Development of Bond Strength Model for FRP Plates Using Back-Propagation Algorithm

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ABSTRACT: For the flexural reinforcement of bridge and building structure, synthetic materials whose dynamic properties are superior and those containing the merit of corrosion-proof are widely used as the substitute for a steel plate. Since FRP plate has improved bond strength owing to the fibers externally adhering to the plate, many researches regarding the bond strength improvement have been substantially performed. To search out such bond strength improvement, previous researchers had ever examined the bond strength of FRP plate through their experiment by setting up many variables. However, since the experiment for a research on the bond strength takes much of expenditure for setting up the equipment and is time-consuming, also is difficult to be carried out, it is limitedly conducted. The purpose of this study was to develop the most suitable artificial neural network model by application of various neural network models and algorithm to the data of the bond strength experiment conducted by previous researchers. Many variables were used as input layers against bond strength: depth, width, modulus of elasticity, tensile strength of FRP plate and the compressive strength, tensile strength, and width of concrete. The developed artificial neural network model has been applied back-propagation, and its error was learned to be converged within the range of 0.001. Besides, the process for the over-fitting problem has been dissolved by Bayesian technique. The verification on the developed model was executed by comparison with the test results of bond strength made by other previous researchers, which was never been utilized to the learning as yet. © 2006 Wiley Periodicals, Inc. J Appl Polym Sci 100: 5119–5127, 2006

Key words: FRP; bond strength; back-propagation algorithm; neural network

INTRODUCTION

For the flexural reinforcement of bridge and building structure, synthetic materials whose dynamic properties (turning point intensity, turning point strength) are superior and those containing the merit of corrosion-proof are widely used as the substitute for steel plate.

Fiber reinforced plastic (FRP), as the most representative material among the synthetic materials, has strong intensity and higher elasticity modulus. Since its lightweight property, corrosion-proof characteristic, nonelectric and nonelectronic property, durability are all predominant, and hence they are increasingly used in shipbuilding, space, automobile, and leisure industry, and it is expected to play an important function in the future construction industry. Particularly, the bonding technique in engineering using high intensive FRP sheet or plate is quite securing the safety and engineering character owing to those merits that are able to fairly exclude the defect of technical bonding method of steel plate. Therefore, FRP sheet or plate not only structurally improves the load carrying capacity of the side-material but also improves the durability of concrete side-material by diminishing its size of the deflection and crack at a service load condition, and as it is effective for promotion of bond strength as the stiffened plate attached on the exterior, many researches have been ever conducted.

To search out such bond strength improvement, previous researchers had ever examined the bond strength of FRP plate through their experiment by setting up many variables. However, since the experiment for a research on the bond strength is taken much of expenditure for setting up the equipment and is time-consuming, also is difficult to be carried out, it is limitedly conducted.

In this study, the optimal artificial neural network model has been developed by an application of the diversified neural network model and algorithm to the data of the bond strength experiment conducted by previous researchers. When the learning has been practiced, many variables were used as input layers against bond strength: depth, width, modulus of elasticity, tensile strength of FRP plate and the compressive strength, tensile strength, and width of concrete.

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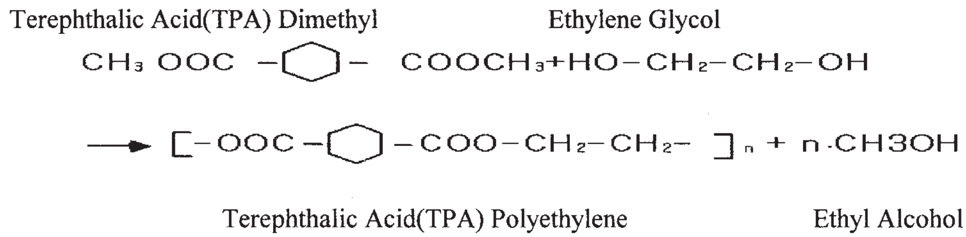

Figure 1 Structure of FRP.

The developed artificial neural network model has been applied back-propagation, and its error was learned to be converged within the range of 0.001. Besides, the process for generalization has been dissolved about the problem of over-fitting in the way of more generalized method by introduction of Bayesian technique.

The verification on the developed model was executed by comparison with the test results of bond strength made by other previous researchers, which was never been utilized to the learning as yet.

GENERAL

Thermoplastic polyester

Terephthalic acid (TPA) polyethylene is a chain-shaped polyester and is a thermoplastic resin. Because its tensile strength is high and its wearing resistance is superior, it is used for films and in textiles. The material added glass fiber to the resin is used as thermoplastic molding material. The adding of glass fiber is to use the long fiber of 30–50% at its weight percentage. Glass Fiber is structured as multiarrayed to the lengthy direction of cylinder-shaped pellet.

Manufacturing method

TPA polyethylene can be made by condensation with TPA dimethyl and ethylene glycol for polymerization as shown in Figure 1. After melting the manufactured resin, a pellet-shaped plastic material can be made by addition of glass fiber and stain.

