International Journal of Engineering

Journal Homepage: www.ije.ir

Prediction of Engineered Cementitious Composite Material Properties Using Artificial Neural Network

F. Nateghi-A.*, M. H. Ahmadi

International Institute of Earthquake Engineering and Seismology, Tehran, Iran

PAPER INFO

Paper history:
Received 20 July 2019
Received in revised form 13 September 2019
Accepted 14 September 2019

Keywords:
Engineered Cementitious Composites
Experimental Study
Artificial Neural Network
Local Admixtures
Mechanical Properties

ABSTRACT

Cement-based composite materials like Engineered Cementitious Composites (ECCs) are applicable in the strengthening of structures because of the high tensile strength and strain. Proper mix proportion, which has the best mechanical properties, is so essential in ECC design material to use in structural components. In this paper, after finding the best mix proportion based on uniaxial tensile strength and strain, the correlation between these parameters were calculated. Since material properties depend on the content ratios, six mixtures with different Fly Ash (FA) content were considered to find the best ECC mixture called Improved ECC (IECC). Also, The influence of local fine aggregates and FA on the tensile behavior of ECC was considered to introduce IECC which has the best tensile properties. To predict the mechanical properties of ECC based on experimental results, Artificial Neural Network (ANN) was used. Training and validation of the proposed model were carried out based on 36 experimental results to find the best results. Numerical analysis is utilized to find the best mix proportion of ECC in structural design. The results show that the effects of FA and fine aggregates are considerable. Also, The proposed ANN model predicts the tensile strength and strain of ECC with different FA ratios accurately. Furthermore, the model can estimate mechanical properties of ECC in previous experimental results.

***doi**: 10.5829/ije.2019.32.11b.04*

1. INTRODUCTION

ECC material, known as a type of HPFRCC invented about 25 years ago, has special properties such as ultra-high ductility and tensile strength [1]. Although there are several specs introduced in the literature, common ductility for ECC is more than 0.03, and the width of cracks is about 60 μm. Figure 1 shows that unlike normal concrete, these properties of ECC and strain-hardening should be met in the tensile stress-strain curve [2]. Interaction between matrix and fiber and their interfaces makes high tensile strain and ductility in ECC material [3]. ECC is widely used in structures to retrofit the elements such as RC members, especially in retrofit to improve their seismic behavior [4-6]. Since ECC is made of several materials, the mechanical properties of ECC depend on these parameters, mix proportions and type of them. Finding the effects of each of these materials is difficult. However, finding a relationship between one of them and mechanical properties of ECC is valuable and applicable in composites. There is much study on ECC and using it in structural elements. However, few works have been conducted on the effect of each parameter and estimation of each parameter on mechanical properties of ECC. Especially using artificial models and numerical methods can be applicable to predict the tensile behavior of ECC.

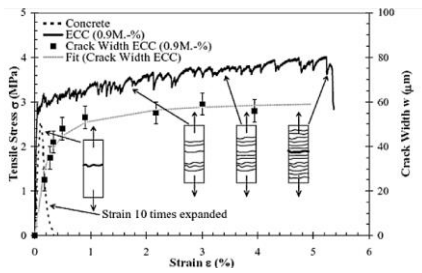


Figure 1. Comparison of the tensile behavior of concrete and ECC [2]

*Corresponding Author's Email: *nateghi@iiees.ac.ir* (F. Nateghi-A.)

Please cite this article as: F. Nateghi-A., M. H. Ahmadi, Prediction of Engineered Cementitious Composite Material Properties Using Artificial Neural Network, International Journal of Engineering (IJE), IJE TRANSACTIONS B: Applications Vol. 32, No. 11, (November 2019) 1534-1542

Fiber dispersion is one of the most effective parameters on the tensile behavior of ECC to achieve strain-hardening in the tensile stress-strain curve. The type of aggregate is affected on this parameter whether coarse aggregates cause poor dispersion like plain concrete or fine and appropriate aggregates enhance tensile behavior and ductility like ECC [7, 8]. Moreover, cement content and its quality play a noticeable role in hardening of the strain of ECC as the most valuable specs of ECC that should be met with experimental results. Previous works show that the performance of ECC is better than regular concrete in tension due to utilizing very fine aggregates [9, 10]. Using fine sands without any coarse aggregates increases the price of ECC material and makes it more expensive. However, using a suitable gradation of aggregates economize the mixture.

