neural network consists of artificial neurons and media that connect these neurons.

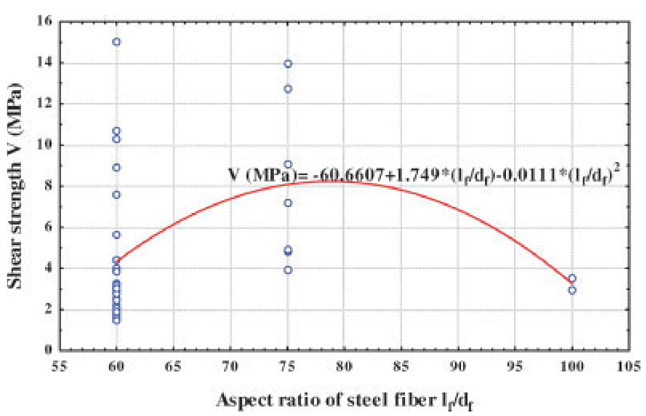

Figure 3 A comparison of the shear strength and aspect ratio of steel fiber. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

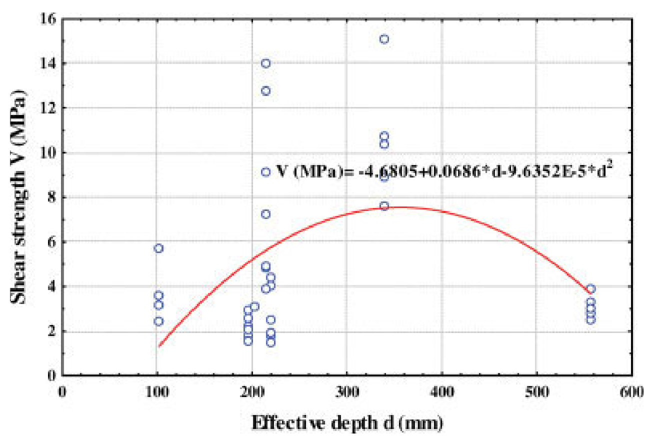

Figure 5 A comparison of the shear strength and effective depth. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

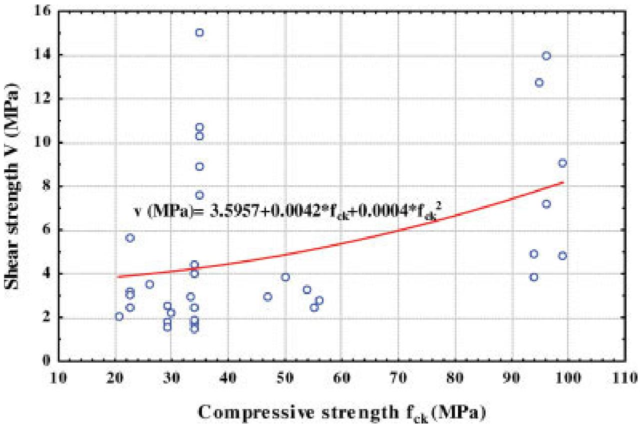

Figure 6 A comparison of the shear strength and compressive strength. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

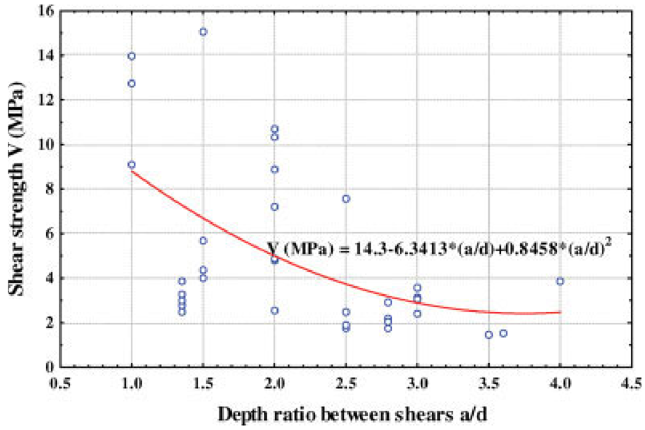

Figure 7 A comparison of the shear strength and depth ratio between shear. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

Backpropagation learning algorithm

The backpropagation algorithm is a method to minimize the average square error value between the actual output value and the pattern that is input into the neural network in order to give a desired target against each unit of the output layer when a neural network is learned. Methods to optimize an objective function are backpropagation, Levenberg–Marquardt, quasi-Newton, and conjugate gradient. In this study, the most widely used and easy backpropagation was chosen. Figure 1 is a diagram of the backpropagation learning algorithm.