Structure and property of molecule

As the resin contains the polarity molecule, it is apt to be crystallized. It matches well with glass fiber, and makes a powerful plastic material. The physical property of FRP made by thermoplastic polyester is shown in Table I.

Model of artificial neural-network

Theory of neural-network

Neural-network model (Fig. 2) is a modeling technique that finds out the hidden pattern in the data on the field of neurophysiology to understand a brain activity. This technique was started from an attempt to explain nervous working, and initiated from an effort for modeling its biological process by using of computer, imitating the neural-network of human-being brain and passing through the repeated learning process from the data what oneself actually owns.

Especially, the model of neural-network is to find out the related connection among vast scope of data with very complicated structure or pattern, and is also useful in predicting the future.

TABLE I
Property of FRP Containing Thermoplastic Polyester

Item	Measured value	Standard
Tensile strength (MPa)	135–145	
Bending strength (MPa)	160–170	ASTM 695
Shear strength (MPa)	200–220	ASTM 790
Bending elastic Ratio (MPa)	9000–10,000	ASTM 790
Impact value (kg/cm/cm)	12.5–13.5	
Volume resistivity	1.5×10^{16}	
Surface resistivity	5×10^{15}	
Withstand voltage (kV/mm)	30–35	
Permittivity, 0–10^6 Hz	3.8–4.3	
tan δ, 60–10^6 Hz	0.003–0.016	
Arc resistance (s)	90–120	

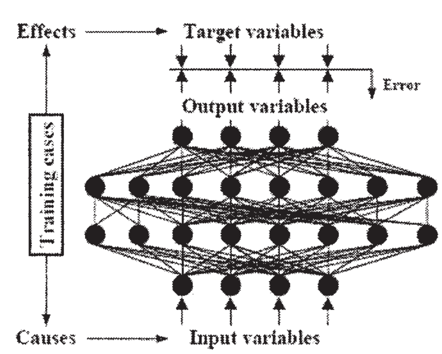

Figure 2 Schematic diagram of Neural Networks.

TABLE II
Analysis on Preceded Research (Learning)

		FRP Plate					Concrete			
Reference	Specimen	Thickness (mm)	Width (mm)	Bond length (mm)	Elastic modulus (GPa)	Tensile strength (MPa)	Compressive strength (MPa)	Tensile strength (MPa)	Width (mm)	Ultimate bond strength (kN)
Takeo et al.[2]	1–11	0.167	40	100	230	3481	36.56	2.86	100	8.75
	1–12	0.167	40	100	230	3481	33.75	2.74	100	8.85
	1–21	0.167	40	200	230	3481	36.56	2.86	100	9.30
	1–22	0.167	40	200	230	3481	33.75	2.74	100	8.50
	1–31	0.167	40	300	230	3481	36.56	2.86	100	9.30
	1–32	0.167	40	300	230	3481	33.75	2.74	100	8.30
	1–41	0.167	40	500	230	3481	36.56	2.86	100	8.05
	1–42	0.167	40	500	230	3481	36.56	2.86	100	8.05
	1–51	0.167	40	500	230	3481	33.50	2.73	100	8.45
	1–52	0.167	40	500	230	3481	33.50	2.73	100	7.30
	2–11	0.167	40	100	230	3481	31.63	2.64	100	8.75
	2–12	0.167	40	100	230	3481	31.63	2.64	100	8.85
	2–13	0.167	40	100	230	3481	33.13	2.71	100	7.75
	2–14	0.167	40	100	230	3481	33.13	2.71	100	7.65
	2–15	0.167	40	100	230	3481	30.88	2.61	100	9.00
	2–21	0.334	40	100	230	3481	31.63	2.64	100	12.00
	2–22	0.334	40	100	230	3481	31.63	2.64	100	10.80
	2–31	0.501	40	100	230	3481	33.63	2.64	100	12.65
	2–32	0.501	40	100	230	3481	33.63	2.64	100	14.36
	2–41	0.165	40	100	373	2942	30.88	2.61	100	11.55
	2–42	0.165	40	100	373	2942	31.88	2.61	100	11.00
	2–51	0.167	40	100	230	3481	31.13	2.71	100	9.85
	2–52	0.167	40	100	230	3481	31.13	2.71	100	9.50
	2–61	0.167	40	100	230	3481	31.13	2.71	100	8.80
	2–62	0.167	40	100	230	3481	30.13	2.71	100	9.25
	2–71	0.167	40	100	230	3481	30.13	2.71	100	7.65
	2–72	0.167	40	100	230	3481	33.13	2.71	100	6.80
	2–81	0.167	40	100	230	3481	33.25	3.87	100	7.75
	2–82	0.167	40	100	230	3481	33.25	3.87	100	8.05
	2–91	0.167	40	100	230	3481	33.88	2.61	100	6.75
	2–92	0.167	40	100	230	3481	33.88	2.61	100	6.80
	2–101	0.111	40	100	230	3481	33.63	2.64	100	7.70
	2–102	0.111	40	100	230	3481	63.13	2.71	100	6.95
Tan[3]	PG1–11	0.169	50	130	97	2777	37.60	2.90	100	7.78
	PG1–12	0.169	50	130	97	2777	37.60	2.90	100	9.19
	PG1–1W1	0.169	75	130	97	2777	37.60	2.90	100	10.11
	PG1–1W2	0.169	75	130	97	2777	37.60	2.90	100	13.95
	PG1–1L11	0.169	50	100	97	2777	37.60	2.90	100	6.87
	PG1–1L12	0.169	50	100	97	2777	37.60	2.90	100	9.20
	PG1–1L21	0.169	50	70	97	2777	37.60	2.90	100	6.46
	PG1–1L22	0.169	50	70	97	2777	37.60	2.90	100	6.66
	PG1–21	0.338	50	130	97	2777	37.60	2.90	100	10.49
	PG1–22	0.338	50	130	97	3500	37.60	2.90	100	11.43
	PC1–1C1	0.111	50	130	235	3500	37.60	2.90	100	7.97
	PC1–1C2	0.111	50	130	235	3550	37.60	2.90	100	9.19
Zhao et al.[4]	NJ2	0.083	100	100	240	3550	20.50	2.08	150	11.00
	NJ3	0.083	100	150	240	3550	20.50	2.08	150	11.25
	NJ4	0.083	100	100	240	3550	36.70	2.87	150	12.50
	NJ5	0.083	100	150	240	3550	36.70	2.87	150	12.25
	NJ6	0.083	100	150	240	3481	36.70	2.87	150	12.75
Ren[5]	DLUT15–2G	0.507	20	150	83	3271	28.70	2.50	150	5.81
	DLUT15–5G	0.507	50	150	83	3271	28.70	2.50	150	10.60
	DLUT15–7G	0.507	80	150	83	3271	28.70	2.50	150	18.23
	DLUT30–1G	0.507	20	100	83	3271	45.30	3.22	150	4.63
	DLUT30–2G	0.507	20	150	83	3271	45.30	3.22	150	5.77
	DLUT30–3G	0.507	50	60	83	3271	45.30	3.22	150	9.42
	DLUT30–4G	0.507	50	100	83	3271	45.30	3.22	150	11.03
	DLUT30–6G	0.507	50	150	83	3271	45.30	3.22	150	11.80
	DLUT30–7G	0.507	80	100	83	3271	45.30	3.22	150	14.65

