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Short fiber-reinforced cementitious extruded plates with high percentage of slag and different fibers

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Abstract

In this paper, the reinforcing effect of two kinds of short fibers, glass fibers and PVA fibers, on the tensile strength and impact resistance of extruded plates is experimentally studied. The results show that the strong but less ductile glass fibers can largely increase the tensile strength, impact strength and impact stiffness of the plates while the ductile PVA fibers are more efficient in increasing the toughness of the plates. By mixing the use of these two fibers, the products can achieve a better mechanical behavior. The effects of high percentage of ground blast-furnace slag in the mixtures were also investigated. An optimum mixing ratio of this mineral admixture was proposed based on the experimental investigations. After the experiments, a back-propagation neural network methodology is used to evaluate the static and dynamic properties of these extruded plates. The well-trained neural network can provide reasonable predictions for the properties of such kinds of materials. © 2000 Elsevier Science Ltd. All rights reserved.

Keywords: Fiber-reinforced concrete; Tensile strength; Impact resistance; Neural network; Slag

1. Introduction

The impact toughness and tensile strength of a product are an index of its resistance to a suddenly applied transverse load and to a direct longitudinal tension, respectively. It is well known that the tension behavior of quasi-brittle mortar can be improved by the incorporation of high-strength, small-diameter short fibers [1,2]. Mindess et al. [3] pointed out that fibers can also increase the impact resistance of cementitious products. The toughening effect comes from the sliding and debonding between the surface of fibers and matrix that increase the fracture resistance by energy dissipation. Using an extrusion technique, the randomly oriented short fibers can be aligned approximately in the loading direction. So short fiber-reinforced extrudates can achieve some properties similar to those of long fiber-reinforced composites, such as the strain-hardening response in tension [4]. However, the reinforcing effects of fibers are varied. The product with different reinforcements has different static and dynamic behaviors. To get a product with satisfactory mechanical properties, the mixing use of several different reinforcements is highly desired. The mixing use of the glass and the PVA fibers are investigated here.

The ground blast-furnace slag can largely lower the cost of cementitious products and at the same time improve the strength and durability of the products by certain pozzolanic reactions and packing effect [5]. Thus, it is practical to study the products with high percentages of blast-furnace slag. Using slag can also improve the extrudability because of its glassy particle texture. High percentage of ground blast-furnace slag up to 70% replacement of cement is studied in this paper. Based on the experimental investigations, an optimum mixing ratio of slag to cement is proposed.

To facilitate engineering application, it is desirable to develop a theoretical model to predict and evaluate the experimental results of the short fiber-reinforced extruded products. Recently, neural network analyses has been successfully applied to many disciplines in civil engineering [6,7]. Compared with the rule-based system, the neural network system allows a much more precise representation of complex relationships between the inputs and the outputs. A neural network can make a generalization for the unknown situations from the known experience or examples. A neural network can also provide an output decision for

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unfamiliar inputs by the generalization of the output decisions from familiar inputs. By virtue of this property, a neural network-based system, unlike a conventional rule-based expert system, can handle the inexact and incomplete inputs. Even if the user could not provide answers to some of the queries, the system can arrive at a recommendation based on the available knowledge about this problem. The feasibility of using a neural network as an adaptive synthesizer as well as a predictor to meet the practice applications is investigated in this paper. The most common and widely used model, back-propagation model, is employed.

2. Experimental procedures

In the experiment, the short PVA fibers, manufactured by Kuraray, and alkali-resistant glass fibers used have a length of 6 mm with an average diameter of 14 μm and 12 mm with an average diameter of 8 μm, respectively. The former has a density of 1.3 g/cm^3 and an average tensile strength and elastic modulus of 1500 MPa and 36 GPa, respectively. The latter has a density of 2.53 g/cm^3 and an average tensile strength and elastic modulus of 3600 MPa and 70 GPa, respectively. The type I cement together with ground blast-furnace slag were used as the basic cementitious materials. The chemical composition of the slag is listed in Table 1. To improve the workability and extrudability of the mixture, a small amount of superplasticizer was used.

The mixing proportions are listed in Table 2. Batches #1 to #5 were prepared for studying the influence of ground blast-furnace slag on the static and dynamic properties of the products, which adopted a water powder ratio of 0.3 and a PVA fiber volume ratio of 2%. Batches #6 to #12 with a water powder ratio of 0.28 were designed for studying the reinforcing effects of different fibers and fiber volume ratios. The 6 mm thin sheet products were extruded by a single screw extruder.

