Cost Comparison of Traditional Glass Fiber Test Methods and Computer Aided Neural Prediction Supported Systems

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Abstract: Within the complexity of the industrial production strategies, computer aided technologies have been becoming a survival key for company administrators for reducing expenses. Furthermore, new production methods and adaptation of dynamic market requirements force owners to apply computer aided solutions to reduce to production time of goods to the market. Nowadays, prefabricated concrete producers are facing the same problem and trying to apply new solutions to overcome these high costs. In this research, artificial neural networks and traditional glass fiber testing methods were compared to reduce the quality control and assurance processes of prefabricated glass fiber reinforced concrete (GRC) production. 143 different four-point flexural test results of glass fiber reinforced concrete mixes with the varied parameters as temperature, fiber content and slump values were introduced the artificial neural networks models. The proportional limit properties (LOP) of glass fiber reinforced concrete and trained neural network analysis are taken into consideration for comparison. The outcomes of the analysis reflected that there is a strong correlation between the proportional limit of glass fiber reinforced concrete on-site test and the artificial swarm-based optimization algorithm results. Depending on this secure data, on-site test quantities are reduced and checked for cost deduction of traditional test results.

Keywords:Cost Reduction; Computer Aided Prediction Methods; Glass Fiber Reinforced Concrete; Traditional Test Methods

1. Introduction

Glass fiber reinforced concrete (GFC) includes the high-strength glass fibers, silica-based aggregates, Portland cement CEM I 42,5R (density: 3.15 g/cm^3) and other chemical additives which are added for improving the mechanical properties. Lately, GRC products are extensively preferred by the architects for facade panels by reason of due to providing highly aesthetical and durable solutions.

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GRC mechanical properties differ depending on may factors as fiber content, density, production line temperatures. Their content in concrete mixtures significantly effects the flexural characteristics of the specimens. One of the important indicator of flexural characteristics of a material is the proportional limit (LOP) value. LOP value is defined as the maximum stress level before any plastic deformations of the concrete products. Detailed visualization of the LOP value can be seen in **Figure 1**. As seen in **Figure 1** first and second diagrams have the same LOP values depending on having low fiber contents comparing with its critical values.

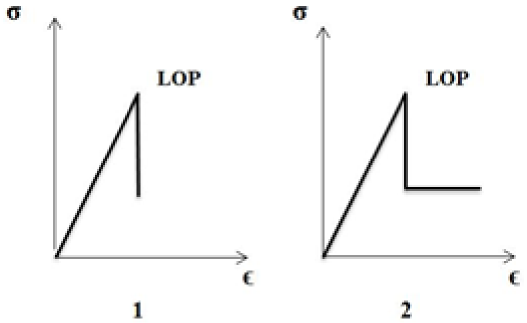

Figure 1. LOP values

LOP value of a fiber reinforced concrete, depends on many factors such as the specimen size, porosity and the fiber content of the concrete and production environment conditions. LOP is also an important parameter to produce the road slab and facade panels designs, because the flexure tension is one of the main criteria for determining concrete's mechanical performances[1]. For determining the LOP values, four-point flexural test method is used as per the standard EN 1170 requirements (**Figure 2**).

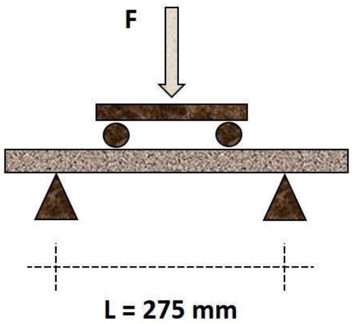

Figure 2. Schematic diagram of three-point flexural test[2]

