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Prediction of Bending Strength of Self-Leveling Glass Fiber Reinforced Concrete

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Abstract: Many studies have been conducted on the prediction of fiber reinforced concrete strength; however, there are very rare data concerning the prediction of bending strength values of self-leveling glass fiber reinforced concrete. And there is no study for prediction of bending strength of self-leveling glass fiber reinforced concrete from mixture ingredients and slump values. In the present study, relationships between the bending strength and the mixture proportions are explored. An artificial neural network model (ANN) is designed with an extensive experimental data including 395 four-point bending tests, and input parameters as white cement amount, maximum aggregate size, glass fiber content, water cement ratio, superplasticizer and metakaolin content and slump test results. Effect of each parameter on the bending strength is investigated with the developed model. An empirical and user-friendly formula was obtained with the generalization capabilities of the ANN. Results showed that the prediction results are in good agreement with the field data. And these numerical results with high efficiency can make it possible to use the neural design for real-life self-leveling glass fiber reinforced concrete applications.

Keywords: *Bending strength, self-leveling concrete, glass fiber, glass fiber reinforced concrete.*

1. Introduction

Self-leveling concrete (SLC) has the capability of consolidating under its own weight and flowing easily. SLC has been widely used for placing in difficult sections due to its fluid nature. In addition, SLC has other advantages as reducing concrete placement time, increasing overall quality and profit of the concrete based construction works [1]. SLC is very sensitive to any changes in mix design and for this reason detailed quality control procedures are needed. The fresh mix properties of the SLC have a significant effect on hardened properties such as bending strength and durability [2]. There are many approaches for improving SLC fresh and hardened properties: addition of pozzolans in to the mixture as a cement replacement material and use of various superplasticizers [3].

The hardened SLC has very similar engineering properties compared to the conventional vibrated concrete [4]. However, they differ in concrete mix ingredients. Ultra-fine materials and high range of superplasticizers are in need during the mix design process of the SLC [5].

Fiber reinforced concrete (FRC) is primarily consisting of hydraulic cement, aggregates, and fibers [6]. FRC is widely used in civil engineering projects including precast concrete elements, bridge decks, highways and in tunnel works depending on their comparatively higher load bearing capacity and crack resistance properties [7, 8]. Many researches have been focused on the effects of using different types of fibers in SLC mixes [9-11].

The inclusion of glass fiber (GF) enhances the mechanical properties of the SLC such as compressive, bending, and split strength. GF addition also reduces the crack width and negative temperature effects [12, 13].

Data based prediction models including ANN, Multiple Linear Regression (MLR) are widely used in various engineering applications [14-17]. These models can give further information for a better understanding of the material properties [18]. Among the prediction models, ANN provides more accurate predictions for concrete mechanical properties [19].

In recent years, mechanical properties and the complex behavior of the concrete have been analyzed with the aid and abilities of the artificial intelligence-based methods [20, 21]. Prediction of bending strength of the SLC from the mix ingredients and fresh properties is a particularly complex question. And literature review shows that previous approaches for the prediction of SLC strength properties do not include sufficient and detailed investigations [22].

2. Research Significance

Early determination of bending strength property of glass fiber reinforced SLC is an essential factor for any design purposes. The bending strength of the SLC can also give basic and exact information for the prediction of other mechanical properties. However, there exist no proved relationship for glass fiber reinforced self-leveling concrete (GFRSLC). For this reason, it has to be analyzed with experimental data and tests.

Fresh properties of the GFRSLC directly effect the hardened state and the mechanical properties. Obtaining a relationship for evaluating bending strength values from fresh state properties and ingredients would be an effective achievement for improving GFRSLC production industry. Quasi- Newton method was utilized as training algortih in this experimental study, due to the fact that the algorithm is more suitable and reliable for cementitious product strength production compared to the other conventional methods such as regression based systems.

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3. MATERIALS AND METHODS

3.1. Artificial Neural Network Development

Various functions and optimization methods such as gaussian, sigmoid, back propagation and quasi-newton are widely used for concrete strength prediction studies [23]. Quasi- Newton method was used as the training algorithm within the scope of this study. It is based on Newton's method but does not require calculation of second derivatives. Instead, the Quasi-Newton method computes an approximation of the inverse Hessian at each iteration of the algorithm, by only using gradient information. This algorithm is generally preferred for estimating concrete properties. Training rate method was utilized as Brent Method. Detailed information is given in Table 1. Data classification of the proposed model was carried out as 20 % data for training, 30 % for validation and 50 % for testing.