The steps of the backpropagation learning algorithm are as follows:

1. set up the initial values of the weights (W_{ki}, W_{ji}), bias (θ_j, θ_k), learning rate (η), and momentum (α);
2. calculate a generalized error (δ_k) at the output layer;
3. learn the weighting value between the hidden layer and output layer to be studied in accordance with the following formula:

$$\Delta W_{ki}(k+1) = \eta\delta_k y_i + \alpha W_{ki}(k) \tag{1}$$

where k is the iterative process (layering) and y_i is the output value of the hidden layer;

4. calculate the generalized error at the hidden layer (δ_j),

$$\delta_j = y_j(1 - y_j)\Sigma\delta_k + W_{kj} \tag{2}$$

5. learn the weighting value between the output layer and the hidden one:

$$\Delta W(k+1) = \eta\delta_j\, x_i + \alpha W_{ii}(k) \tag{3}$$

2. check error functions, and in the case of a lower than a given target value, then repeat steps 1–5.

Generalization process (Bayesian regularization)

For an application of the artificial neural network model, one of the problems is overfitting. In other words, materials used in training make a very small error, but the error could be much bigger in a new material provided in the network. In contrast, if the number of the unknown in the network is much smaller than the total number of the materials for training, the possibility of the overfitting problem is very low. Hence, it is necessary to acquire as many materials as possible. However, in the case of non-sufficient materials, reliability for the learning result of the neural network can be guaranteed by using a

TABLE III
Model Summary Report

Index	Profile[a]	Train perf.	Select perf.	Test perf.	Train error	Select error	Test error	Hidden (1)	Hidden (2)
1	RBF 3 : 3–9–1:1	0.4000	0.5201	0.5561	0.1335	0.2874	0.3518	9	0
2	GRNN 5 : 5–20–2–1 : 1	0.2606	0.4573	0.4936	0.0871	0.2567	0.3430	20	2
3	RBF 4 : 4–9–1 : 1	0.2623	0.3821	0.4800	0.0875	0.2228	0.3422	9	0
4	MLP 6 : 6–2–1 : 1	0.2179	0.3127	0.2859	0.0567	0.1293	0.1726	2	0
5	MLP 6 : 6–4–1 : 1	0.1930	0.2926	0.3104	0.0491	0.1232	0.1646	4	0

[a] Profile: <type> <input> : <layer 1>–<layer 2>–<layer 3> : <outputs>.

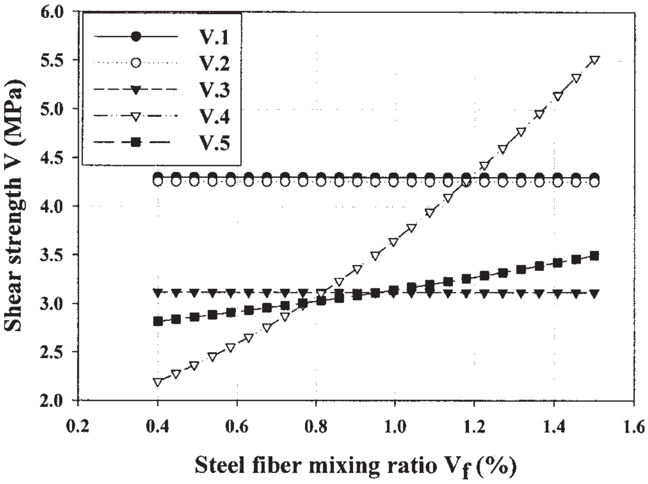

Figure 8 A comparison of the shear strength and steel fiber mixing ratio (prediction).

