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Investigation of Mechanical Properties of Self Compacting Polymeric Concrete with Backpropagation Network

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ABSTRACT

Acrylic polymer that is highly stable against chemicals and is a good choice when concrete is subject to chemical attack. In this study, self-compacting concrete (SCC) made using acrylic polymer, nanosilica and microsilica has been investigated. The results of experimental testing showed that the addition of microsilica and acrylic polymer decreased the tensile, compressive and bending strength of the concrete. The addition of nanosilica and an increase in polymer content increased the bending strength of concrete and decreased the tensile and compressive strengths. Because, in the laboratory, the number of samples were limited and the amount of variation was small, comprehensive results cannot be achieved. With the help of neural networks, estimating any amount within the range of the input data is possible. In this paper, in addition to the experimental results, a backpropagation neural network (BNN) was used to simulate the testing on the strength of self-compacting polymeric concrete. The results showed that the use of the normalized mean squared error, resilient backpropagation training, tangent-sigmoid and log sigmoid transfer functions and five neurons in each hidden layers in a two-layer BNN produced good results with a regression value of 0.95 and error of 0.17.

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NOMENCLATURE

x_i	Input units	j	Neuron counter
X	sample	O_Z	Actual output value
x_{max}	Maximum sample	t_Z	Output of the network
$x_{\min}$	Minimum sample	E	Error function
w_{ij}	Weight on the connections	**Greek Symbols**	
b_j	Bias of each neuron	ξ	training parameter
n	Number of input units		

1. INTRODUCTION

Different types of concrete are produced in different areas according to available mineral resources, which can be a concern for area governments [1, 2].

Polymers are used in the concrete industry as additives to improve the properties of concrete. SCC is the smoothest concrete and the casting of the concrete is not needed to any vibration. Polymers are good alternatives to cement and have benefits such as reducing cement production and environmental contamination. Giustozzi [3] showed that the use of polymers in the manufacture of concrete structures that must resist high-powered marine waves or form road pavements produce a more effective product than ordinary Portland cement and Polyvinyl acetate polymer is the best polymer thus far to produce high-strength concrete. Researchers have used polysulphide polymer in concrete and have concluded that this type of concrete offers high-performance and can satisfy up to

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300 freeze/thaw cycles [4]. Shen et al. [5] produced a super absorbent polymer and used internal curing to produce polymeric concrete with a low water-to-cement ratio and decreasing the shrinkage of the concrete. Another research showed that the use of acrylic polymer with micro-silica in SCC can improve strength and water absorption parameters [6]. Bulut and Şahin [7] found that using plastic waste from electronic devices in polymer concrete to increase the polymer did not dramatically effect the concrete properties. In addition, the use of this waste product decreased the strength properties of polymer concrete.

The use of rubberized polymer in concrete was shown increase its porosity and air content. This concrete also had a lower cost and density [8]. Singh and Siddique [9] used metakaolin and rice husk ash in SCC and recorded positive effects on the compressive strength and splitting tensile strength of the concrete.

In the current study, 36 self-compacting polymeric concrete samples were constructed and the effects of nanosilica, microsilica and acrylic polymer on the concrete mechanical characteristics of the compressive, bending and tensile strengths were investigated. Next, 36 BNNs were constructed using the various materials forming the self-compacting polymeric concrete. The results of the best network showed that the use of a two-layer BNN which used the normalized mean squared error (MSE), resilient training, log sigmoid and tangent sigmoid transfer functions and five neurons in each hidden layers produced appropriate results.

2. STUDY PLAN

A total of 36 self-compacting polymeric concrete samples were constructed and studied in three phases. In the first phase, 18 concrete designs for control samples and samples containing acrylic polymer were made. In these samples, the acrylic polymer content comprised 0.5 to 2% and the superplasticizer comprised 0.5 to 2% of the weight of the cement. In the second phase, microsilica was added to the mixing plan. In this phase, 10 samples were made with a microsilica content of 10% (wt). In the third phase, eight concrete samples were made by removing the microsilica and adding 5% (wt) nano-SiO_2 to the mixing plan.