2.1. Tension test

After a 28-day equivalent low pressure steaming curing [8], the specimens were cut to 75×50 mm plates for direct tension test. Each end of a specimen was glued by two aluminum plates that were fixed to the loading fixtures through pins (Fig. 1). The loading fixtures were connected to the MTS hydraulic grips. On each side of a specimen, a LVDT was attached to measure the deformation of the specimen. The average displacement of these two LVDTs was used as a feedback signal to form a closed loop control.

2.2. Impact test

Impact tests were conducted on $90 \times 90 \times 4$ mm^2 specimens on the Ramana ITR-2000 instrumented impact tester. The impact tester consisted of a hemispherical nose of 12.7 mm in diameter and a loading road of 200 mm in total length including the nose. The specimen center was impacted while its edge was firmly fixed between two circular rings having a test window of 75 mm in diameter. The velocity of the punch at the moment of first contact with the specimen was almost constant at 3 m/s. The peak load, fracture energy and load gradient of the specimen were recorded directly from the data-acquisition system via the punch equipped with a piezoelectric device. These parameters provide the indices for impact strength, toughness and stiffness of a specimen.

3. Back-propagation neural network

Artificial neural networks are computing systems made up of a number of simple and highly interconnected processing elements that process information by their dynamic state response to external inputs. In the type of back-propagation network, the weighted connections feed activation only in the forward direction from the input layer to the output layer. As discussed by Funahashi [9], a three-layered back-propagation network is able to approximate the shape of an arbitrary nonlinear function by precisely adjusting connection weights, between neurons. The three-layered neural network consists of an input layer, a hidden layer, and an output layer. Each layer has a group of neurons, and the output of a neuron in one layer is input to all the neurons of the next layer. In the operating phase, the values of the input neurons are set by the user, and the neural network produces the output values. In the training phase, the user simultaneously sets the input and corresponding output values. Then all the weight values are modified using a gradient descent method in which weights of the connections are updated using partial derivatives of error with respect to the weights.

In the present paper, the three-layered back-propagation neural network is adopted to simulate the experimental results (Fig. 2). There are eight nodes in the input layer representing the ratio of slag to cement, the PVA fiber volume ratio, the glass fiber volume ratio, the water/binder ratio, the PVA fiber aspect ratio (PVAFAR), the glass fiber aspect ratio (GFAR), the PVA and glass fiber strength (PVAFS and GFS), respectively. The four nodes in the

Table 1
Chemical composition of slag

	SiO_2	Al_2O_3	Fe_2O_3	TiO_2	K_2O	Na_2O	CaO	MgO	LOI	SO_3
Slag	28.48%	12.56%	1.56%	0.44%	0.44%	0.20%	39.50%	7.40%	0.50%	8.48%

Table 2
Mixing proportions

	Slag/C	SS1/B	SS2/B	PVAF (%)	GF (%)	W/B
Batch #1	–	0.2	0.13	2	–	0.3
Batch #2	0.18	0.2	0.13	2	–	0.3
Batch #3	0.43	0.2	0.13	2	–	0.3
Batch #4	1.00	0.2	0.13	2	–	0.3
Batch #5	2.33	0.2	0.13	2	–	0.3
Batch #6	1.00	0.2	0.13	–	4	0.28
Batch #7	1.00	0.2	0.13	–	2	0.28
Batch #8	1.00	0.2	0.13	–	1	0.28
Batch #9	1.00	0.2	0.13	2	1	0.28
Batch #10	1.00	0.2	0.13	1	1	0.28
Batch #11	1.00	0.2	0.13	2	0.5	0.28
Batch #12	1.00	0.2	0.13	2	–	0.28

C: cement; SS1 and SS2: 300 to 600 μm and 90 to 150 μm silica sand, respectively; PVAF and GF: PVA and glass fiber volume ratio, respectively; B: binder (cement+slag).

output layer represent the tensile strength, the impact toughness, the impact strength, and the impact stiffness, respectively. The number of nodes in the hidden layer is chosen to be 20 based on the calculation experience. The interconnection weights between nodes in the input and hidden layers are w_{ij}^{IH} (i=1, 8 and j=1, 20). The interconnection weights between nodes in the hidden layer and the output is w_{jk}^{HO} (j=1, 20 and k=1, 4).