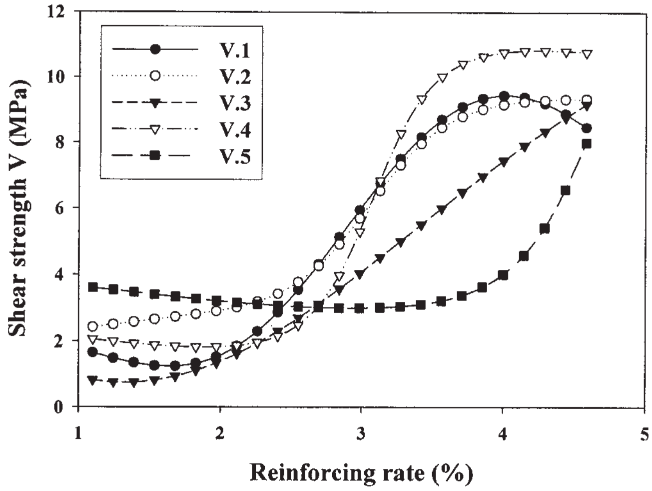

Figure 10 A comparison of the shear strength and reinforcement ratio (prediction).

generalization technique. Generally, reliable materials are classified into two categories: training materials and verification materials of learned results. However, using the generalization technique, it is possible to use valuable materials to optimize the coefficients of the inside of the neural network. For the generalization technique, the early stopping method, which stops learning before errors reach the target, and the Bayesian method are mainly used. The Bayesian method was used in this study.

Shear strength presumption of SFRC beam using artificial neural network model

The parameters affecting the shear strength of SFRC beams are the blend ratio of the steel fiber (V_f, %), the aspect ratio (l_f/d_f), the reinforcement ratio (ρ), the effective depth (d, mm), the concrete design strength (f_{ck}, MPa), and the ratio between the shear length and depth (a/d). We confirmed that they have correlations and influence the increase in the shear strength, based on former studies,[2,11] as shown in Table II.

The analysis of the data mentioned above revealed that, as the blend ratio of the steel fiber increases, so does the shear strength. The shear strength tends to increase until the aspect ratio reaches about 70–75, but the strength decreases beyond this range. In the case of the reinforcement ratio, the shear strength increases in proportion to the rise of the reinforcement ratio; in the case of the effective depth, the shear strength increases until about 330 mm, but the strength tends to decrease gradually after this value. As the concrete design strength increases, the shear strength also tends to increase; but as the ratio between the shear length and depth increases, the strength continuously falls, which is shown in Figures 2–7.

Therefore, a presumed optimal artificial neural network model based on former studies and the

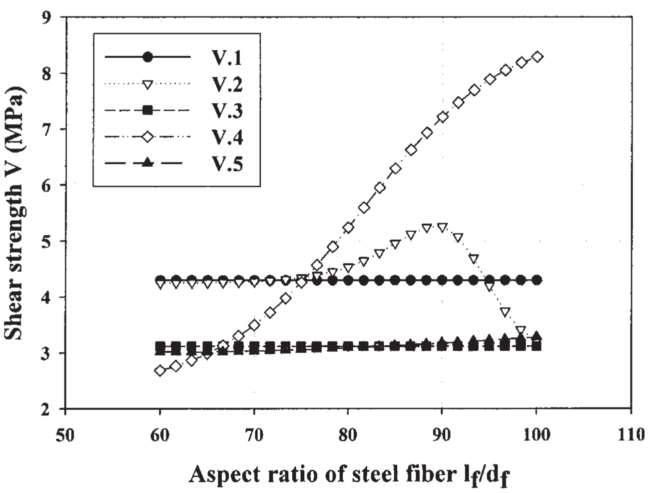

Figure 9 A comparison of the shear strength and aspect ratio of steel fiber (prediction).

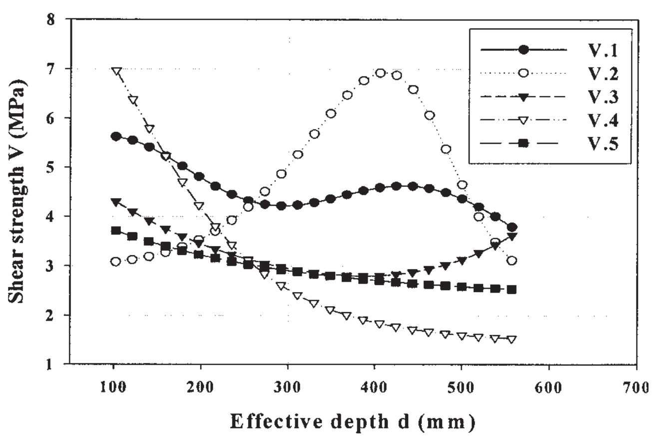

Figure 11 A comparison of the shear strength and effective depth (prediction).