TABLE II
Continued

Reference	Specimen	FRP Plate					Concrete			Ultimate bond strength (kN)
		Thickness (mm)	Width (mm)	Bond length (mm)	Elastic modulus (GPa)	Tensile strength (MPa)	Compressive strength (MPa)	Tensile strength (MPa)	Width (mm)	
	DLUT30–8G	0.507	80	150	83	3271	45.30	3.22	150	16.44
	DLUT50–1G	0.507	20	100	83	3271	55.50	3.60	150	5.99
	DLUT50–2G	0.507	20	150	83	3271	55.50	3.60	150	5.90
	DLUT50–4G	0.507	50	100	83	3271	55.50	3.60	150	9.84
	DLUT50–5G	0.507	50	150	83	3271	55.50	3.60	150	12.28
	DLUT50–6G	0.507	80	100	83	3271	55.50	3.60	150	14.02
	DLUT50–7G	0.507	80	150	83	3271	55.50	3.60	150	16.71
	DLUT15–2C	0.330	20	150	207	3890	28.70	2.50	150	5.48
	DLUT15–5C	0.330	50	150	207	3890	28.70	2.50	150	10.02
	DLUT15–7C	0.330	80	150	207	3890	28.70	2.50	150	19.27
	DLUT30–1C	0.330	20	100	207	3890	45.30	3.22	150	5.54
	DLUT30–2C	0.330	20	150	207	3890	45.30	3.22	150	4.61
	DLUT30–4C	0.330	50	100	207	3890	45.30	3.22	150	11.08
	DLUT30–5C	0.330	50	100	207	3890	45.30	3.22	150	16.10
	DLUT30–6C	0.330	50	150	207	3890	45.30	3.22	150	21.71
	DLUT30–7C	0.330	80	100	207	3890	45.30	3.22	150	22.64
	DLUT50–1C	0.330	20	100	207	3890	55.50	3.60	150	5.78
	DLUT50–5C	0.330	50	150	207	3890	55.50	3.60	150	16.72
	DLUT50–6C	0.330	80	100	207	3890	55.50	3.60	150	16.24
	DLUT50–7C	0.330	80	150	207	3890	55.50	3.60	150	22.80

Type of neural-network

Although there are various models, the most widely used model for data-analysis is MLP (multi layer perception) neural network. Besides, there are also RBF (radial basis function) and EBF (elliptical basis function) though they are not chiefly used to MLP.