The output of a hidden layer node is given as [Eq. (1)]:

$$x_j = f\left(\sum_{i=1}^{9} w_{ij}^{\mathrm{IH}} a_i\right). \tag{1}$$

The output of an output layer node is given as [Eq. (2)]:

$$y_k = f\left(\sum_{j=1}^{21} w_{jk}^{\mathrm{HO}} x_j\right). \tag{2}$$

The sigmoid activity function is [Eq. (3)]:

$$f(\alpha) = 1/(1 + e^{-\alpha}) \tag{3}$$

w_{9j}^{IH} represents the threshold values of the hidden nodes, i.e. $a_9 = -1$, and $w(_{21k})^{\mathrm{HO}}$ represents the threshold values of the output nodes, i.e. $x(_{21}) = -1$.

Suppose the number of samples trained is P, then the residual of the prediction can be expressed as:

$$R = \frac{1}{2}\sum_{l=1}^{p}\sum_{k=1}^{4}(t_k^l - y_k^l)^2 \tag{4}$$

where $t(_k)(^l)$ is the experimental result.

The purpose of the scheme is to decrease the residual of R in Eq. (4) to zero or a specified tolerance through modifying the interconnection weights, w_{ij}^{IH} and w_{jk}^{HO}.

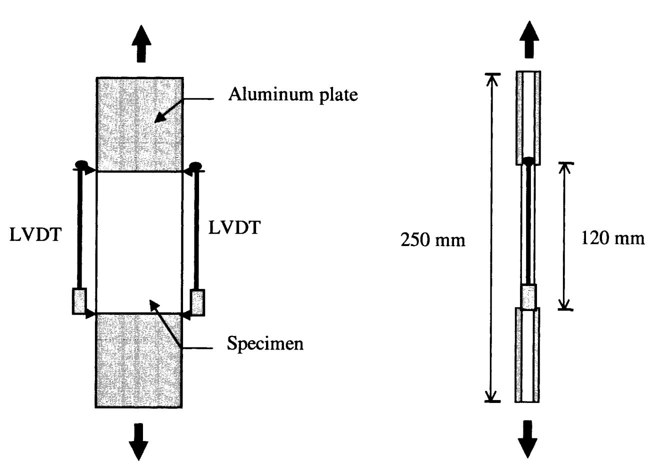

Fig. 1. Setup of direct tension test.

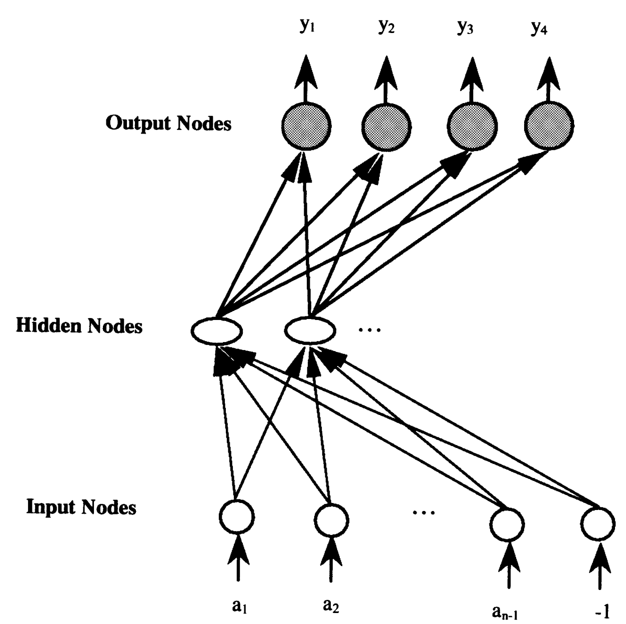

Fig. 2. The B–P neural network used in the paper.