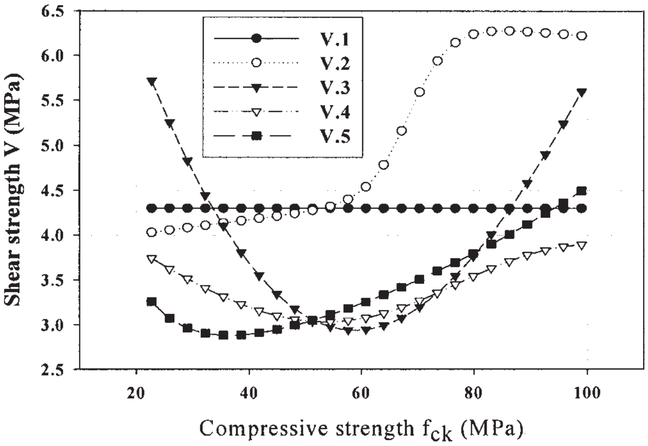

Figure 12 A comparison of the shear strength and compressive strength (prediction).

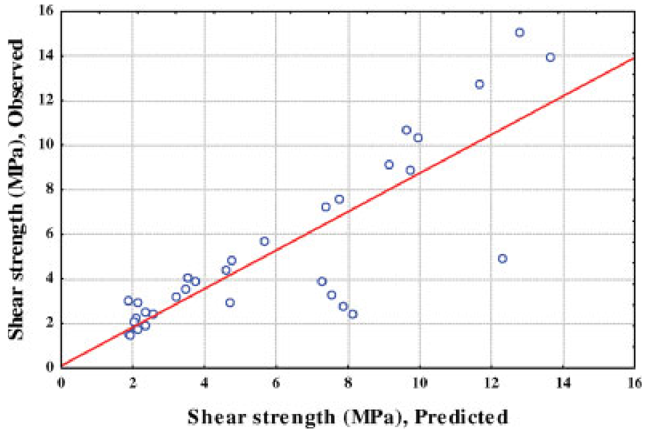

Figure 14 A comparison of preceding researchers and the prediction. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

shear strength given by direct experiments were applied as verification materials. To construct an optimal artificial neural network model, Intelligence Problem Solver was used for analysis and five neural network models were attained, as shown in Table III. The number 5 model was presumed to be very close to the given data, so we selected this model as a learning model.

Learning was performed a total of 3000 times, and a nonlinear function was chosen for the activation function of the multilayer perceptron (MLP). Based on the analysis, we found that the MLP model was the fittest neural network model to the given data. Accordingly, the shear strength of the SFRC beam was presumed by the MLP model and the presumption results are provided in Figures 8–13.

Learning for the shear strength presumption was started by using the number 5 model of the MLP. The learning was set by a total of 20,000 epochs, and the error was adjusted to converge to a range up to 0.001. The backpropagation learning algorithm was applied for a learning algorithm, and 0.9 was selected as the initial momentum; the Bayesian technique was applied as a generalization technique. The learning result of the number 5 model shown in Figure 14 confirmed that the shear strengths of the former studies and our model were almost the same.

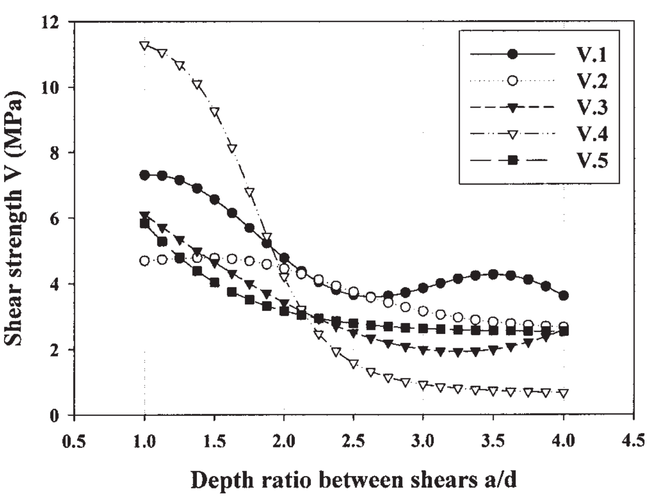

Figure 13 A comparison of the shear strength and depth ratio between shear (prediction).

