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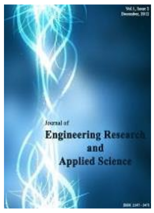

Flexural strength estimation of basalt fiber reinforced fly-ash added gypsum based composites

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Abstract

Gypsum and fiber reinforced gypsum-based composites are widely used in many construction projects. Many researches have been conducted on these types of composites; however, there are very limited literature studies focused on the estimation of flexural strength of the fiber reinforced gypsum-based composites. And there is no current study on the mechanical strength estimation of these types of composites. An extensive experimental data covering 275 flexural strength test results with five input parameters (fly-ash, basalt, superplasticizer contents, water to binder ratio and slump values) were utilized for the artificial neural network (ANN) model designation. Effect of each parameters on the flexural strength were carefully analyzed. An empirical formula was developed with the generalization capabilities of the proposed ANN system, as well. Analysis results showed a good agreement between the site and field data. And these highly efficient numerical data can make it possible to predict flexural strength of gypsum-based composites.

Keywords: Flexural strength; gypsum; basalt fiber; gypsum-based composites.

1. Introduction

Gypsum-based composites have been widely preferred for various construction purposes in construction industry; since they have good fire resistance, thermal and sound insulation properties [1,2]. Different types and length of building materials can be mixed during the production stage to enhance mechanical properties of the gypsum-based composites [3]. Many fiber types and filler materials such as pozzolans can also be added to improve the mechanical behavior of the composites [4,5]. Carbon fibers, glass fibers and PVA fibers are generally used within the latest literature studies [6,7].

Gypsum soft structure can be severely damaged by hydration reactions. Gypsum can be used with a water permeable material in order to prevent its easy solubilization when contact with water [8]. Silica fume, fly-ash, iron oxide can be utilized with gypsum to improve the water-resistant property [9].

Mechanical properties of the gypsum-based composites such as fracture energy and toughness can be enhanced with the fiber inclusion [10]. Fibers can be classified as natural and manufactured types. Basalt fibers has gained popularity compared to the other fiber types, since it has a high tensile strength [11]. Basalt fiber inclusion can be changed for different aims; however, generally added with the rate of 0.5 % by volume. Production costs are very low and basalt fibers can be produced under more environment-friendly conditions.

Data based estimation methods such as ANN are commonly used in many engineering applications. These systems can also give further information for better understandings of the composite material properties. ANN based models provides more efficient data for construction material mechanical properties compared to the other estimation systems [12].

2. Material and method

Gypsum complying TS EN 13279-1[13] was used in this study. Material properties of the gypsum are given in Table 1. Basalt fibers were added into the composite mixes with the length of 12 mm and 0.6 % by volume. Fiber properties are given in Table 3. Fly-ash was utilized as filling material. The chemical

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composition of the fly-ash is presented in Table 2.

Table 1. Properties of Gypsum.

Chemical composition	CaSO4.xH2O (x=0, ½ ,2)
Comp. Strength (MPa)	2.7
Flexural Strength (MPa)	1.2
Dry density (kg/m^3)	600-1000
Initial setting (min.)	70-100
Final setting (min.)	140

Table 2. Composition of fly-ash.

Constituent	% by weight
SiO_2	29.6
Al_2O_3	10.66
Fe_2O_3	6.19
CaO	32.91
MgO	5.93
SO_3	9.98
Na_2O	0.72
K_2O	0.63
Loss on ignition	2.09

Table 3. Basalt fiber properties.

Basalt fiber	Property
Breaking Strength (MPa)	2.7
E (GPa)	1.2
Thermal cond. (W/mK)	600-1000
Density (kg/m^3)	70-100
Alkali resistance	140

Polycarboxylate based plasticizer was used as the chemical agent. 160 x 40 x 40 rectangular specimens were prepared for the flexural tests. 28-day flexural strength tests were conducted according to the TS EN 13279-2 [14]. Four-point flexural strength test machine was operated for the strength tests. Potable water was used in this study.

Static consistency of the mixes was measured as per the requirements of EN 1170-1 [15]. Slump test was performed with a cylindrical funnel (height:60mm, inner radius:57mm, outer radius:65mm).

Fresh and hardened material properties of the fiber reinforced gypsum-based composites were collected from field studies.

Quasi- Newton algorithm was used as training algorithm in this study. The number of inputs is 5. The size of scaling layer is also 5. The following Table 4 shows the values which are used for scaling the inputs, which include the minimum, maximum, mean and standard deviation. The number of the layers in neural network is 2. The size of each layer and its corresponding activation function are given in Table 5. The architecture of this neural network can be written as 5:3:1.