Back-propagation algorithm[1]

As for the method to optimize an objective function, among the algorithms such as back-propagation, Levenberg-Marquardt, Quasi-Newton, conjugate gradient, the simplest and extensively used back-propagation algorithm was applied to this study. The arrangement on back-propagation algorithm by sequential stage is as follows:

Step 1: Initial value of weight (W_{ki}, W_{ji}), bias (θ_j, θ_k), learning rate (η), and momentum (α) value to be fixed.

Step 2: The generalized error (δ_k) at output layer to be calculated.

Step 3: The weighting value between hidden layer and output layer to be studied in accordance with the following formula.

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

where, k: iterative process (layering); η: learning rate; α: momentum; y_i: output value of hidden layer.

Step 4: The generalized error at hidden layer (δ_j) to be calculated.

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

Step 5: Weighting value between output layer and hidden layer to be studied.

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

Step 6: As a result of checking the error function, if it lacks than the given objective value, the steps 1–5 must be repeated.

ANALYSIS ON PRECEDED RESEARCH MATERIAL

With regard to the bond strength of FRP plate, the data that those previous researchers had ever performed were used as the learning material. The learning data to be utilized, which were arranged of the previous research materials, are displayed at Table II,[2,3,4,5] and the data that will be used as the verification materials are shown in Table III,[6] respectively. Likewise, to raise up its reliability of verification, it was examined by the use of the formula of what the existing researchers have ever proposed. The learning range of the parameter that will be used for the learning is shown in Figure 3.

By analyzing the previous research material (learning material), the data can be schematized as shown in Figures 4–7. Regarding the bond strength, according to the compressive strength of concrete, it was noted

TABLE III
Analysis on Preceded Research (Verification)

		FRP Plate					Concrete			
Reference	Specimen	Thickness (mm)	Width (mm)	Bond length (mm)	Elastic modulus (GPa)	Tensile strength (MPa)	Compressive strength (MPa)	Tensile strength (MPa)	Width (mm)	Ultimate bond strength (kN)
Wu et al.[6]	D-CFS-150–30a	0.083	100	300	230	4200	58.85	3.71	100	12.20
	D-CFS-150–30b	0.083	100	300	230	4200	73.85	4.21	100	11.80
	D-CFS-150–30c	0.083	100	300	230	4200	73.85	4.21	100	12.25
	D-CFS-300–30a	0.167	100	300	230	4200	73.85	4.21	100	18.90
	D-CFS-300–30b	0.167	100	300	230	4200	73.85	4.21	100	16.95
	D-CFS-300–30c	0.167	100	300	230	4200	73.85	4.21	100	16.65
	D-CFS-600–30a	0.333	100	300	230	4200	73.85	4.21	100	25.65
	D-CFS-600–30b	0.333	100	300	230	4200	73.85	4.21	100	25.35
	D-CFS-600–30c	0.333	100	300	230	4200	73.85	4.21	100	27.25
	D-CFM-300–30a	0.167	100	300	390	4400	73.85	4.21	100	19.50
	D-CFM-300–30b	0.167	100	300	390	4400	73.85	4.21	100	19.50
	D-AR-280–30a	1.000	100	300	24	4400	73.85	4.21	100	12.75
	D-AR-280–30b	1.000	100	300	24	4400	73.85	4.21	100	12.85
	D-AR-280–30c	1.000	100	300	24	4400	73.85	4.21	100	11.90
	S-CFS-400–25a	0.222	40	250	230	4200	73.85	4.21	100	15.40
	S-CFS-400–25b	0.222	40	250	230	4200	73.85	4.21	100	13.90
	S-CFS-400–25c	0.222	40	250	230	4200	73.85	4.21	100	13.00
	S-CFM-300–25a	0.167	40	250	390	4400	73.85	4.21	100	12.00
	S-CFM-300–25b	0.167	40	250	390	4400	73.85	4.21	100	11.90
	S-CFM-900–25a	0.500	40	250	390	4400	73.85	4.21	100	25.90
	S-CFM-900–25b	0.500	40	250	390	4400	73.85	4.21	100	23.40
	S-CFM-900–25c	0.500	40	250	390	4400	73.85	4.21	100	23.70

that the bond strength was almost linearly increased as the increase of compressive strength. Also, the bond strength was increased according to the intensity of FRP plate, and no matter how long the adhesion length may increase, bond strength was not increased; no matter how long it may be, it could not absolutely reach to the tensile strength of stiffener. However, the more increase of the adhesion length, the more increase of the ductility in the fracture process. It was known that bond strength was increased even in a little bit according to the depth ratio of FRP-concrete.

