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BACK PROPAGATION ARTIFICIAL NEURAL NETWORK MODELING OF FLEXURAL AND COMPRESSIVE STRENGTH OF CONCRETE REINFORCED WITH POLYPROPYLENE FIBERS

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ABSTRACT: The production of fiber reinforced concrete involves a complex reaction system. This imposes an immense challenge in deriving appropriate material proportions of concrete to achieve desired mechanical properties. In order to facilitate selection of a design matrix for fiber reinforced concrete, a novel artificial Neural Network models for compressive and flexural strengths using back propagation feed-forward algorithm were proposed in this research. A wide range of varied concrete design mixes of cylindrical and beam samples was respectively tested for compressive and flexural tests. A polypropylene type of fiber reinforcement was used in the preparation of samples that were cured for 28 days in a water-saturated lime. Results showed that the compressive and flexural strength models provided predictions in good agreement with experimental results as described by high correlation values of 99.46% and 98.57% respectively. Mean squared errors of 0.0024 and 0.44 were obtained respectively in selecting the best fit model for compressive and flexural strengths. In the parametric analysis conducted, the proposed models were able to describe analytically the constitutive relationships of the material components and capture the dominant characteristics of concrete samples.

Keywords: Concrete, Fiber reinforcement, Flexural strength, Compressive strength, Artificial neural network

1. INTRODUCTION

Fiber reinforced polymer remains a highlight in the development of concrete technology to deliver better performance and sustainability of concrete structures. This short discrete fibrous material that is introduced in the concrete mix enhances both the mechanical and serviceability performance of concrete. The efficiency of fiber reinforced concrete is dependent on the proportions of material components. The fiber material type such as Polypropylene, Nylon, and steel fibers offer individual distinct benefits. In some cases, blending is necessary to integrate the desirable properties [1-4]. In the study of Hsie et al. [5], the hybridization of two different forms of polypropylene fibers offered 24.6% increase in the flexural strength of beams tested using third point loading. Combined steel and polymer fibers improved the resistance of the concrete in the development of cracks [6]. Shape, dosage, distribution, and orientation, in particular, are also key factors in developing high performance concrete [7] – [9]. Various studies were conducted to develop guidelines for engineers to properly design fiber reinforced concrete [10] – [14].

In the interest of providing prediction models on the mechanical performance of concrete with fiber reinforcement, an adaptation of system simplifications in parallel with destructive testing of concrete is necessary. In understanding the micromechanical properties and geometry of concrete samples with arbitrarily dispersed fibers, an explicit analytical model in predicting the flexural resistance of concrete was developed [15]. The model utilized the concrete components and sample geometry and provided estimated results in good agreement with values obtained from the experiment. The effect of fibers on the flexural strength of concrete as well as the interactions of the concrete components is complex in nature.

The use of Artificial Neural Network (ANN) can work on such a system to capture the complex nonlinear relationships between the variables [16] – [19]. The neural network is a powerful algorithm that process information based on the biology of the human nervous system. The algorithm is allowed to learn from an existing training data of input-output observations forming a network of interconnected neurons that can estimate values from a large number of inputs. ANN was used to develop a shear capacity model of concrete beams and compared with different existing models available in the literature [20]. The derived equation provided high accuracy in forecasting shear strengths in comparison with results from laboratory tests.

The mechanism of the interaction of material components in the mixture defines the overall resistance of hardened concrete. It is hardly possible to obtain a suitable design concrete mix without understanding the contribution of every material component in the flexural performance of concrete. There are simplified assumptions considered in developing empirical, numerical, and analytical models that are inconsistent with actual concrete mixture conditions. This, in turn, provides significant deviations of the predicted values against experimental results. In the presence of highly complicated interactions involved in the system, the neural network is found to be useful to develop the models [21]. This method is proven to be effective and convenient means of analyzing complex relationships from nonlinear data. Thus a novel prediction model using an artificial neural network for flexural strength of fiber reinforced concrete is proposed in this study. The equation will be able to identify the actual properties of the concrete matrix eliminating ideal assumptions and thereby expected to provide realistic prediction results in a simple and rapid approach.