A graphical representation (Figure 1) of the network architecture is depicted next. It contains a scaling layer, a neural network and an unscaling layer. The yellow circles represent scaling neurons, the blue circles perceptron neurons and the red circles unscaling neurons. The number of inputs is 5, and the number of outputs is 1. The complexity, represented by the numbers of hidden neurons, is 3. The norm of the parameters gives a clue about the complexity of the predictive model. If the parameters norm is small, the model will be smooth. On the other hand, if the parameters norm is very big, the model might become unstable. Also note that the norm depends on the number of parameters. The norm of the neural parameters is 2.64. The architecture of this neural network is 5:3:1, and the number of parameters is 22. The loss index plays an important role in the use of a neural network. It defines the task the neural network is required to do and provides a measure of the quality of the representation that it is required to learn. The choice of a suitable loss index depends on the application.

Table 4. Scaling layer.

	Minimum	Maximum	Mean	Deviation
Fly-ash	0	5	1.88	2.08
Basalt fiber	0	0.6	0.218	0.248
Water to binder ratio	0	0.42	0.279	0.169
Superplasticizer	0	1.25	0.799	0.485

Table 5. Size of layers and activation functions.

	Minimum	Maximum	Mean	Deviation
	Inputs number	Neurons number	Activation function	
1	5	3	Hyperbolic tangent	1
2	3	1	Linear	2

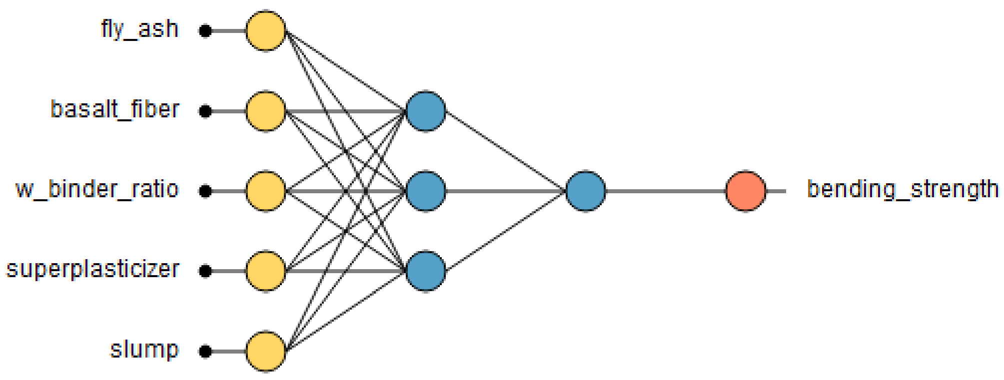

Figure 1. Neural network graph.

The root mean squared error was used in this research as the error method. It takes the square root of the mean squared error between the outputs from the neural network and the targets in the data set. The neural parameters norm was used as the regularization method. It was applied to control the complexity of the neural network by reducing the value of the parameters. The weight of this regularization term in the loss expression is 0.001.

The Quasi-Newton method is based on the Newton's method but does not require calculation of second derivatives; however, the quasi-Newton method computes an approximation of the inverse Hessian at each iteration of the algorithm, by only using gradient information. Training algorithm is given in Table 6. A normalization procedure was applied to the input signals for eliminating bias and improving the prediction performance. All prediction studies have been conducted with the aid of Neural Designer software.

Table 6. Training algorithm (order selection).

Description	Value
Training rate method	Brent Method
Training rate tolerance	0.005
Min. parameters increment form	1e-008
Min. loss increase	1e-012
Gradient norm goal	0.001
Max. iterations number	1500

3. Discussions

The following plot (Figure 2) shows the losses in each iteration. The initial value of the training loss is 0.0170357, and the final value after 17 iterations is 0.0136828. The initial value of the selection loss is 0.0113455, and the final value after 17 iterations is 0.0109603.

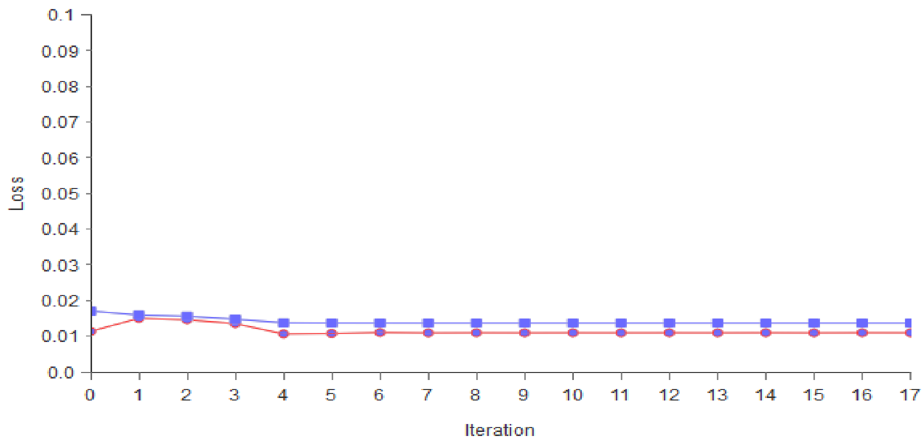

Figure 2. Iteration vs losses.

The Table 7 shows the training results by the quasi-Newton method. They include some final states from the neural network, the loss functional and the training algorithm.