Verification of artificial neural network model through experiments

Mix proportion

For the materials to be verified, a V_f of 1% and l_f/d_f of 65 were selected, both respectively representing the most suitable strength and workability when steel fiber is mixed in concrete. Type I Portland cement and a maximum 19-mm aggregate were used. A superplasticizer was also used to acquire adequate workability.

Manufacture of specimen

Specimens with a 15 × 30 mm section beam and different ratios between the shear length and depth (1.5, 2.8, and 3.6) were manufactured. All specimens

TABLE IV
Details of Specimens

Specimen no.	f_{ck} (MPa)	Size (mm)	Shear span ratio
1	32	15 × 30 × 130	1.5
2	32	15 × 30 × 190	2.8
3	32	15 × 30 × 240	3.6
4	52	15 × 30 × 130	1.5
5	52	15 × 30 × 190	2.8
6	52	15 × 30 × 240	3.6
7	80	15 × 30 × 130	1.5
8	80	15 × 30 × 190	2.8
9	80	15 × 30 × 240	3.6

TABLE V
Model Summary Report Comparison

Research	Fiber Type	V_f	$l_f\,d_f$	ρ	d (mm)	f_{ck} (MPa)	a/d	V	Pred.	Zsutty's [11] formula
This study	Hooked	1.53	65	1.51	250	32	1.5	1.42	1.75	1.79
		1.53	65	1.51	250	32	2.8	1.11	1.34	0.99
		1.53	65	1.51	250	32	3.6	1.65	1.18	0.97
		1.53	65	1.51	250	52	1.5	1.65	1.87	1.59
		1.53	65	1.51	250	52	2.8	1.45	1.63	1.51
		1.53	65	1.51	250	52	3.6	1.31	1.17	1.49
		1.53	65	1.51	250	80	1.5	1.95	1.76	2.07
		1.53	65	1.51	250	80	2.8	1.54	1.39	1.9
		1.53	65	1.51	250	80	3.6	1.31	1.1	1.86

were supposed to be fractured by shear. Table IV provides the details of the specimens.

Verification of artificial neural network model

For the verification of the developed neural network model, test variables were input into the neural network model and compared with the presumed shear strength and the shear strength from the test and formula of Zsutty.[12]

Equation (1) is an ultimate shear strength formula by Zsutty:[12]

$$V_{cr} = 10.02(f'_c \cdot \rho_a \cdot a/d)^{1/3}\text{kgf/cm}^2 \qquad (4)$$

Zsutty's[12] formula can be applied as follows: when $a/d > 2.5$,

$$V_{11} = 10.77(f'_c \cdot \rho_a \cdot a/d)^{1/3}\text{kgf/cm}^2 \qquad (5)$$

When $a/d < 2.5$,

$$V_{11} = (2.5\ a/d)\text{kgf/cm}^2 \qquad (6)$$

As shown in Table V and Figures 15 and 16, we confirmed that the presumed shear strength from the artificial neural network model, the shear strength from the test, and the shear strength from Zsutty's[12] formula were almost the same.

Sensitivity analysis

Based on the sensitivity analysis for the given variables, we found that the biggest influential factor on the shear strength was the ratio between the shear length and depth, followed by the quantity of steel fiber. The analysis revealed that the blend ratio and aspect ratio of steel fiber have much less influence compared to the ratio between the shear length and depth, the reinforcement ratio, the compressive strength, and the effective depth against the shear strength, as shown in Table VI.

CONCLUSION

To develop an artificial neural network model of the shear strength presumption of an SFRC beam, neural

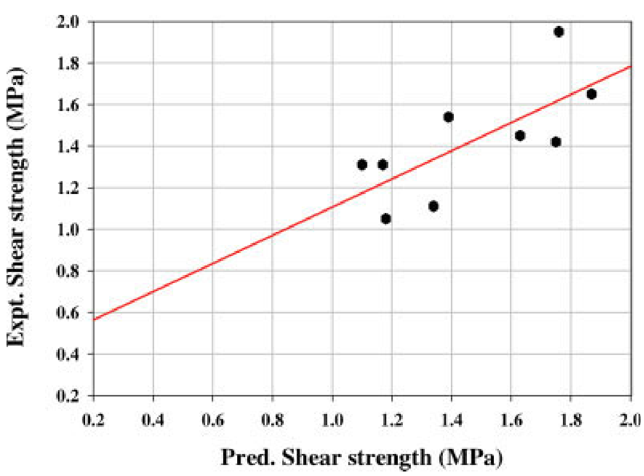

Figure 15 A comparison of the prediction and experiment. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