2. METHODOLOGY

2.1 Mixture Composition

Forty mixtures with different amounts of cement, sand, gravel, water and fiber reinforcement were produced and used as input data for the models. The mixtures in 6’’x6’’x21’’ beam mold and 6’’ diameter x 12’’ height cylindrical mold was tested for compressive and flexural strengths, respectively. Center point loading was used for the testing of flexural strength and compressive strength test for the cylinders. The samples were cured in water for 27 days, air dried for a day and tested on the 28th day. All design mix was reflected in Table I which was used as input for the neural network modeling except for the water-cement ratio.

Table 1 Mixture composition

ID	w/c	cement kg	water kg	sand kg	gravel kg	fiber kg
1	0.50	300	150	840	1003	1.48
2	0.50	300	150	846	995	1.60
3	0.50	300	150	912	930	1.26
4	0.50	300	150	886	984	1.45
5	0.50	300	150	886	998	1.15
6	0.50	300	150	946	947	1.17
7	0.50	300	150	860	997	1.20
8	0.50	300	150	933	1043	1.54
9	0.45	340	153	853	1041	1.32
10	0.45	340	153	872	987	1.67
11	0.45	340	153	900	994	1.43
12	0.45	340	153	948	1050	1.08
13	0.45	340	153	896	996	1.80
14	0.45	340	153	869	1036	1.03
15	0.45	340	153	905	920	1.58
16	0.45	340	153	836	968	1.50
17	0.40	380	152	839	960	1.04
18	0.40	380	152	897	993	1.55
19	0.40	380	152	840	944	1.00

Table 1 continued

20	0.40	380	152	873	963	1.49
21	0.40	380	152	950	982	1.27
22	0.40	380	152	915	986	1.60
23	0.40	380	152	897	929	1.69
24	0.40	380	152	892	996	1.30
25	0.35	420	147	853	959	1.27
26	0.35	420	147	882	962	1.37
27	0.35	420	147	898	921	1.04
28	0.35	420	147	891	1020	1.34
29	0.35	420	147	932	939	1.24
30	0.35	420	147	907	945	1.22
31	0.35	420	147	845	972	1.28
32	0.35	420	147	924	970	1.38
33	0.30	460	138	856	991	1.03
34	0.30	460	138	822	954	1.19
35	0.30	460	138	920	1027	1.05
36	0.30	460	138	860	1023	1.20
37	0.30	460	138	910	1030	1.75
38	0.30	460	138	941	960	1.11
39	0.30	460	138	834	1044	1.49
40	0.30	460	138	820	955	1.45

2.3 ANN Modeling

The researchers utilized ANN toolbox from Matlab 2015b for the creation of models to forecast the flexural resistance and compressive strength of fiber reinforced concrete. Eighty-five percent of the data were used as training and validation of the models. The remaining 15% were utilized as testing for the accuracy of the models. The researchers applied to feed forward back propagation algorithm for modeling. The best models were selected based on the least value of Mean Squared Error (MSE) [22-23]. Fig.1 shows an example of an ANN structure that will be 0000 m the results of training. Biases and weights are the key components being optimized to yield better prediction of the models.

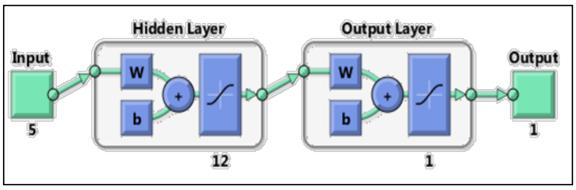

Fig. 1 Artificial neural network structure.

2.3 Reinforcing Fiber

The reinforcing fiber used in this study was polypropylene with a tensile strength of 570 to 660 MPa. The length of the fiber varies from 38mm to 54mm with a specific gravity of 0.91 that conforms to the standard of ASTM C1116 (Standard Specification for Fiber-Reinforced Concrete). The fiber used was a blend of two fibers, the first one is the standard fibrillated polypropylene fiber that can control temperature cracks and the other one is monofilament fiber made from synthetic copolymer that has significant contribution to post-crack performance.

3. RESULTS AND DISCUSSION

3.1 Mechanical Tests

Table II shows the corresponding flexural and compressive strengths of all samples. These results were used as output data for the ANN modeling and accuracy test of the derived models.