Table 1: Training algorithm

Description	Value
Training rate method	BrentMethod
Training rate tolerance	0.0005
Min. parameters increment form	1e-009
Min. loss increase	1e-012
Gradient norm goal	0.001
Max. iterations number	1000

The ANN structure was designed with six input variables for estimating the bending strength values as shown in **Figure 1**. In this study, six input parameters: maximum aggregate size, glass fiber content, water to cement ratio, superplasticizer and metakaolin content and slump values were selected based on physical considerations and the experimental test results. Other factors (air content, curing conditions, etc.) that may affect the bending strength are ignored due to the rare information in the literature.

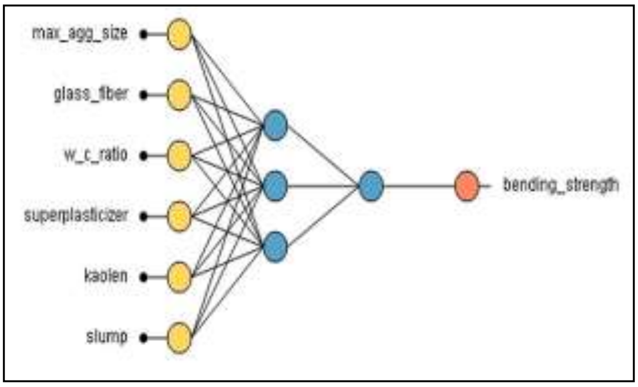

Figure 1: Proposed ANN structure

The order selection algorithm chosen for this application is the incremental order. This method starts with the minimum order and adds a given number of perceptron in each iteration. The order selection algorithm details are presented in **Table 2**. All prediction studies have been conducted with the aid of Neural Designer software.

Table 2: Order selection algorithm

Description	Value
Minimum order	1
Maximum order	10
Trials number	4
Tolerance	0.01
Selection loss goal	0
Maximum selection failures	5
Maximum iterations number	1000

A normalization procedure was applied to the input signals for eliminating bias and improving the prediction performance. The following formula where x_n, x_{min} and x_{max} represent the normalized data set, minimum and maximum values, respectively was used during the normalization process (1):

$$x_n = \frac{x_n - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

Proposed model performance was evaluated with Sum Squared Error (SSE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Normalized Squared Error (NSE) and Minkowski Error (ME) operators. Training, selection and testing errors are given in **Table 3**.

Table 3: Proposed network errors

	Training	Selection	Testing
Sum squared error	3.1711	1.4408	1.2966
Mean squared error	0.0133	0.0184	0.0166
Root mean squared error	0.1156	0.1359	0.1289
Normalized squared error	0.1361	0.2375	0.1945
Minkowski error	7.2715	3.1868	2.6220

3.2. Field studies and data collection

Fresh and hardened properties of the GFRSLC have been collected from field studies to carry out a precise assessment of the bending strength output.

3.2.1. Materials

Cement type CEM I 52.5 R in accordance with EN 197-1 [24] was utilized as the binder material in this study. Chemical composition and physical properties of the cement are presented in **Table 4**.

Table 4: Properties of the cement

Chemical composition (%)										
SiO_2	Al_2O	Fe_2O	CaO	MgO	Na_2O	K_2O	SO_3	Free CaO	Cl	LOI
21.5	4.05	0.26	65.7	1.3	0.30	0.35	3.25	1.60	0.01	3.2
Mechanical and physical properties										
Specific Weight (t/m^3)	3.06									
Specific surface (cm^2/g)	4600									
Whiteness (%)	85.5									
0.045 Sieve residue (%)	1									
0.090 Sieve residue (%)	0.1									
Compressive Strength at 2 days (MPa)	37									
Compressive Strength at 7 days (MPa)	50									
Compressive Strength at 28 days (MPa)	60									

Silica sand and metakaolin were used as the filler. The properties of these materials are given in **Table 5** and **Table 6**, respectively.