Many studies have been conducted considering the application of the GRC for improving the strength and durability properties of concrete products. Literature research can be summarized as follows: The flexural strength of a specimen increases in parallel with the increase of the glass fiber (GF) amount while compressive strength decreases due to the low shearing strength of the GF[3]. The fatigue life of the GRC can be obtained with the two-parameter Weibull distribution [4]. Adding condensed silica-fume in to the GRC mixes improves its quality[5]. Use of glass in concrete mixes can cause some problems due to the alkali nature of GRC[6]. Studies have shown that the usage of glass fibers in concrete can control shrinkage cracking and its harm effects[7,8]. Small temperature changes play an important role on the mechanical behavior of GRC products[9]. Slump value of the concrete signifies the ease, with which concrete in fresh state can be compacted without any segregation[10]. Artificial Neural Network (ANN) can include prediction of Slump and strength values of ready mix concrete with retarders[11]. Fibers are one of the widely used materials to improve concrete tensile behavior[12]. High fiber content in concrete mixes resulted high energy absorption of the flexural load[13].

There are numerous application of ANN focusing on the strength value estimation of concrete products. Some of them emphasizes the importance of them as a rapid test method for predicting long-term compressive strength of concrete[14,15]. And one of them includes the strength prediction of high performance concrete[16]. Despite the numerous applications of ANN for predicting the mechanical properties of common concrete mixes, there exist no application of neural networks for predicting the LOP values of concrete specimens reinforced with glass fibers.

Research significance

Early determination of flexural strength property of glass fiber reinforced concrete is an essential factor for the design purposes. The flexural strength value also provides basic and close information for the evaluation of other mechanical properties. Nondestructive test methods and neural estimation of the strength properties have not been widely preferred by the prefabricated glass fiber concrete sector depending on many reasons such as limited information on neural network-based prediction systems, their applicability and cost. A cost comparison analysis has been conducted in order to show the power of ANN based systems and its low cost compared to the other test systems. It is aimed to reduce worker dependent test numbers and their cost on the production site.

2. Material and Methods

2.1. Experimental Study

CEM I 52,5 R (White Portland) cement which complies the EN 197-1 was preferred for production line experimental tests. Silica sand and superplasticizer are also added to the mixes for the experiments. Technical specifications of cement and silica sand are given in **Table 1** and **Table 2**.

Chemical Properties (%)		Physical and Mechanical Properties	
SiO_2	21.6	Specific Weight (t/m^3)	3.06
Al_2O_3	4.05	Specific Surface (cm^2/gr)	4600
Fe_2O_3	0.26	Whiteness (%)	85.5
CaO	65.7	Initial Setting (min.)	100
MgO	1.30	Final Setting (min.)	130
Na_2O	0.30	Water Used for Consistency (%)	30
K_2O	0.35	Volume Constancy (mm)	1.0
SO_3	3.30	Remnants Obtained Using 0.045 Sieve (%)	1.0
Free CaO	1.60	Remnants Obtained Using 0.090 Sieve (%)	0.1
Chloride (Cl)	0.01	Compressive Strength for 2 days (MPa)	37.0
Insolubles	0.18	Compressive Strength for 7 days (MPa)	50.0
Loss on Ignition	3.20	Compressive Strength for 28 days (MPa)	60.0

Table 1. Technical Specifications of CEM I 52.5 R cement.

Sieve Aperture Size	1 mm	710 µm	500 µm	355 µm	250 µm	180 µm	125 µm	90 µm	63 µm
Production Range (%)	0	0	0	0.2	0.3	20.1	60.4	16.1	1.8

Mean Grain Size (µm)	140-170	Specific Weight	2.68
Clay Content (%)	0.6-0.8	AFS Value (%)	84.6

Table 2. Silica Aggregate Properties

European standards for GRC as TS EN 1170-1, TS EN 1170-2, TS EN 1170-3, TS EN 1170-4, and TS EN 1170-5 are followed and applied during the on-site experiments. Slump value of the mix was kept constant during the pouring of GRC. Ingredients of the mix is given in **Table 3**.

Five test team are assigned for the implementation of TS EN 1170's standards and their performances are recorded for the cost calculation of workmanship and machinery (Cost-A). Work order of test phases can be found in detail in **Figure 3.** Obtained results from the experiments are stored as Result-A and used for the training of ANN system.