Table 2 Mechanical test result

ID	fb Mpa	fc' Mpa	ID	fb Mpa	fc' Mpa
1	2.62	23.31	21	3.52	26.41
2	2.88	23.75	22	4.16	29.34
3	2.13	22.07	23	4.50	30.22
4	2.55	23.08	24	3.68	27.25
5	1.90	20.67	25	4.43	28.29
6	1.93	21.61	26	4.69	27.97
7	2.09	21.74	27	4.08	26.28
8	2.60	23.54	28	4.52	28.52
9	2.96	24.21	29	4.39	27.74
10	3.63	26.68	30	4.32	27.42
11	3.10	24.88	31	4.53	27.86
12	2.28	22.66	32	4.56	29.01
13	3.83	27.67	33	4.76	33.12
14	2.35	21.87	34	5.09	34.79
15	3.54	26.57	35	4.64	33.70
16	3.40	25.23	36	4.99	34.89
17	3.23	25.69	37	6.07	38.00
18	4.18	29.20	38	4.86	34.15
19	3.13	24.92	39	5.61	36.82
20	4.03	28.51	40	5.69	36.11

Table III show results of Pearson Coefficient (P) and Regression (R), cement (0.92 and 0.89) and water (0.72 and 0.81) are the two factors significantly contributing to the strength of the concrete mixture. Although not significant (0.19 and 0.15), polypropylene fiber reinforcement imparts additional strength to both flexural and compressive. The main purpose of the fiber in concrete is to minimize the micro-cracks that will yield to long term deflection and durability. In general, both concrete strengths demonstrate a positive linear association with cement and negative for water as described by their respective correlation coefficients.

Table 3 Statistical analysis

material	statistic	Fb	fc'
cement	R	0.921095	0.888967
	P	3.76E-17	1.86E-14
water	R	-0.71762	-0.814452
	P	1.87E-07	1.62E-10
sand	R	0.159918	0.154527
	P	0.32428	0.341067
gravel	R	0.071629	0.048801
	P	0.660499	0.764911
fiber	R	0.192133	0.153558
	P	0.23494	0.344139

3.2 Artificial Neural Network Modeling

The set of data were split for the three phases of modeling which are training, validation, and testing as shown in Fig. 2 and Fig. 3. Training data composed of 70% of the total data and 15% for the validation data were used in the derivation of the models. Validation data were simultaneously tested on the derived model and checked if the results are comparable to the actual data. The validation was used as a tool to minimize the over-fitting which is the typical problem for ANN modeling. The mean squared errors for validation of flexural strength and compressive strengths models was 0.0024 and 0.44 respectively. In figure II, the model was retrained for several times and if there will be no improvement from the previously trained model, it will reflect epoch zero in the graph. In Matlab, the data final weights and biases were chosen based on the lowest MSE of validation data even if the training and testing were still improving.

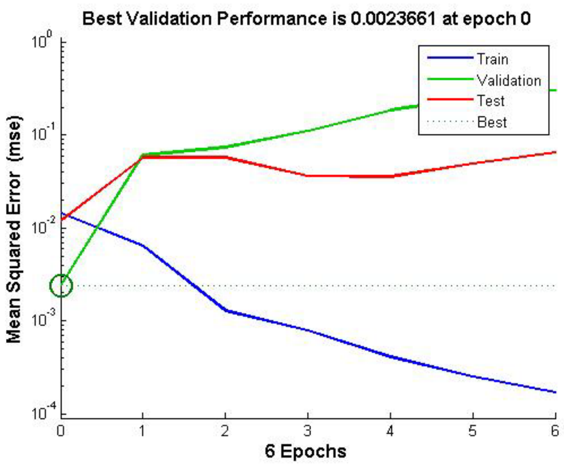

Fig. 2 Validation performance for flexural model.