DEVELOPMENT OF NEURAL-NETWORK MODEL

In this study, an optimal artificial neural-network model has been developed by an application of the various neural-network models and algorithms to the data of the bond strength experiment by previous researchers. The independent variables for development of the model included the depth, width, bond length, modulus of elasticity, tensile strength of FRP plate (data of previous researches), and the compressive strength, tensile strength and width of concrete were used; the bond strength was used as a dependent variable. Also the nonlinear function was used as an activation function, the formation time for optimal network was carried out five thousand times through several times of learning in consideration of time-accuracy, and the optimized model was derived among linear model, stochastic model, and MLP model. As the result of analysis, the conclusion as Table IV has been obtained. Among the five types of model, MLP model was mostly accorded well with the given data. Figure 8 is the flowchart that schematized MLP model.

The learning on MLP model was regulated as total 30,000 epochs, and the error was adjusted to be converged to the range of 0.001. Back-propagation algorithm has been used as learning algorithm, which is the most widely used, and Bayesian technique has been applied as the generalization technique. As the result of training, the model that is able to predict the following FRP-concrete bond strength has been developed. Figure 9 is the graph in which the bond strength presumed by MLP model and the test results of bond strength are compared. Investigating the graph, some errors between the actually measured bond strength and the predicted value of bond strength that was developed in this study were appeared more or less at some parts; however it was appeared almost linearly in view of the entire aspect.

VERIFICATION ON THE MODEL

To verify the MLP model that was developed in this study, Table III was used as the verification material, and its reliability on MLP model that was developed

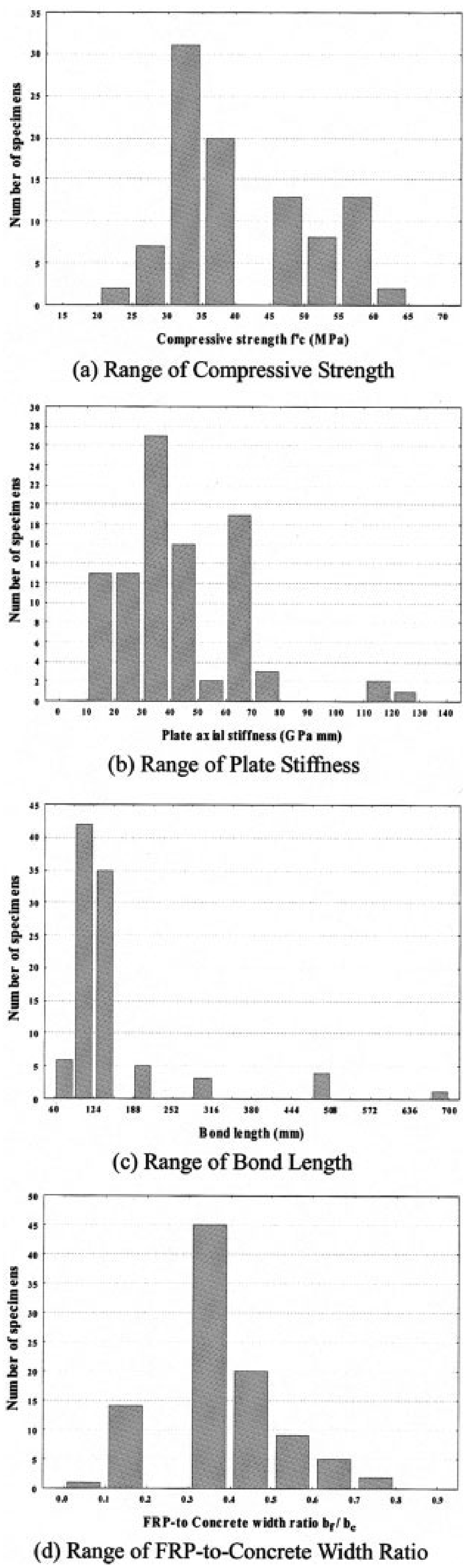

Figure 3 Learning range of parameter. (a) Range of Compressive strength, (b) range of plate stiffness, (c) range of bond length, (d) range of FRP-to-concrete width ratio.

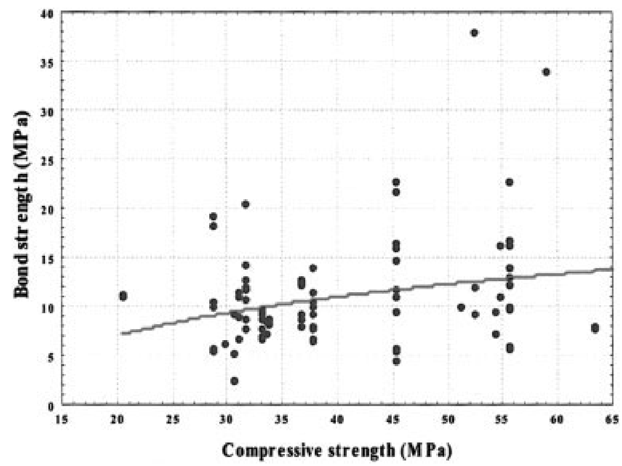

Figure 4 Relation between bond strength and compressive strength of concrete.

in this study was proved through the comparison of the result value (Table V)which was analytically researched by the suggested formulas provided by Sato's model and Yang's model.[7,8]

As the result of comparison with the bond strength predicted value that presumed to the MLP model (Fig. 10), which developed in this study, and the test result value of Wu (2001), the correlative coefficient value of the mentioned two values was analyzed as high as $R^2 = 0.815$. The correlative coefficient of bond strength value calculated by Sato's (Fig. 11) and Yang's (Fig. 12) suggested formulas with the test result value was analyzed as $R^2 = 0.741$ and $R^2 = 0.126$, respectively.