Table 5: Silica sand properties

Silica sand	
Mean Grain Size (μm)	140-165
Clay content (%)	06.-0.8
Specific weight	2.68
AFS value (%)	84.6

An acrylic based superplasticizer was used as chemical admixtures in all GFRSLC mixes. Drinking water was added into the all mixes in this study.

Table 6: Physical properties and chemical composition of metakaolin

Chemical composition (%)										
SiO_2	Al_2O_3	Fe_2O_3	CaO	MgO	Na_2O	K_2O	SO_3	Free CaO	Cl	LOI
52.22	43.18	0.6	1.03	0.08	-	-	-	-	-	-
Physical properties										
Specific Weight (t/m^3)									2.54	
Specific surface (cm^2/g)									8 –14 m^2/g	
Brightness									80-81	
Color									Gray	
Physical form									powder	

Alkali resistant glass fibers were preferred within the scope of this study. Physical and mechanical properties of the glass fiber are given in **Table 7**.

Table 7: Physical and mechanical properties of glass fibers

Property	
Tensile strength	1,750 MPa
Modulus of elasticity	71,500 MPa
Fiber diameter	12 microns
Aspect ratio	852
Specific Weight	2.69 t/m^3
Water absorption	< 0.11 %

3.2.2. Preparation of the GFRSLC mixes and test procedure

Mix designs and experimental sets are given in **Table 8**. Glass fibers were added into the mixes with the rates of 3 %, 3.25 % and 3.5 % of wt. Cement amount was replaced by metakaolin with the weight of 2.5 and 5 kg. In prior to the water inclusion, cement, silica sand and metakaolin were mixed for 60 s. Then, 2/3 of water was added, and silica sand, cement and metakaolin were mixed for 120 s. After homogenization of the mix, remaining water, glass fiber and super plasticizer were added and mixed for 60 s.

Table 8: GFRSLC mixture designs

Mixture materials	**Quantity**
White cement	45 - 50 kg
Metakaolin	2.5 – 5 kg
Silica sand	50 kg
Glass fiber	(3 %, 3.25 %, 3.5 % of wt.)
Superplasticizer	300 – 330 g
W/C	0.3 – 0.38

Slump values were measured with the aid of a cylindrical funnel (height of 60 mm, inner and outer radiuses respectively, 57 mm and 65 mm) according to the requirements of TS EN 1170-1 (**Figure 2** and **Figure 3**). Specimens with the dimensions of 160 x 40 x 40 mm were prepared for the bending tests. Bending strength of the GFRSLC specimens at 28 days was recorded complying the TS EN 1170-4, 5 standards. Four-point bending test machine was used during the bending strength tests.

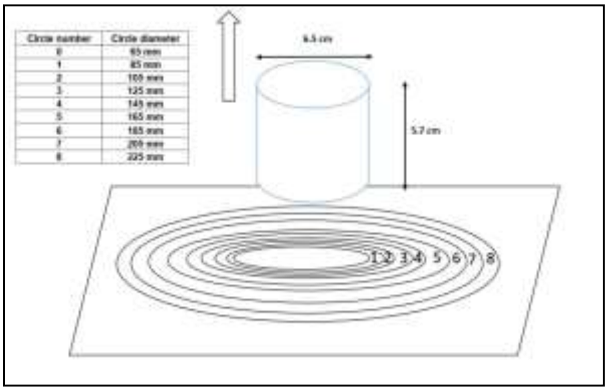

Figure 2: Slump test (TS EN 1170-1)

Figure 3: Slump test (Mixture w/o superplasticizer)

3.2.3. Field test results and discussion

Bending strength, white cement content and maximum aggregate size relations are given in **Figure 4**. The test results showed that bending strength values increase with the increasing aggregate size and cement content.

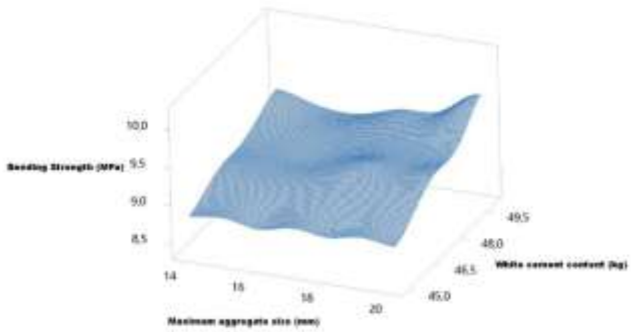

Figure 4: White cement content, max. aggregate size and bending strength relation

Glass fiber content and bending strength property of the GFRSLC are related to each other. Bending strength increases when the glass fiber content of the mix is higher (**Figure 5**). It was also observed that maximum bending strength was recorded as 10.2 MPa when the slump value was 185 mm.