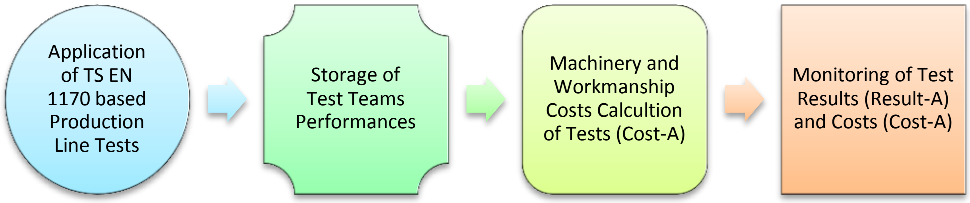

Figure 3. Schematic diagram of test phases work order

Additional water per 1 g of pigment (g)	4.5	13	4.13	4.75	-
Additional water (kg)	5.625	16.25	5.163	5.938	-
Aggregate (kg)	625	625	625	625	625
Cement (kg)	625	625	625	625	625
Superplasticizer (kg)	3.69	3.69	3.69	3.69	3.30
Water (kg)	190	190	190	190	190
Slump value (cm)	4	4	4	4	4

Table 3. Material content of the experimental mixes

2.2. ANN Model Development

Artificial Bee Colony (ABC) algorithm was implemented as the training method for the ANN by modifying the nodal interconnection weights and biases (ANN-ABC). During the training phase of the ANN, the ABC algorithm implements several parameters controlling the performance and characteristics of the algorithm execution such as: search range for the model parameters, colony size, number of the food sources. The maximum number of cycles are used as a stopping criterion for algorithm. These parameters considered in the ABC algorithm are shown in **Table 4**.

Table 4. ABC Algorithm Parameters Parameter Search Range	[-5,5]
Colony Size	50
Number of Food Sources or Bees	25
Stopping Criterion	
Max. Number of Cycles	500

The experimental results were proposed to the network as four candidate of input variables and a single output variable. The candidate input parameters were temperature, fiber ratio, density, and slump value of the specimen. The proposed ANN structure was given in **Figure 4.**

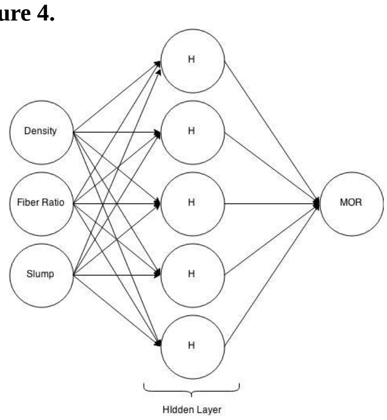

Figure 4. Scatter plot of the ANN-ABC model with 12 hidden layer neurons.

All these values are taken from the Cost-A and Result-B data. The scatter plots of the ANN-ABC models are shown in **Figure 5.**