Table 3
Tensile strength and impact resistance of cementitious sheets

	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12
Tensile strength (MPa)	5.13	5.35	5.74	6.83	7.35	11.68	9.55	8.13	8.91	8.60	7.87	7.22
Impact toughness (J)	2.93	3.13	3.46	3.14	3.03	3.07	2.91	2.65	3.35	2.95	3.28	3.18
Impact strength (N)	437	445	461	488	549	711	658	534	624	576	546	504
Impact stiffness (N/mm)	498	555	615	631	656	737	706	634	684	649	641	638

The well-known gradient descent method is employed and the weights are adjusted as follows [10]:

$$w_{jk}^{\mathrm{HO}}(n+1) = w_{jk}^{\mathrm{HO}}(n) + \eta \sum_{l=1}^{p} \delta_{jk}^{l} x_j^{l} \tag{5}$$

where $\delta_{(jk)}^{(l)} = (t_{(k)}^{(l)} - y_{(k)}^{(l)}) y_{(k)}^{(l)} (1 - y_{(k)}^{(l)})$ and

$$w_{ij}^{\mathrm{IH}}(n+1) = w_{ij}^{\mathrm{IH}}(n) + \eta \sum_{l=1}^{p} \delta_{ij}^{l} a_j^{l} \tag{6}$$

where $\delta_{ij}^{l} = x_j^{l}(1 - x_j^{l}) \sum_{k=1}^{4} \delta_{jk}^{l} w_{jk}^{\mathrm{HO}}$.

The training of the back-propagation neural network is composed of two steps. The first step is to calculate the results of the input samples in the forward direction from the input to the output layer. The second step is to correct the interconnection weights and the threshold values of the nodes in the hidden and output layers based on Eqs. (5) and (6). The process is from the output layer to the input layer. These two steps are repeated in turn until the R in Eq. (4) is less than a specified tolerance. Considering the gradient search technique that may find a local minimum in the least mean square cost function [Eq. (4)] instead of a global minimum, the two following concerns to improve performance and reduce the occurrence of local minimum are desired. The first is to lower the gain term, η ($0 < \eta < 1$), used to adapt the interconnection weights [Eqs. (5) and (6)]. The second is to start the calculation from different sets of initial weights.

4. Results and discussions

The tension strength and impact resistance of short fiber-reinforced sheets with different proportions of ground blast-furnace slag (batch #1 to batch #5) are listed in Table 3. To compare the influence of slag, batch #1, without any slag, is served as a control mix. From batch #2 to batch #5, the slag to cement ratios vary from 0.18 to 2.33 as shown in the Table 2. It is known that the slag has the packing effect and pozzolanic reactivity. Subsequently, the matrix properties and fiber bonding conditions can be effectively improved. To illustrate the packing effect of the slag, its particle size distribution was measured by the LS Particle Analyzer (COULTER LS2300). The results are shown in Fig. 3. It can be seen that the mean particle size of the slag is much smaller that that of cement. Thus it is able to fill the capillary pores and entrapped air voids in the mortar paste.

As can be seen in Table 3, the tensile strength increases with increase of the amount of slag. The tensile strength of the batch with slag to cement ratio of 2.33 is about 50% higher than that of the control batch. For the impact indices, both the impact strength and stiffness increase with increasing the proportion of slag, similar to the tensile strength. However, the impact toughness, which is the energy absorbed during the impact process, is proportional to the addition of the slag. The optimum slag to cement ratio for impact toughness is 0.43. If taking the tensile strength of batch #5 as one unit and the impact

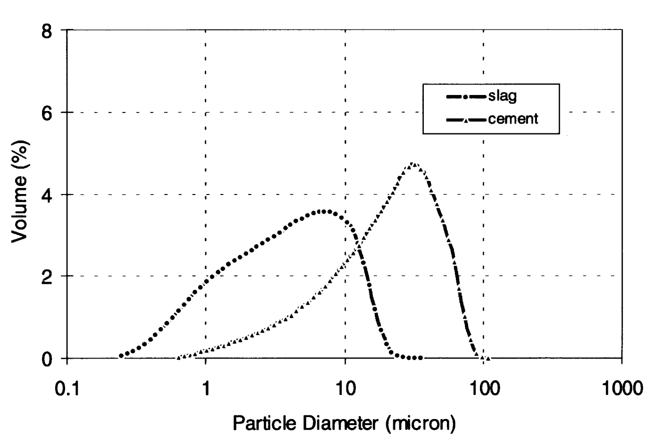

Fig. 3. Particle size distributions of slag and cement.