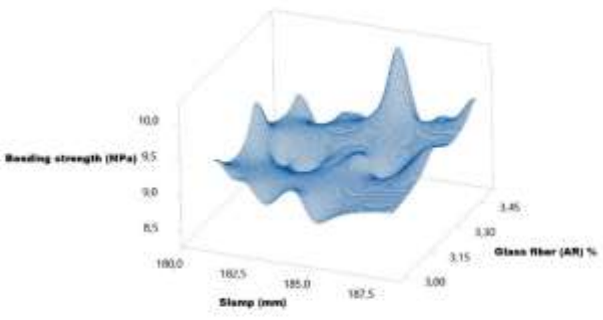

Figure 5: Glass fiber content and bending strength relation

Figure 6 shows the effects of water to cement ratio and metakaolin addition to the bending strength test results. It can be seen from the figure that the maximum bending strength test results are obtained when the water to cement ratio is close to 0.33. In addition, utilization of 2.5 kg metakaolin gives the better bending test results.

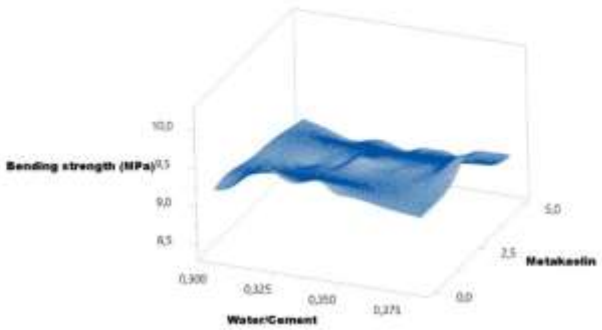

Figure 6: Water/cement ratio, metakaolin content and bending strength relation

4. DISCUSSIONS

Linear regression of the predicted bending strength is given in **Figure 7**. The predicted values are plotted versus the actual ones as squares. The blue line shows the best linear and the grey line would indicate the perfect fit. R-squared value accounts for 91.17 and proposed ANN model exhibits good fitting performance.

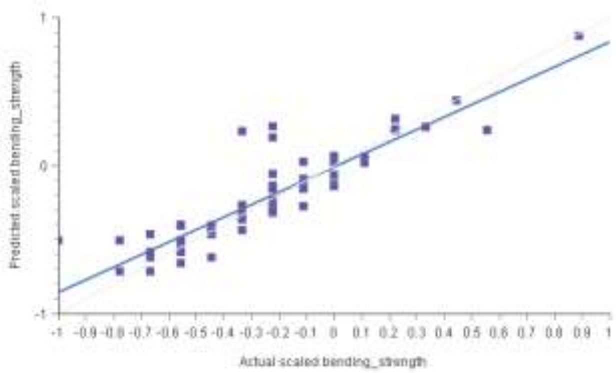

Figure 7: Linear regression chart (bending strength)

Figure 8 represents the output bending strength as the function of input parameters. The x and y axes are defined by the range of inputs and the output bending strength. The testing results are compared with the predicted data. The relationship between the input data with the output data is constant and independent; however, it is not valid in ANN environment. The main reason is that each input of the model significantly effect the proposed structure. The best fitting model includes all mixture materials to obtain the most appropriate prediction of bending strength of the GFRSLC.