3. MATERIALS

In this research, coarse aggregate of Manzarie mineral, sand of Kharaji mineral, Shahrekord drinking water, Portland cement type 2, acrylic polymer Z90 which has been produced by NSG company (Tehran, Iran). superplasticizer, microsilica and nanosilica (is produced by WACKER company from Germany) were used in order to construct the concrete.

4. MIX DESIGN

Table 1 shows the mixing plans in phase 1 of this study. Samples 1 to 4 were control samples and samples 5 to 18 were made with acrylic polymer. It should be noted that acrylic polymer and superplasticizer in mixing design plans were used as a weight percentage of cement. Also, the amount of cement in all plans of this phase was 410 kg/m^3. In the second phase, microsilica was used as an additive to improve the concrete strength properties (Table 2). Microsilica was equivalent to 10% by weight of cement. Polymer and resin were also changed from 0.5 to 2% by weight of cement. In this phase, 10 concrete projects were implemented, in which the amount of cement was 369 kg/m^3, and the content of microsilica was 10% by weight of cement and in all designs were constant. In the third phase, 8 concrete designs to investigate the nanosilica affect were carried out. In this phase, the nanosilica was added as an additive to the concrete and the microsilica removed from the mixing designs. Table 3 shows the mixing designs in this study.

5. METHOD OF MIXING

At first, sand and gravel were poured into a 120-liter mixer and throughly mixed for 1 to 1.5 minutes. Then some water was added to the mixer and then cement was added to the mixture. Acrylic polymer, nanosilica or microsilica and some of the remaining water were mixed. After mixing the polymeric and powdered materials in the mixture, superplasticizer with some water was added to the mixture. It was mixed throughly for about 5 minutes.

6. RESULTS AND DISCUSSION

The results of testing showed that without the addition of nanosilica and by increasing the superplasticizer content of concrete containing microsilica, acrylic polymer increased the tensile and bending strengths, but decreased the compressive strength. Increasing the amount of superplasticizer added to the control samples containing acrylic polymer decreased all three resistance parameters. In the second phase, the addition of microsilica decreased the tensile and bending strengths with an increase in the polymer and resin. A 1% increase in superplasticizer increased the compressive strength, but an increase in polymer decreased the compressive strength.

TABLE 1. Mix design in phase 1

Sample	S1	S2	S3	S4	S5	S6	S7	S8	S9
Superplasticizer (%)	0.5	1	1.5	2	0.5	0.5	1	1	1
Acrylic polymer (%)	-	-	-	-	0.5	1	0.5	1	1.5
Sample	**S10**	**S11**	**S12**	**S13**	**S14**	**S15**	**S16**	**S17**	**S18**
Superplasticizer (%)	1	1.5	1.5	1.5	1.5	2	2	2	2
Acrylic polymer (%)	2	0.5	1	1.5	2	0.5	1	1.5	2

TABLE 2. Mix design in phase 2

Sample	S19	S20	S21	S22	S23
Superplasticizer (%)	0.5	0.5	1	1	1
Acrylic polymer (%)	0.5	1	0.5	1	1.5
Sample	**S24**	**S25**	**S26**	**S27**	**S28**
Superplasticizer (%)	1	1.5	1.5	1.5	2
Acrylic polymer (%)	2	0.5	1	1.5	0.5

TABLE 3. Mix design in phase 3

Sample	S29	S30	S31	S32
Superplasticizer (%)	0.5	0.5	1	1
Acrylic polymer (%)	0.5	1	0.5	1
Sample	**S33**	**S34**	**S35**	**S36**
Superplasticizer (%)	1.5	1.5	2	2
Acrylic polymer (%)	0.5	1	0.5	1