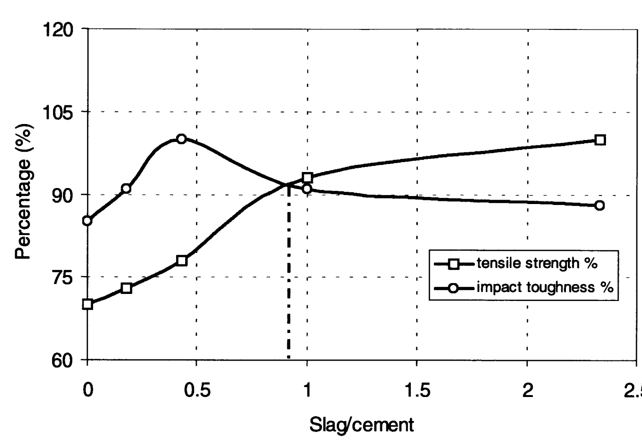

Fig. 4. Tensile strength and impact toughness percentages with different slag to cement ratios.

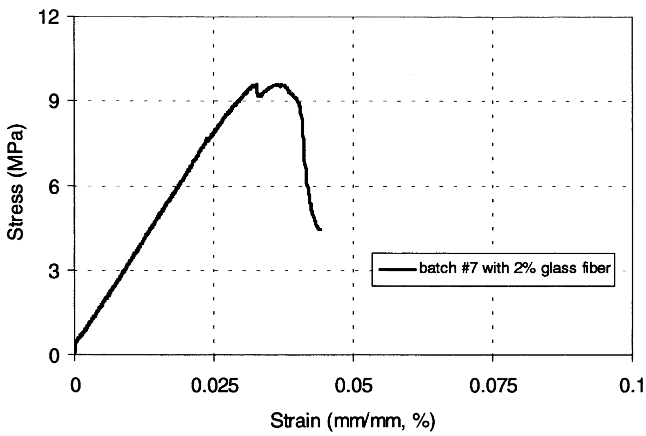

Fig. 5. Tensile stress and strain curve for batch #7.

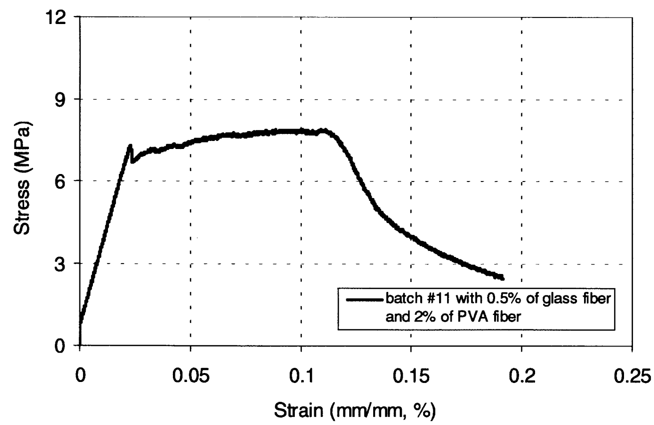

Fig. 7. Tensile stress and strain curve for batch #11.

toughness of batch #3 as one unit, the tensile strengths and impact toughnesses of batch #1 to #5 can be drawn as percentages of these two, respectively (see Fig. 4). From this figure, if the tensile strength and impact toughness are of equal importance to the design criterion, it can be drawn that the slag to cement ratio of about 0.9 to 1.0 is the optimum range.

Glass fiber reinforcement and PVA fiber reinforcement were investigated and compared. The tension and impact results were shown in Table 3 from batch #6 to #12. It is found that glass fiber reinforcement is more efficient in enhancing the tensile and impact strength of the specimens. However, the tensile ductility of glass fiber-reinforced specimen is poor and after the bend over point (where the first throughout transverse crack appears in the matrix), the stress drops sharply (Fig. 5). During the tension test, the specimens with glass fiber only were usually broken suddenly without any warning when the stress peaks were reached. To overcome this shortage of the brittle glass fibers, ductile PVA fibers were introduced. Fig. 6 gives the tensile stress–strain relationship of the specimen with 1% of glass fiber and 1% of PVA fiber reinforcement (batch #10). From the figure, it can be seen that after the stress peak most of the glass fibers are out of bridging function, while the PVA fibers can still sustain some part of the external loading at this moment. Then, the curve shows a small plateau region after a sudden drop of the stress. The tensile strain and toughness are both improved. A more effective case for the mixing use of these two fibers is shown in Fig. 7, which shows the stress and strain relationship for a specimen with 0.5% of glass fiber and 2% of PVA fiber (batch #11). In the figure, after the bend over point, a strain hardening response starts and multiple cracking is observed in the specimen. The impact toughness is also largely increased (Table 3).