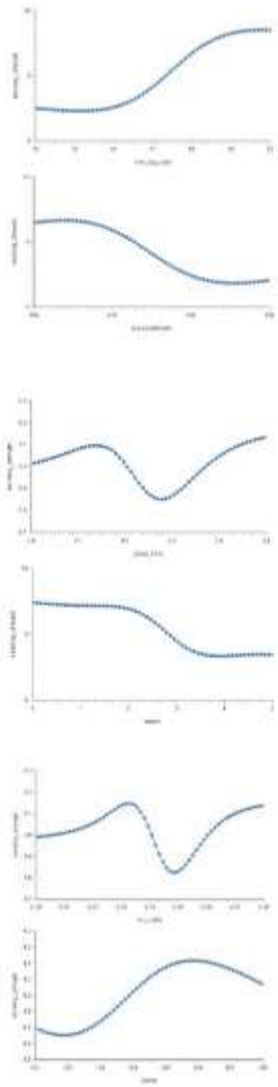

Figure 8: Predicted bending strength as a function of inputs

According to the results of the estimation, the most consistency is observed between the slump value and the bending strength in the model. By analyzing the results, it can be concluded that both inputs have an effect on the predicted bending strength values.

The maximum size of the aggregates up to 20 mm improves the bending strength property of the GFRSLC. Increasing the superplasticizer content up to 330 g decreases the bending strength. The use of metakaolin up to 2.5 kg have no significant effect on the bending strength; however, the bending strength decreases when metakaolin added in the mixture above 2.5 kg. Glass fiber and water to cement ratio showed similar graphical behavior. The consistency of the mixes directly effects the bending strength values when water to cement ratio is close to 0.35. By combining the results, the effect of the water to cement ratio on the bending strength of GFRSLC is higher than the effect of the glass fiber in the mentioned graphical area.

The mathematical expression of the neural network is given in the following equations. It takes the inputs as maximum aggregate size, glass fiber, water to cement ratio, superplasticizer, metakaolin and slump to produce the output bending strength. For prediction problems, the information is propagated in a feed-forward fashion through the scaling layer, the perceptron layers and the unscaling layer:

A= Scaled maximum aggregate size
B= Maximum aggregate size
C= scaled glass fiber
D= glass fiber
E= scaled water to cement ratio
F= scaled superplasticizer
G= superplasticizer
H= scaled metakaolin
I= I=scaled slump

A=2x(B-14)/(20-14)-1 (2)

C= 2x(D-3)/(3.5-3)-1 (3)

E=2x(w/c–0.3)/(0.38–0.3)-1 (4)

F= 2*(G-300)/(330-300)-1 (5)

H=2x(kaolin-0)/(5-0)-1 (6)

I= 2 * (slump – 181) / (188-181)-1 (7)

y_{11} = tanh (-0.234236 – 0.0387631 * scaled maximum aggregate size – 0.0261527 * scaled glass fiber - 0.0239992 * scaled water to cement ratio – 0.22511 * scaled superplasticizer + 0.318074 * metakaolin +0.203628 * scaled slump) (8)

y_{12}= tanh (-0.596048 - -2.10893 * scaled maximum aggregate size +3.04245 * scaled glass fiber + 4.4843 * scaled water to cement ratio – 0.224436 * scaled superplasticizer + 3.03609 * metakaolin + 0.656546 * scaled slump) (9)

y_{13}= tanh (0.316535 + 0.351154 * scaled maximum aggregate size - 2.11777 * scaled glass fiber - 2.11777 * scaled water to cement ratio + 1.75788 * scaled superplasticizer - 1.62116 * metakaolin - 1.55636 * scaled slump) (10)

scaled bending strength = (-0.538875 - 1.42512 * y_{11} - 1.00905 * y_{12} - -1.06635 * y_{12}) (11)

bending strength = (0.5 * (scaled bending strength + 1) * (10.2 -8.4) + 8.4) (12)

5. CONCLUSIONS

395 bending strength test results of the GFRSLC have been analyzed in proposed neural model. Six input parameters (maximum aggregate size, glass fiber content, water to cement ratio, superplasticizer and metakaolin content and slump values) and their effects to bending strength of GFRSLC were analyzed within the scope of this study. The following conclusions can be drawn from the results of the prediction analysis:

- The ANN model approves the strong correlation between the bending strength of GFRSLC with the mixture proportions.
- The analysis results showed that the weighting factor is well calibrated. They showed a good correlation with the previously conducted experimental data.
- In the analysis and field study, increasing the metakaolin content up to 2.5 kg improves the bending strength property. However, the use of more than 2.5 kg and up to 5 kg decreases strength analysis and test results.
- The outcomes of the study can be assessed by other artificial and mathematical systems for a better understanding of the mixture proportions and fresh state effects on the bending strength of GFRSLC.
- 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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