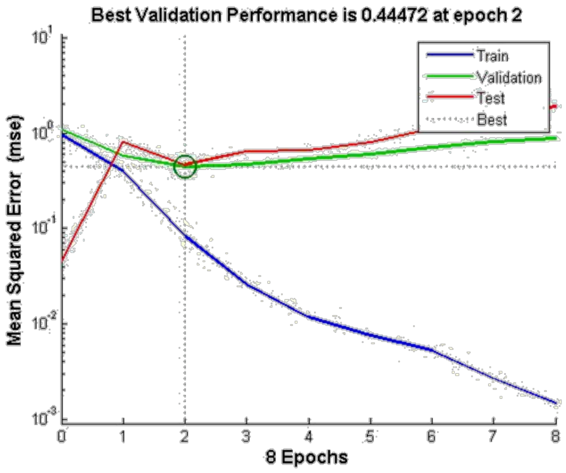

Fig. 3 Validation performance for flexural model.

3.3 Simulations

Remaining 15% of the data was independently used to test the accuracy of the models as shown in tables 4 and 5. All data simulated in the derived models were compared to their corresponding actual test results. For the flexural data, a maximum of 6.08% error was calculated and an average of 2.88% error for all 6 data. For the compressive strength data, a maximum of 3.29% error and an average of 2.28% for the 6 data.

The recorded R values of 0.995 and 0.986 for flexural and compressive strength models respectively represents a highly correlated results as shown in fig. 4 and fig. 5. These values provided accurate model prediction in excellent agreement with experimental results.

Table 4 Flexural Strength Actual vs ANN

cement (kg)	water (kg)	sand (kg)	gravel (kg)	fiber (kg)	Actual (Mpa)	ANN (Mpa)
340	153	900	994	1.43	3.10	2.91
340	153	948	1050	1.08	2.28	2.33
380	152	839	960	1.04	3.23	3.16
380	152	897	993	1.55	4.18	4.07
380	152	840	944	1.00	3.13	3.01
460	138	820	955	1.45	5.69	5.71

3.4 Parametric Study

A parametric study for the fiber content was conducted to show the impact to the strength of concrete. Five increments of fiber content were used. Mixture with the term “high” and “low” was based on the mixture that yields the maximum and minimum flexural and compressive strength from the actual test

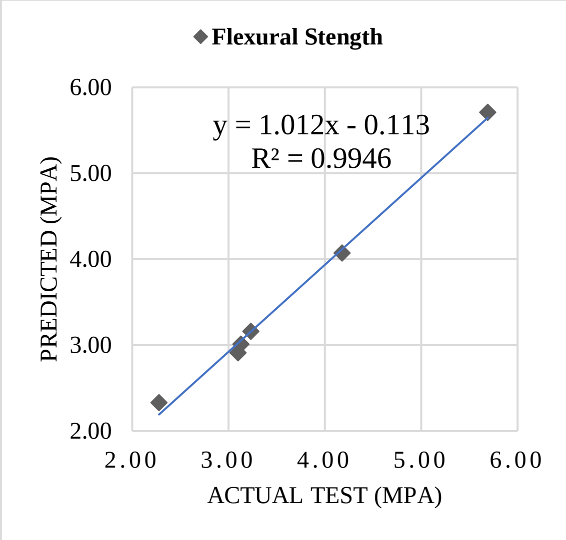

Fig. 4 Accuracy test - flexural.

Table 5 Compressive Strength Actual vs ANN

cement (kg)	water (kg)	sand (kg)	gravel (kg)	fiber (kg)	Actual (Mpa)	ANN (Mpa)
300	150	860	997	1.20	21.74	21.27
380	152	950	982	1.27	26.41	26.93
420	147	898	921	1.04	26.28	27.09
420	147	891	1020	1.34	28.52	27.58
460	138	856	991	1.03	33.12	33.42
460	138	820	955	1.45	36.11	36.93

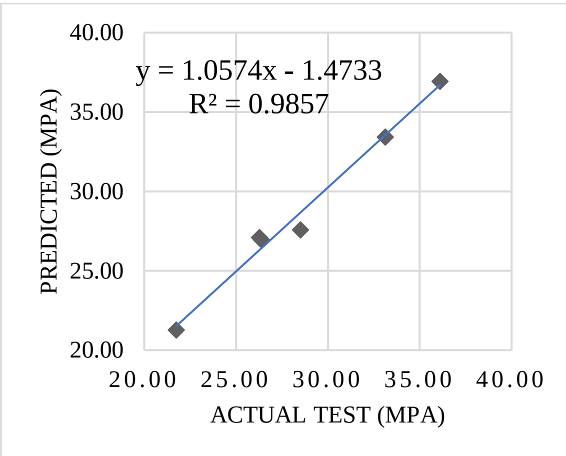

Fig. 5 Accuracy test - compressive.