SENSITIVITY ANALYSIS

As the result of sensitivity analysis (Table VI)on the variables, which are affected by bond strength, it could be confirmed that the width ratio of FRP-con-

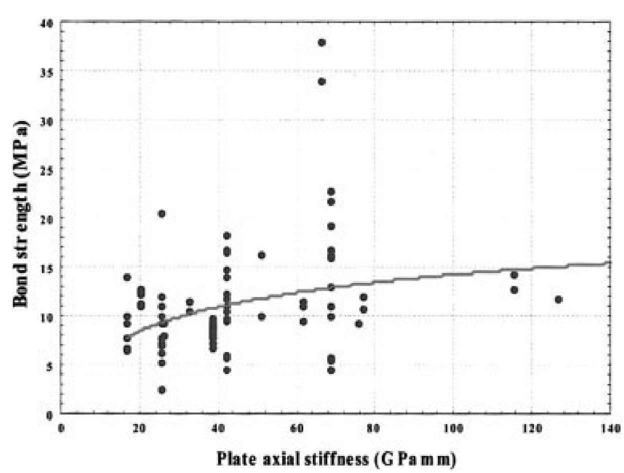

Figure 5 Relation between bond strength and stiffness of FRP.

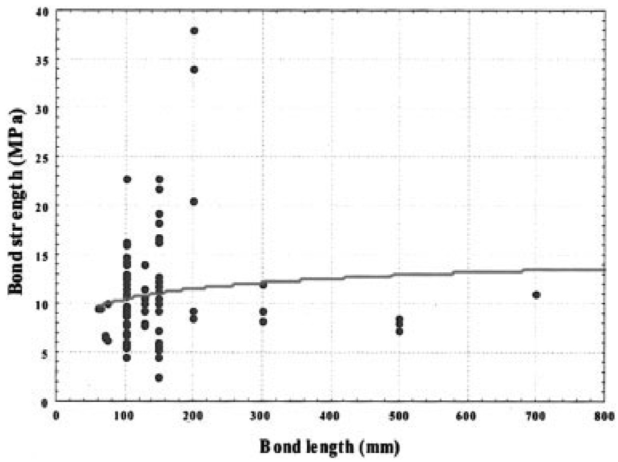

Figure 6 Relation between bond strength and bond length.

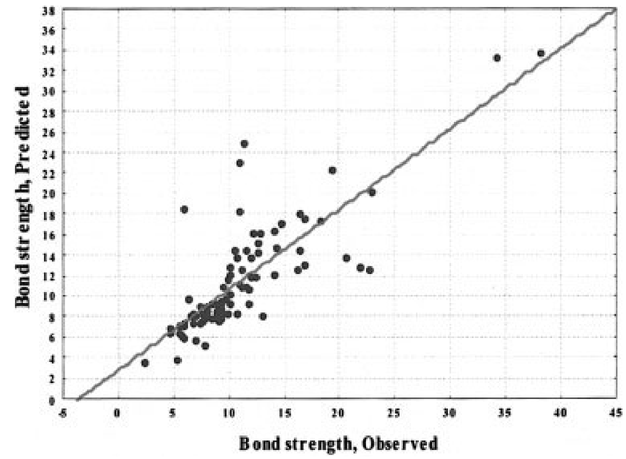

Figure 9 Comparison of Predicted bond strength and test results.

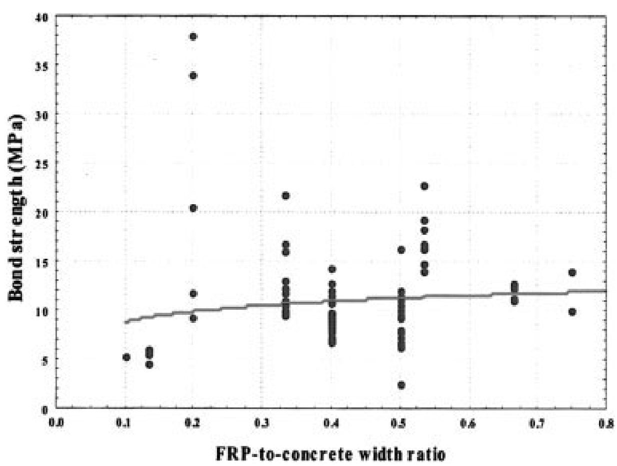

Figure 7 Relation between bond strength and FRP-to-concrete width ratio.