For neural network analysis, the test results of batch #1 and #2, #4 to #10 and #12 are used to train the network. After being trained, the network is employed to predict the tensile strength, impact toughness, impact strength, and impact stiffness of batches #3 and #11. The comparison between the test results and the network predictions for batches #3 and #11 are shown in Figs. 8 and 9, respectively.

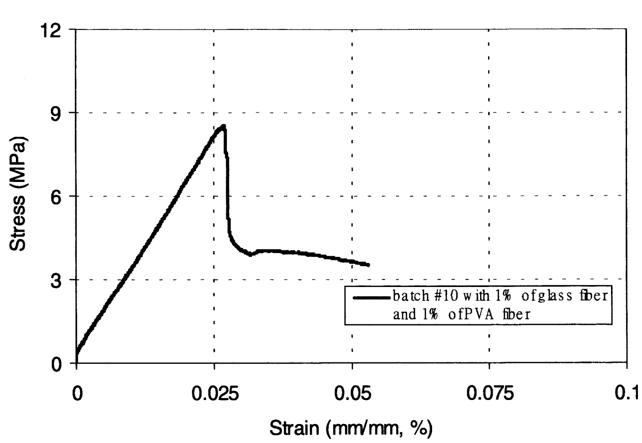

Fig. 6. Tensile stress and strain curve for batch #10.

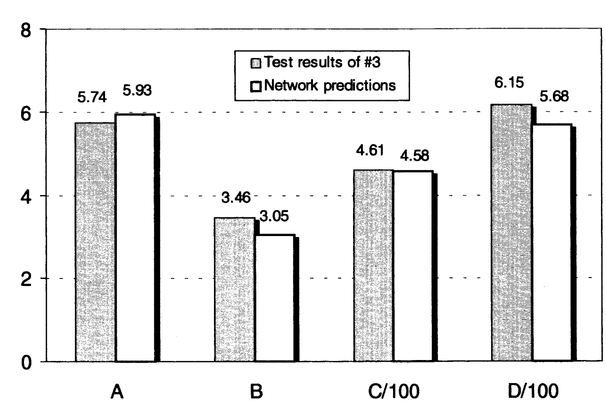

Fig. 8. The test results and network predictions for batch #3 (A: tensile strength (MPa); B: impact toughness (J); C: impact strength (N); D: impact stiffness (N/mm)).

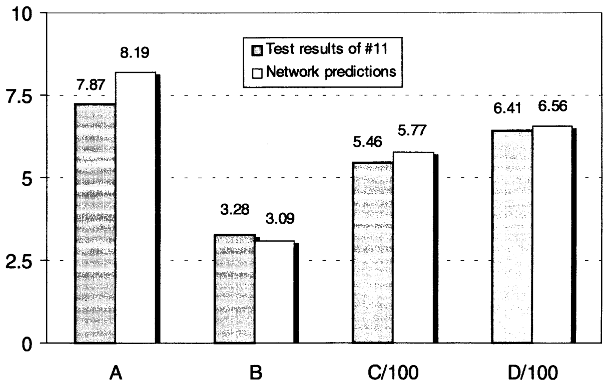

Fig. 9. The test results and network predictions for batch #11 (A: tensile strength (MPa); B: impact toughness (J); C: impact strength (N); D: impact stiffness (N/mm)).

It can be see that the theoretical predictions compare well with the experimental data.

5. Conclusions

The static and dynamic mechanical properties of the short fiber-reinforced cementitious sheets manufactured by extrusion were investigated by the direct tension test and impact test. After the tests were conducted, the applicability of back-propagation neural networks for predicting the test results was evaluated. It is found that cementitious sheets incorporating with a large amount of slag to cement ratio exhibit better mechanical properties. An optimum range of slag to cement ratio is 0.9 to 1.0. It is also found that the glass fiber is much more effective in reinforcing the matrix tensile and impact strength. However, the composite reinforced by glass fiber is more brittle as compared to that reinforced by PVA fiber. The mixing use of the two fibers can achieve a better performance in both strength and toughness.

The back-propagation neural network analysis is a black-box approach and the user need not know much about the mechanism of the static and dynamic properties of short fiber-reinforced cementitious sheets. With its abstraction, generalization, and fault-tolerant properties, the back-propagation neural network has good potential in the prediction of the mechanical properties of cementitious materials. It can provide reasonable predictions if trained properly.

Acknowledgments

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