In the last phase, addition of nanosilica increased the bending strength of the sample with 1.5% superplasticizer, but, in the other samples, the addition of polymer increased the bending strength. The tensile strength decreased with an increase in superplasticizer and acrylic polymer. The results also showed that increasing the superplasticizer content increased resistance, but increasing the polymer content decreased the compressive strength. Figure 1 shows the results for compressive strength for the concrete samples. Figure 2 shows the tensile and bending strengths. After the resistance tests, water absorption tests for polymeric concrete were carried out in each phase. The results are shown in Figure 3. The results in the first phase indicated that the sample with 1% superplasticizer and 0.5% acrylic polymer performed best, because the compressive strength after 28 days was 65 MPa and the bending and tensile strengths were 13.3 and 3.1MPa, respectively. The obatined results were much better than the control samples. The water absorption of this design was also about 29% less than the control sample. In the second phase, the design containing 0.5% superplasticizer and 0.5% polymer performed best. This design recorded a compressive strength of 59.9 MPa, tensile strength of 2.7 MPa and bending strength of 14.5 MPa, which are much better than for the other designs. The water absorption was 12% less than for the control sample. In the third phase, a polymeric sample containing nano-SiO_2 with a 1% superplasticizer and 0.5% polymer was the best concrete design. In this design, the tensile, bending and compressive strengths were 3.3, 14.2 and 62.6 MPa, respectively, and water absorption was about 22% less than for the control sample.

7. BACKPROPAGATION NEURAL NETWORK

The processed information is transferred to the neuronal cell again and this cycle repeats [10]. Up to now, various neural networks have been presented with various functions and conditions. The BNN is used in many branches of science for modeling. This network is capable of modeling non-linear relationships between components without the need for specific information about the communication mechanism [11]. Writers can refer to some relevant papers such as references [12-14] for more information. In this network, the neurons are the location of information processing and are distributed within the hidden layers. Among these neurons there are communication channels that contain the weight [15]. The training of the network is in order to find the weights that are available to minimize the total errors resulting from the network output and actual value. This type of network is able to train from examples without the need of legal information from the studied basin [16]. The BNN used in this study is shown in Figure 4. As shown in this figure, the main compounds and additives used in the polymeric concrete were studied as inputs of the neural network and compressive, bending and tensile strength as network outputs have been used. Before building the network, the data normalization method attempts to homogenize the data in order to reduce the network error. For this work, Equation 1 was used [17].

$$X_i = 0 \cdot 8\left(\frac{X - X_{min}}{X_{max} - X_{min}}\right) + 0.1 \quad (1)$$

In a BNN the inputs initially called. Next, the inputs of the network that are supposed to enter the first layer are calculated from the following equation:

$$Net_j = \sum_{i=1}^{n} x_i w_{ij} + b_j \quad (2)$$

In which x_i is input units, w_{ij} is the weight on the connections, i is the input counter and j is the neuron counter, b_j is the bias of each neuron, and n is the number of input units. Assuming that the output function of the first hidden layer is tangent sigmoid, the following formula will be used:

$$O_j = f(Net_j) = \frac{-1+e^{-2Net_j}}{1+e^{-2Net_j}} \quad (3)$$

Total of inputs in second hidden layer is:

$$Net_k = \sum_{j=1}^{n} w_{jk} O_j + b_k \quad (4)$$

After entering the second hidden layer, the inputs are multiplied by weight and accumulated with the bias of the second layer. Then they are imported in the transfer function of the second layer and after processing entered into the output layer. Transfer function is in relation to Equation (5):

$$O_k = f(Net_k) \quad (5)$$

In the output layer, the same steps are repeated again. In the end, the network error is calculated. The error formula is as follows:

$$e_l = t_z - O_z \quad (6)$$

which t_z is the output of the network and O_z is the actual output value. The total resulting error for mean squared normalized error (MSE) and sum squared error (SSE) are calculated from the following equations:

$$E = 0 \cdot 5 \sum_{z=1}^{n} (t_z - O_z)^2 \text{ (MSE)} \quad (7)$$

$$E = \sum_{z=1}^{n} (E_Z)^2 \text{(SSE)} \quad (8)$$

In fact, network training is the process of achieving the optimal amount of network space. In order to minimize the error, the weight parameter must be changed:

$$\nabla W_{jz} = -\xi(\delta E/\delta W_{jk}) \quad (9)$$

ξ is the training parameter and E is the error function. The rehanged weight for the next patterns will be as follows:

$$W_{jz}(n+1) = W_{jz}(n) + \nabla W_{jz}(n) \quad (10)$$

This process continues until the network error according to the user definition reaches the desired level.