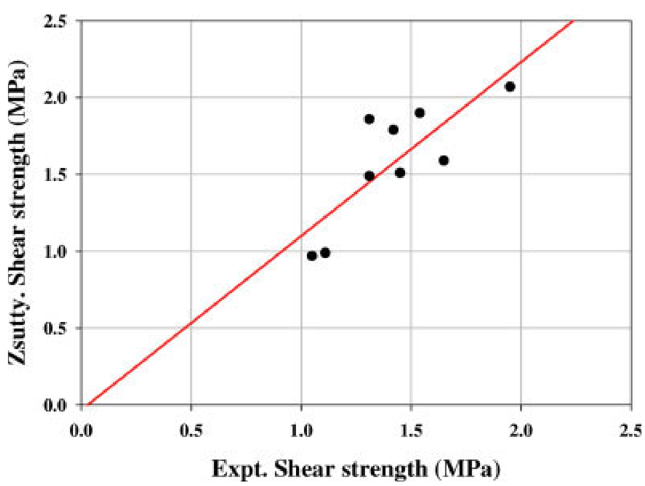

Figure 16 A comparison of Zsutty's[12] formula and prediction. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

TABLE VI
Sensitivity Analysis

	Sensitivity analysis					
	V_f	l_f/d_f	ρ	d	f_{ck}	a/d
Ratio	1.0159	0.9691	1.1633	1.042	1.0597	1.4795
Rank	5	6	2	4	3	1

network models were learned through preceding study materials and the shear strength of the test data were compared with one of Zsutty's[12] formulas. Thus, the artificial neural network model that we developed was verified. As a result, the following conclusions were drawn:

1. With independent variables (such as steel fibers, blend ratio, aspect ratio, reinforcement ratio, concrete design strength, effective depth, and ratio between shear length and depth) and dependent variables (such as shear strength), Intelligence Problem Solver was used for analysis. As a result, the most suitable model was presumed to be MLP, which has one hidden layer and four hidden units.
2. Sensitivity analysis was performed against the given independent variables with the artificial neural network model. From the results we concluded that the shear strength was affected by the ratio between the shear length and depth, the reinforcement ratio, the concrete design strength, the effective depth, the blend ratio, and the aspect ratio in sequence.
3. To identify the reliability of this artificial neural network model, the values from the shear strength test of the SFRC beam were compared with the values from the model, which revealed correspondence between them. Therefore, we concluded that, if many test variables and data are used as materials for learning input for the neural network model developed in this study, it is possible to attain much more reliable predictions.

References

1. Romualda, J. P.; Baston, G. B. J ACI 1963, 60, 775.
2. Mansur, M. A.; Ong, K. C. G.; Paramasivam, P. J Struct Eng ASCE 1986, 112, 2066.
3. Lim, T. Y.; Paramasivam, P.; Lee, S. L. Mag Concrete Res 1987, 39, 148.
4. Ashour, S. A.; Hasanain, G. S.; Wafa, F. F. ACI Struct J 1992, 89, 176.
5. Adebar, P.; Mindess, S.; St. Pierre, D.; Olund, B. ACI Struct J 1997, 94, 68.
6. Tann, K. H.; Murugappan, K.; Paramasivam, P. ACI Struct J 1992, 89, 3.
7. Han, G. C.; Satish, K. J Appl Polym Sci 2006, 100, 791.
8. Pottick, L. A.; Allen, S. R.; Farris, R. J. J Appl Polym Sci 1984, 29, 3915.
9. De Bruyne, E. A.; Vanhoutte, J. S. J Appl Polym Sci 1973, 17, 2033.
10. Tan, S. T.; Zhang, M. Q.; Rong, M. Z.; Zeng, H. M.; Zhao, F. M. J Appl Polym Sci 2000, 78, 2174.
11. Li, V. C.; Ward, R.; Hamza, A. M. ACI Mater J 1992, 78, 499.
12. Zsutty, T. C. ACI J 1971, 138.