Final gradient norm and selection loss were obtained as 0.00746 and 0.011, respectively. Model selection was also applied to find a neural network with a topology that optimizes the loss on new data. There are two different types of algorithms for model selection: Order selection algorithms and input selection algorithms. Order selection algorithms were used to find the optimal number of hidden neurons in the network. Inputs selection algorithms were responsible for finding the optimal subset of input variables.

Table 7. Quasi-Newton method results.

	Value
Final parameters norm	2.64
Final loss	0.0137
Final selection loss	0.011
Final gradient norm	0.00746
Iterations number	17
Stopping criteria	Minimum parameters norm

A standard method to test the loss of a model is to perform a linear regression analysis between the scaled neural network outputs and the corresponding targets for an independent testing subset. This analysis leads to 3 parameters for each output variable.

The first two parameters, a and b, correspond to the y-intercept and the slope of the best linear regression relating scaled outputs and targets. The third parameter, R2, is the correlation coefficient between the scaled outputs and the targets. If we had a perfect fit (outputs exactly equal to targets), the slope would be 1, and the y-intercept would be 0. If the correlation coefficient is equal to 1, then there is a perfect correlation between the outputs from the neural network and the targets in the testing subset. The bending strength linear regression chart is presented in Figure 3. The colored line indicates the best linear fit. The grey line would indicate a perfect fit. Results showed a good fitting between the predicted and actual scaled test results.

The mathematical expression represented by the neural network is presented in Figure 4. It takes the inputs fly-ash, basalt-fiber, water to binder, superplasticizer and slump to produce the output flexural strength. For forecasting problems, the information is propagated in a feed-forward fashion through the scaling layer, the perceptron layers and the unscaling layer.

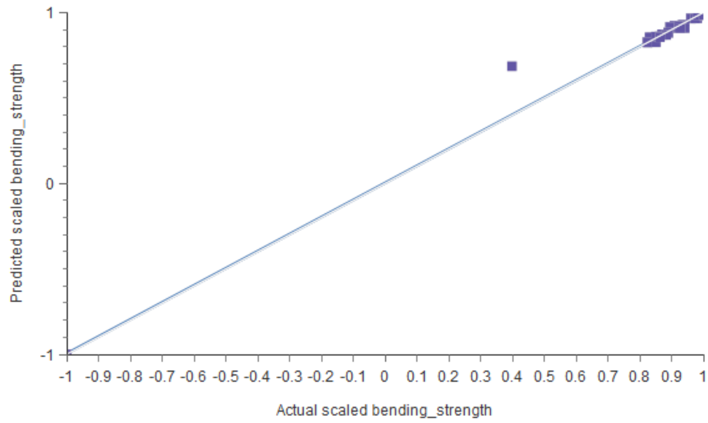

Figure 3. Flexural strength linear regression chart.

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scaled_fly_ash=2*(fly_ash-0)/ (5-0)-1;
scaled_basalt_fiber=2*(basalt_fiber-0)/ (0.6-0)-1;
scaled_w_binder_ratio=2*(w_binder_ratio-0)/ (0.42-0)-1;
scaled_superplasticizer=2*(superplasticizer-0)/ (1.254-0)-1;
scaled_slump=2*(slump-0)/ (1118-0)-1;
y_1_1=tanh (0.203457
-0.205215*scaled_fly_ash
-0.056107*scaled_basalt_fiber
+0.888679*scaled_w_binder_ratio
+0.885888*scaled_superplasticizer
-0.0577063*scaled_slump);
y_1_2=tanh (0.53043
-0.691118*scaled_fly_ash
-0.788587*scaled_basalt_fiber
+0.585695*scaled_w_binder_ratio
-0.124338*scaled_superplasticizer
-0.333381*scaled_slump);
y_1_3=tanh (-0.207293
+0.420269*scaled_fly_ash
+0.664987*scaled_basalt_fiber
-0.651238*scaled_w_binder_ratio
-0.374232*scaled_superplasticizer
+0.285416*scaled_slump);
scaled_flexural_strength= (0.0711034
+1.23997*y_1_1
+0.351495*y_1_2
+0.704555*y_1_3);
(flexural strength) = (0.5*(scaled_bending_strength+1.0) *(3.08-0)
+05);
```

Figure 4. Mathematical expression.

4. Conclusions

275 flexural strength test results of the basalt fiber reinforced gypsum-based composites were analyzed in this study. Five input parameters (fly-ash, basalt, superplasticizer contents, water to binder ratio and slump values) and their effects on flexural strength were studied. The following conclusions can be drawn:

- The ANN model provides the strong correlation between the flexural strength values of predicted and site data.
- The analysis results showed that the weighting factor are well calibrated. They

showed a good correlation with the previously conducted experimental data.

- The outcomes of the study can be assessed by other artificial and mathematical systems for better understanding mixture behavior of gypsum-based composites.

It seems that resulted and simple mathematical expressions are very important over the existing empirical equations conducted in other analysis. However, more reliable equations can be provided on condition that other fresh state property effects are examined in detail.

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