8. ANALYSIS OF LABORATORY RESULTS WITH NEURAL NETWORK

With the help of neural networks, it is possible to estimate any amount within the range of input data. In this study at first input and output data were normalized. In the next step, the neural network needed to be adjusted for optimal performance. A two-layer network with 5 neurons in each layer was constructed. Then the training functions and the network error were changed. In addition, the speed and performance of network were investigated. After selecting the best answers, in the second step, the number of neurons in each loop was set with permutation method. Again, by choosing the best response in the last step, the network transfer function was selected.

8. 1. Choosing Training and Error Functions

The purpose of training in the BNN is to set up free network parameters to get the optimal response from it. Therefore, in the training process, the inputs for the part of the training set are presented to the network and the output is calculated [18, 19]. The training function in toolbox of Matlab includes various optimization functions which result in different responses in the neural network [20]. In order to assess the ability of training algorithms, two MSE function and SSE function are Simultaneously used. Since the Levenberg-Marquardt training function only supports these two error functions, so for the better result of the network, only these two error functions entered in the network. The results of this study are summarized in Table 4. As it is shown, 16 neural networks were constructed with the use of training and error functions. The results showed that the MSE error for the resilient backpropagation function is the lowest. The conjugate gradient backpropagation with Powell-Beale restarts is also much better than the conjugate gradient backpropagation with Polak-Ribiére updates in many issues, but nevertheless, the memory used in this algorithm is slightly more than the Polak-Ribiére algorithm. The one-step secant algorithm is less memory than the quasi-Newton algorithm.

Therefore, the choice between these algorithms is based on the available memory and processor speed of the user system.

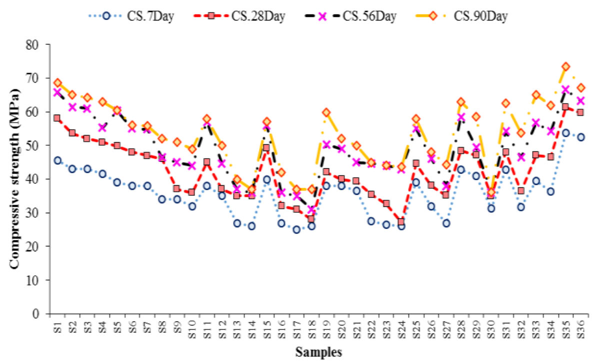

Figure 1. Results of compressive strength

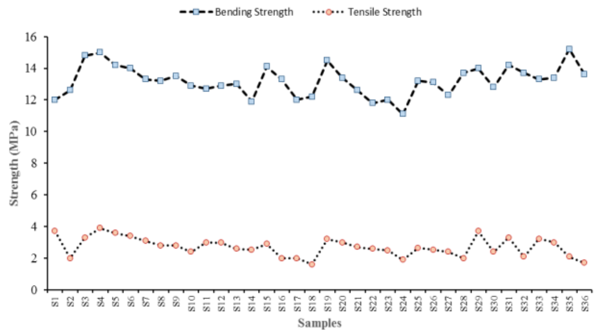

Figure 2. Results of tensile and bending strengths

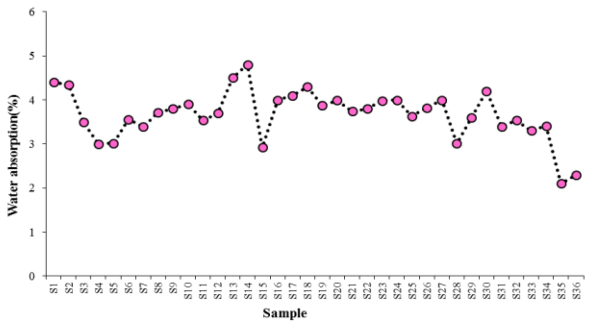

Figure 3. Results of water absorption

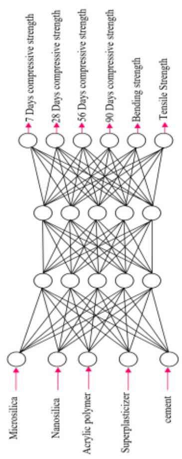

Figure 4. Backpropagation neural network

The system used in this study has a 5-core processor with 6GB of RAM and 700GB of memory, which has no problem in terms of memory performance and has a fairly good speed. With these interpretations, the resilient backpropagation algorithm was selected with the lowest error rate and higher speed compared to other functions for the next step of the review.