An increase of 29.79% for high and 51.43% for low of flexural strength were obtained when the dosage of fiber was increased from 1 kg/m^3 to 1.8 kg/m^3. Compared to flexural strength, fibers contributed minimal enhancement for compressive strength, 14.18% and 17.88% for high and low respectively as shown in Fig. 6 and Fig. 7. It was evident that there is no significant increase in the compressive strength of concrete from 1.6 kg/m^3 [24]

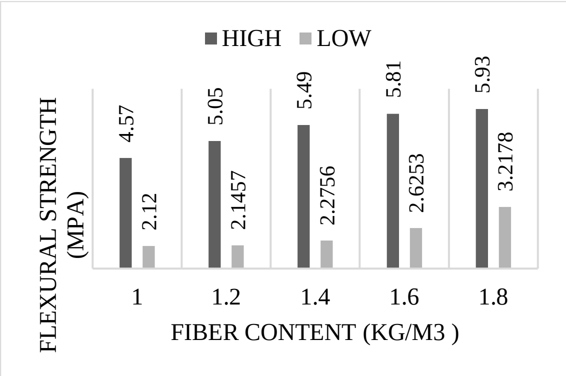

Fig. 6 Parametric study - flexural

Note: The data simulated on this parametric study was based on the mixture that yields the highest and lowest flexural strength and the fiber content were modified on different dosage as stated.

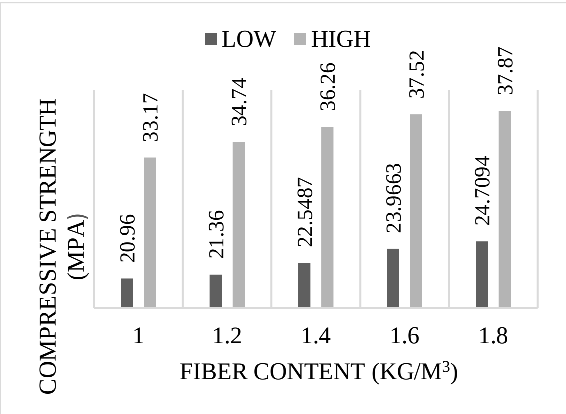

Fig. 7 The parametric study – compressive

Note: The data simulated on this parametric study was based on the mixture that yields the highest and lowest compressive strength and the fiber content were modified on different dosage as stated.

4. CONCLUSIONS

The models derived using Neural Network showed the satisfactory predicting ability for both flexural and compressive strength of concrete as described by highly correlated R values above 0.98. Using 15% of the data for validation test was acceptable in order to reduce the effect overfitting in the neural network model.

The models were able to provide prediction results in good agreement with experimental values. Compressive strength and flexural resistance are at the highest when the fiber content is at 1.8kg per cubic meter of the mix.

An increase of 29.79% and 51.43% were recorded for low and high flexural strengths corresponding to an addition of 1 kg/m^3 to 1.8 kg/m^3 of fiber reinforcement. The fiber in the concrete acts as reinforcement and improve the tensile capacity of the concrete.

An increase of 14.18% and 17.88% were recorded for high and low compressive strengths corresponding to an addition of 1 kg/m^3 to 1.8 kg/m^3 of fiber reinforcement. The added compressive and flexural strength of fiber in concrete may vary in its distribution throughout the mixture. It is necessary to use a mixer in the preparation of the mixtures [25]. Fibers are usually used to decrease the possibility of micro to small scale cracks, but it should not be overlooked its capacity to improve the compressive strength. As observed during the test, fibers hold the concrete from the pressure applied and delayed the cracking.

Despite the improvement of both compressive and flexural strength, it can be observed that the increase was not that significant if the fiber content is close to 1.8kg per cubic meter.

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