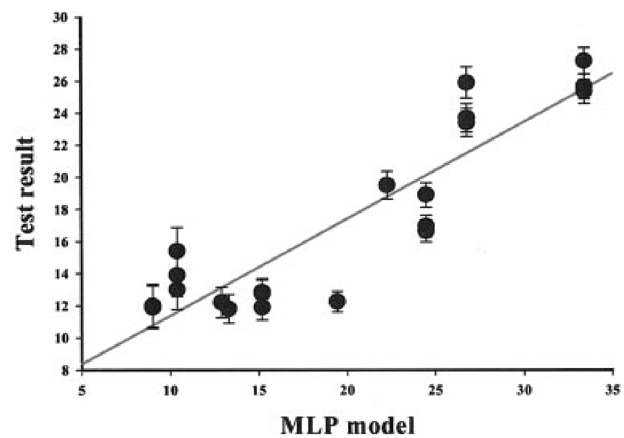

Figure 10 Comparison of bond strength between test results and predicted value (MLP model).

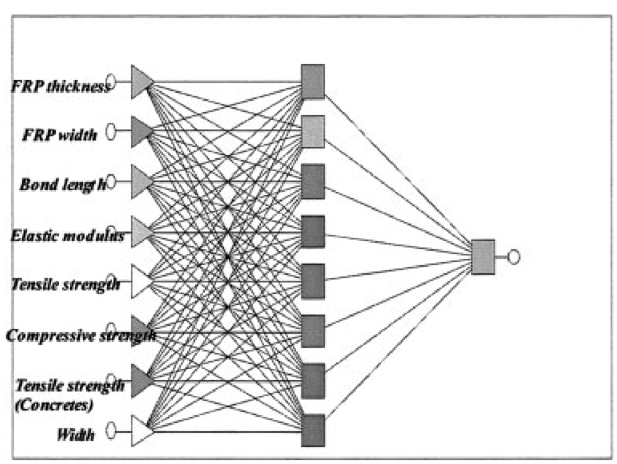

Figure 8 Flowchart for Schematized MLP Model.

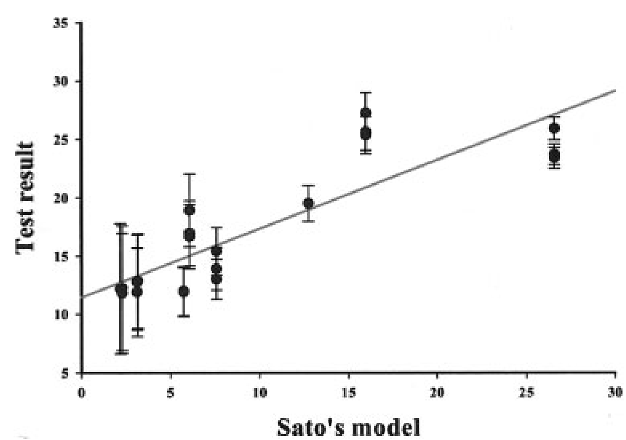

Figure 11 Comparison of bond strength between test results and predicted value (Sato's model).

TABLE IV
Model Summary of Report

Index	Profile	Train perf.	Select perf.	Test perf.	Train error	Select error	Test error	Hidden (1)	Hidden (2)
1	GRNN 1:1–48-2–1:1	0.99148	0.983594	0.992847	0.202869	0.182304	0.308208	48	2
2	Linear 4:4–1:1	0.767177	0.739879	0.596476	0.125541	0.108062	0.161250	0	0
3	Linear 5:5–1:1	0.767014	0.738190	0.595605	0.125514	0.107809	0.160758	0	0
4	MLP 7:7–11-10–1:1	0.350432	0.374932	0.607727	0.045914	0.043801	0.121631	11	10
5	MLP 8:8–8-1:1	0.302571	0.365374	0.590860	0.039620	0.042619	0.115318	8	0