8. 2. Sorting of Neurons After selecting the training function and the error function, it is necessary to set the number of neurons and their arrangements to build a neural network of high precision and proper speed.

TABLE 4. Results of errors for training functions

Numb	Train Function	MSE		SSE	
		Error	Time(Sec)	Error	Time(Sec)
1	TBFG	0.196	7.0814	0.2921	6.9467
2	TCGB	0.168	5.1268	0.433	7.7980
3	TCGF	0.187	5.5332	0.2504	4.9059
4	TCGP	0.311	4.8831	0.2910	4.9565
5	TLM	0.486	1.4238	0.4228	1.7198
6	TOSS	0.352	4.7765	0.3955	6.0358
7	TRP	0.157	2.8303	0.2828	2.4053
8	TSCG	0.2862	3.0306	0.2920	3.3032

As it has been said before, neurons are the place of processing information. Therefore, it is important to select their numbers and layouts carefully. If the neural network is a single-layer network with few neurons in the hidden layer, it can clearly be said that the neural network does not have enough precision in solving complex problems. The exact result of this network is not reliable; On one hand, with the complexity of the network, in solving complex problems, the speed which is given of the system is very high. Therefore, the generated neural network will not be a suitable model. On the other hand, there was no proper formulation to estimate the number of layers and neurons that can be cited for sure yet. Therefore, the trial and error method to build a multi-layer network and testing various values of the neurons in the hidden layers is used as a common method. The trial and error process was repeated to select the network with the least error. Since the network is made up of two layers, the arrangement of neurons in the first and second hidden layers was performed in accordance with Table 5. It should be noted that the selection of the number of neurons with the random variables is smaller than or equal to 10. The results showed that the ordering of neurons in 5 and 5 neurons in the first and second layers produces the best performance for the neural network. Since the number of high-level neurons increases the memory consumption and decreases the speed, the same order of 5-5 neurons in the first and second hidden layers was chosen for the third step. It is remarkable that if the training model has low speed and performance, then it is necessary to choose the layers with lower number of neurons. However, because the results of the previous step confirmed the speed and performance of the network with resilient backpropagation function, this did not need to be change, and the same arrangement was selected. This answer shows that the original assumption of the authors in the first step is correct and confirms the previous answer.

8. 3. Transfer Function At this step the type of transfer function was selected. Transfer function is a function that calculates the output of a layer from the network input. Therefore, the choice of this type of function is very effective in response of the data fitting curve, determining the speed, and accuracy of the network. To select the transfer function, the permutation of the three tangent sigmoid (TS) functions, log sigmoid (LS), and pureline (PL) were used. The results of the change in the combination of stimulation functions on the BNN are summarized in Table 6. The results showed that log-sigmoid, tangent-sigmoid and tangent-sigmoid transfer functions have the best performance compared to other compounds. It should be noted that it is not possible to use three purelin functions or two purelin functions in a network, since the purelin function is a simple linear function, using three forms of it simply causes the function to be moved and cannot help.

TABLE 5. Sorting neurons in layers

Number of neurons		Error
Layer one	**Layer two**	
5	5	0.1574
3	5	0.2026
7	5	0.3323
5	3	0.3141
3	7	0.3148
5	7	0.3380
7	3	0.2410
6	5	0.2829
5	6	0.4163
7	8	0.1987
8	7	0.2398
10	6	0.2380
10	8	0.2576

TABLE 6. Results of changing transfer functions on BNN

Transfer Functions (layer)			Error	Regression	Time
First	**Second**	**Third**			
TS	LS	PL	0.2187	0.9204	1.1062
LS	TS	PL	0.2431	0.9216	1.0897
PL	LS	TS	0.3041	0.9183	1.1729
PL	TS	LS	0.3119	0.7086	1.0814
TS	TS	TS	0.6931	0.9138	1.0914
LS	TS	TS	0.1713	0.9537	1.0653
TS	LS	LS	0.3418	0.7632	1.0996