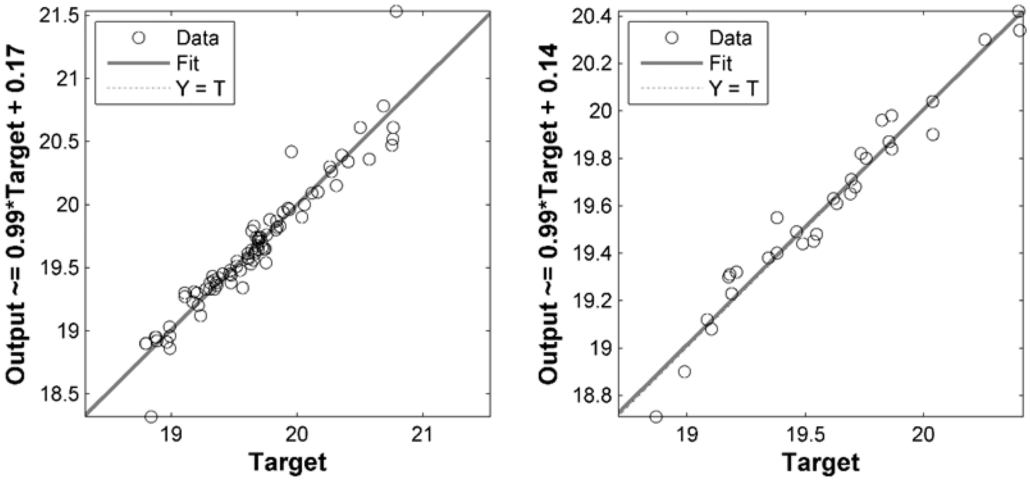

Figure 5. Scatter plot of the ANN-ABC model with 5 hidden layer neurons.

Model results indicates that there is a strong potential of ANN for the estimation of LOP values. As seen in **Figure 5**, proposed ANN model shows a good performance and it can be applied to any glass fiber reinforced concrete estimation research. The performance of the ANN model was given in **Table 5**. The best performed model was obtained with 5 hidden layers and R^2 values were obtained as 0.971 and 0.984 for training and testing respectively.

Hidden layer neurons	Training	Testing
	R^2	R^2
5	0.971	0.984

Table 5. ANN performance table

Following the modelling researches, ANN-ABC results are stored as Result-B and the cost of engineering and management works of the training studies are calculated as Cost-B. More detailed and ANN focused research can be found in the earlier published research as given in[17].

3. Cost Calculation

Five test teams are organized for the fulfillment of production quality control test as per the requirements of GRCA (International Glass Fiber Reinforced Concrete Association). Teams and assigned test methods are given in **Table 6**.

Test Identification	Responsible Design Team
TS EN 1170-1	Team-A
TS EN 1170-2	Team-B
TS EN 1170-3	Team-C
TS EN 1170-4	Team-D
TS EN 1170-5	Team-E

Table 6. Production Line Test Teams

Cost calculation of TS EN 1170-1 standard’s requirements is clarified in **Table 7**.

COST CALCULATION-1 : "Precast concrete products - Test method for glass-fibre reinforced cement - Part 1: Measuring the consistency of the matrix ""Slump test"" method"						
Man Power	Quantity	Unit	Working Hours	Total Working Hours per experiment	Price per Hour($/hr)	Total Price ($)
Skilled Worker	1	ea	0,20	0,20	11,46	2,29
Foreman	1	ea	0,20	0,20	16,8	3,36
Supervisor	1	ea	0,10	0,10	66	6,60
					SUB-TOTAL	12,25
For (average 50 test per day)		Total Price = Sub-Total x 50 tests				612,60
					TOTAL ($)	612,60

Table 7. Cost Calculation-1:TS EN 1170-1(Team A)

Cost Calculation of TS EN 1170-2 standard's requirements is given in **Table 8**.

COST CALCULATION-2 : "Test method for glass-fibre reinforced cement. Measuring the fibre content in fresh GRC, 'Wash out test'"						
Man Power	Quantity	Unit	Working Hours	Total Working Hours per experiment	Price per Hour($/hr)	Total Price ($)
Skilled Worker	2	ea	0,20	0,40	11,46	4,58
Foreman	1	ea	0,20	0,20	16,8	3,36
Supervisor	1	ea	0,10	0,10	66	6,60
					SUB-TOTAL	14,54
For (average 50 test per day)		Total Price = Sub-Total x 50 tests				727,20
					TOTAL ($)	727,20

Table 8. Cost Calculation-2:TS EN 1170-2 (Team B)

Cost Calculation of TS EN 1170-3 standard's requirements is given in **Table 9**.