TABLE V
Comparison of Results

Reference	Specimen	Bond strength, Pu (kN)	MLP model	Expt/MLP model	Sato's model	Expt/Sato's model	Yang's model	Expt/Yang's model
Wu et al.[6]	D-CFS-150–30a	12.20	12.89	0.946	2.18	5.596	9.61	1.269
	D-CFS-150–30b	11.80	13.29	0.888	2.29	5.153	10.89	1.083
	D-CFS-150–30c	12.25	19.43	0.630	2.29	5.349	10.89	1.125
	D-CFS-300–30a	18.90	24.49	0.772	6.08	3.109	11.03	1.713
	D-CFS-300–30b	16.95	24.49	0.692	6.08	2.788	11.03	1.537
	D-CFS-300–30c	16.65	24.49	0.679	6.08	2.738	11.03	1.509
	D-CFS-600–30a	25.65	33.43	0.767	15.99	1.604	11.24	2.282
	D-CFS-600–30b	25.35	33.43	0.758	15.99	1.585	11.24	2.255
	D-CFS-600–30c	27.25	33.43	0.815	15.99	1.704	11.24	2.424
	D-CFM-300–30a	19.50	22.27	0.876	12.74	1.531	11.19	1.743
	D-CFM-300–30b	19.50	22.27	0.876	12.74	1.531	11.19	1.743
	D-AR-280–30a	12.75	15.18	0.839	3.13	4.073	10.93	1.166
	D-AR-280–30b	12.85	15.18	0.847	3.13	4.063	10.93	1.176
	D-AR-280–30c	11.90	15.18	0.784	3.13	3.802	10.93	1.088
	S-CFS-400–25a	15.40	10.38	1.477	7.59	2.021	4.44	3.454
	S-CFS-400–25b	13.90	10.38	1.339	7.59	1.831	4.44	3.131
	S-CFS-400–25c	13.00	10.38	1.252	7.59	1.713	4.44	2.927
	S-CFM-300–25a	12.00	9.00	1.333	5.73	2.094	4.42	2.714
	S-CFM-300–25b	11.90	9.00	1.322	5.73	2.077	4.42	2.692
	S-CFM-900–25a	25.90	26.79	0.967	26.58	0.974	4.58	5.655
	S-CFM-900–25b	23.40	26.79	0.874	26.58	0.880	4.58	5.109
	S-CFM-900–25c	23.70	26.79	0.884	26.58	0.891	4.58	5.175

⟨Sato's model⟩ $\tau_u = 2.68 f'^{0.2}_{c} t_f E_f \times 10^{-5}$; $L_e = 1.89(E_f t_f)^{0.4}$; $P_u = (b_f + 2\Delta b) L_e \tau_u$; where, $\Delta b = 3.7$ mm.
⟨Yang's model⟩ $P_u = (0.5 + 0.08\sqrt{(E_f t_f / 100 f_t)} \times b_f L_e \tau_u$; $\tau_u = 0.5 f_1$; $L_e = 100$ mm.

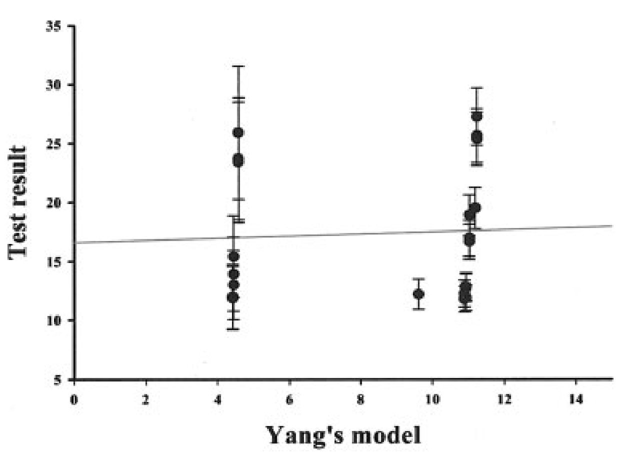

Figure 12 Comparison of bond strength between test results and predicted value (Yang's model).

crete is acting as the largest variable, and was analyzed that the elastic modulus is subsequently sensitive to bond strength, and confirmed that the influence of bond length to bond strength is the lowest one.

CONCLUSIONS

In this study, previous research materials have been investigated and analyzed for the development of the bond strength model of FRP sheet-concrete, and the optimal neural-network model was developed on the basis of the previous research materials as variables, and its reliability has been verified by comparison with other experimental results. Based on the comparison it was concluded as follows:

1. To develop the optimal neural-network model, as the result of application of various models and learning algorithm, the most suitable model was

TABLE VI
Result of less Sensitivity Analysis

	Thickness	Width	Bond length	Elastic modulus	Tensile strength	Compressive strength	Tensile strength	Width
Ratio	1.215	1.720	0.984	1.344	1.020	1.024	1.049	1.318
Rank	4	1	8	2	7	6	5	3

assumed as MLP model, which is consists of one hidden layer and eight hidden nodes.

2. Having with the presumed MLP model, it was trained to be converged within the range of learning error as 0.001, and the optimal neural-network model was developed by the application of back-propagation algorithm to learning algorithm.
3. As the result of comparison of the bond strength predicted by MLP model and measured at the receded study, it could be confirmed that both are almost accord.
4. To verify the confidence of MLP model, as the result of comparison of Sato's model and Yang's model, with bond strength, comparison of the predicted bond strength by MLP model with experimental result value of Wu was performed. The correlative coefficient of the two values have been analyzed as high as $R^2 = 0.815$.
5. As the result of sensibility analysis about the provided variable, the most influencing factor to bond strength was revealed to be width and it was confirmed that the influence of bonding length to bond strength is the lowest one.

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