9. CONCLUSION

The present study was undertaken to investigate the results of laboratory studies on the properties of acrylic polymer properties and evaluate the performance of a backpropagation neural network for predicting and estimating concrete values. The laboratory studies produced the following results:

1. In the first phase, only the effect of the resin on the strength of polymeric concrete was investigated. The results indicated that an increase in the resin content of the artificial aggregate decreased all three resistance parameters (tensile, bending and compressive strengths).
2. In the same phase, acrylic polymer was added to the mixing plan. The results showed that increasing the resin content reduced the compressive, bending and tensile strengths.
3. In the second phase, microsilica was used to improve the concrete properties. The results showed that increasing the polymer content decreased the bending and tensile strengths. An increase in 1% or more of resin increased the compressive strength, but an increase in acrylic polymer again decreased the compressive strength.
4. In the third phase, nanosilica was used to replace the microsilica. The results indicated that the tensile strength decreased with an increase in the resin and polymer contents. Except for the design containing 1.5% superplasticizer, the samples showed a decrease in bending strength. The compressive strength decreased as the resin content of the artificial aggregate increased.
5. In the first stage, the MSE function was selected because it had the lowest value. In the second stage, the BNN function was selected with an error of 0.18, although this function has a longer run time than the Levenberg-Marquardt backpropagation function. The performance criterion in this paper was the lowest error rate, but the selected function had appropriate speed. The processing time was 2.83 s.
6. In the second stage, the number of neurons in the hidden layers of the first and second layers was organized. The 5-5 arrangemen [illegible]n as optimal because the speed of the resilient BNN was appropriate; therefore, the choice of layers with a lower number of neurons was avoided.
7. In the third stage, transfer functions were applied as a permutation in the BNN. The results showed that the combination of log sigmoid and tangent sigmoid-tangent sigmoid gave the best response. The network had a regression of approximately 0.95 and an error of 0.17. The time consumed by the system was 1.6 sec. In the final stage of regression and network error, the processing time decreased to an appropriate level.
8. The BNN was able to estimate the values and laboratory results.

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Acrylic Polymer

چکیده

پلیمر اکریلیک به‌دلیل مقاومت بالا در برابر مواد شیمیایی گزینه مناسبی در ساخت بتن‌های مقاوم در برابر حملات شیمیایی است. در این مطالعه به بررسی بتن پلیمری خودمتراکم ساخته شده با پلیمر اکریلیک، نانوسیلیس و میکروسیلیس پرداخته شده‌است. نتایج حاصل از آزمایش نمونه‌ها نشان داده که افزودن میکروسیلیس و افزایش میزان پلیمر، مقاومت کششی، فشاری و خمشی را کاهش می‌دهد. افزودن نانوسیلیس مقاومت خمشی بتن را افزایش و مقاومت کششی و فشاری با افزایش پلیمر کاهش یافته است. این مقدار کاهش به نسبت سایر طرح‌ها کمتر است. به‌علت آن‌که در آزمایشگاه ساخت نمونه‌ها محدود و میزان تغییرات مقادیر اندک است نمی‌توان به نتیجه مناسبی دست یافت. به کمک شبکه‌های عصبی هر مقداری را که در محدوده داده‌های ورودی باشد را می‌توان تخمین زد. در این مقاله علاوه بر نتایج آزمایشگاهی، عملکرد شبکه عصبی انتشار برگشتی بر تخمین مقاومت بتن خودمتراکم پلیمری پرداخته شده‌است. نتایج شبکه عصبی نشان داده که یک شبکه عصبی انتشار برگشتی دو لایه که در آن از تابع خطای استاندارد میانگین، تابع آموزش انعطاف‌پذیر، تابع تحریک لوگ سیگموئید و تانژانت سیگموئید، و 5 نرون در هر یک از لایه‌های پنهان استفاده شود، نتایج مناسبی حاصل شده که در آن رگرسیون 0/95 و مقدار خطا 0/17 است.

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