COST CALCULATION-3 : "Test method for glass-fibre reinforced cement. Measuring the fibre content of sprayed GRC"						
Man Power	Quantity	Unit	Working Hours	Total Working Hours per experiment	Price per Hour($/hr)	Total Price ($)
Skilled Worker	2	ea	0,20	0,40	11,46	4,58
Foreman	1	ea	0,20	0,20	16,8	3,36
Supervisor	1	ea	0,15	0,15	66	9,90
					SUB-TOTAL	17,84
For (average 50 test per day)		Total Price = Sub-Total x 50 tests				892,20
					TOTAL ($)	892,20

Table 9. Cost Calculation-3:TS EN 1170-3 (Team C)

Cost Calculation of TS EN 1170-4 standard's requirements is given in **Table 10**.

COST CALCULATION-4 : Test method for glass-fibre reinforced cement - Part 4: Measuring bending strength, ""Simplified bending test"" method"						
Man Power	Quantity	Unit	Working Hours	Total Working Hours per experiment	Price per Hour($/hr)	Total Price ($)
Skilled Worker	1	ea	0,20	0,20	11,46	2,29
Foreman	1	ea	0,20	0,20	16,8	3,36
Supervisor	1	ea	0,10	0,10	66	6,60
Test Machinery Works	1	ea	0,15	0,15	13	1,95
					SUB-TOTAL	14,20
For (average 50 test per day)		Total Price = Sub-Total x 50 tests				710,10
					TOTAL ($)	710,10

Table 10. Cost Calculation-4:TS EN 1170-4 (Team D)

Cost Calculation of TS EN 1170-4 standard's requirements is given in **Table 11**.

COST CALCULATION-5 : Test method for glass-fibre reinforced cement. Measuring bending strength, "complete bending test" method						
Man Power	Quantity	Unit	Working Hours	Total Working Hours per experiment	Price per Hour($/hr)	Total Price ($)
Skilled Worker	1	ea	0,25	0,25	11,46	2,87
Foreman	1	ea	0,20	0,20	16,8	3,36
Supervisor	1	ea	0,15	0,15	66	9,90
Test Machinery Works	1	ea	0,25	0,25	13	3,25
					SUB-TOTAL	19,38
For (average 50 test per day)		Total Price = Sub-Total x 50 tests				968,75
					TOTAL ($)	968,75

Table 11. Cost Calculation-5:TS EN 1170-5 (Team F)

Comparing to the production line test costs, ANN ABC model method's cost is very limited, and it can be estimated as follows (**Table 12**):

COST CALCULATION-B : ANN ABC Model Works						
Man Power	Quantity	Unit	Working Hours	Total Working Hours per day	Price per Hour($/hr)	Total Price ($)
Engineer	1	ea	7,00	7,00	21,6	151,20
Supervisor	1	ea	3,00	3,00	66	198,00
					TOTAL ($)	349,20

Table 12. Cost Calculation-B: ANN ABC Model and Its Supervision

4. Results and Discussions

This study indicates the potential of ANN-ABC model for estimating the LOP values of the fabricated GRC panel without or lessened quantities of the destructive strength tests. By this way, a carefully designed and trained ANN model can simulate the traditional experimental phases and this model can be used as preliminary decision criteria for quality check procedures for prefabricated products. However, considering the uncertainty of the models, it is advised to use the prediction models for reducing the number of the experiments for test batches instead of substituting as the only quality control method. The cost impact of reduced production line tests is presented in **Table 13**.

Cost A	Daily Cost (Usd)	Cost B (ANN ABC)	Daily Cost (Usd)
Cost Calculation-1	612.60	349.20	
Cost Calculation-2	727.20		
Cost Calculation-3	892.20		
Cost Calculation-4	710.10		
Cost Calculation-5	968.75		
Total	3910.85		
Variation per day			$3561.65*
*Depending on the decreased number of on-site tests, variation values can be changed.			

Table 13. Cost Comparison Table

This analysis provides useful information for prefabricated GRC producers to decide its financial outcomes for reducing on site test numbers for quality control procedures. Implementation of these kind of prediction models also exhibits great potential to be used as a computer aided real-time quality control system in the fabrication process of the end-products.

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