Previous researches show that Fly Ash (FA) affects on the tensile behavior of ECC like sustainability, tensile strength and strain, and toughness. Few works show that how FA affects of ECC behavior and how to find the best mix proportion. Li and Wang investigated that if FA content increases sustainability performance will be improved whereas matrix toughness will be reduced [11]. Tosun et al. [12] have shown that utilizing proper FA affects on ECC properties in fresh and hardened states directly by using two types of FA. Zhu et al. [13] showed that FA ratio affects on the flexural strain of the specimen so that by increasing FA ratio from 50 to 80%, the deflection has increased 100% in four-point bending test. Also, Wan et al. [14] have represented FA ratio effects on the tensile strain of ECC to find the best mixture. In ratios 50 to 75% FA content, 75% had the highest tensile strain and 50 and 65% had the lowest values. Moreover, the authors represented the influence of FA content on ECC performance under tensile loads using five different mixtures. It was concluded that the best tensile strain and strength belong to 1:1.5 and 1:0.5 C: FA ratios, respectively [15].

There are some researches about using slag in ECC to achieve high ductility and strength in tension. These studies showed that FA was necessary to enhance the tensile behavior of ECC [13, 16, 17].

In the previous study, the authors evaluated two types of aggregates and concluded that utilizing fine aggregate shows the ductile performance of ECC in tension [15]. Although all studies in the literature represent the ECC behavior and material properties, few researches work on ECC design and how to find the best mechanical properties using numerical models. Also, none of them carried out experimental and numerical studies on local materials and effect of FA with different mix proportions.

In this study, two kinds of aggregates and several FA contents were used to exhibit the influences on the tensile behavior of ECC. Different mix proportions affected on tensile strain and strength. Since the authors use ECC in the retrofit of masonry infill walls, finding the best ECC mixture which has the highest tensile strength and strain is extremely significant. So, many parameters which include the type of aggregates, FA, cement contents, and mechanical parameters were considered to find the best ECC called IECC. Using local aggregate and achieve the best ECC behavior are the main purpose of this paper. Local materials make structural design economic and high-ductile behavior of ECC in tension causes to select this material in the retrofit.

Artificial Neural Network (ANN) as a computational approach, is a good technique to solve the sophisticated problems accurately and efficiently. This technique is widely used to simulate and predict complicated problems in science and engineering. The behavior of many structural elements and materials were predicted using ANN. Structural parameters like compressive and tensile strength are predicted using ANN by many researches [18-27]. However, prediction of tensile behavior of ECC was not carried out considerably. In this study, after doing experimental study on tensile behavior of ECC and IECC, ANN models are developed to foresee the mechanical properties of ECC in tension.

2. EXPERIMENTAL INVESTIGATION

2. 1. Material Properties

This section is about the assessment of six ECC mixtures to find the best tensile behavior called IECC. In this investigation, aggregates and binders in two and three types respectively were used to produce ECC. The aggregates include sand and quartz powder, and binders consist of cement, FA and SL. Based on previous studies, mix proportions were opted [5, 6]. The other materials were the same like PVA fiber, water, and superplasticizer. The characteristics of the aggregates and fiber were shown in Figures 2 and 3. PVA fiber used in previous researches by the authors has 8 mm long and diameter, elongation and density are 39 µm, 6% and 1.3 g/cm^3, respectively. Also, the tensile strength of fibers is 1600 MPa and their Young's modulus is 42.8 GPa.

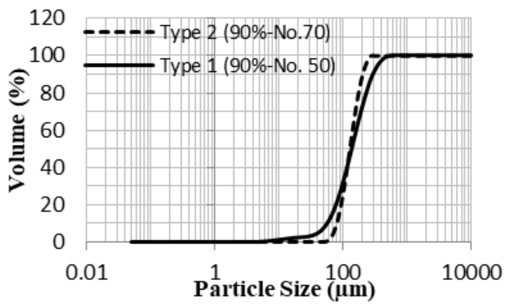


Figure 2. Gradation of fine sands [15]

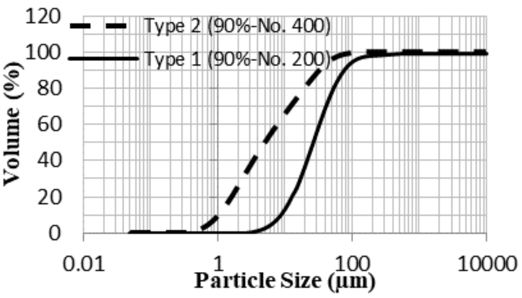


Figure 3. Gradation of quatz powder [15]

As seen in Figures 2 and 3, two kinds of aggregates were evaluated to make ECC more ductile with better mechanical properties. More than 90% of particles of sand type I and type II were smaller than 300 μm and 212 μm. Also, more than 90% of particles of quartz powder type I and type II were smaller than 75 μm and 38 μm [15]. As noted, utilizing good aggregates and limitation of the size and the weight of aggregates enhance the ductility of ECC and fiber dispersion. This consideration controls the material properties to make IECC.

2. 2. Mix Proportions The ratios of the weight of ECC matrix ingredients (cement, fine aggregates, water, superplasticizer, and PVA) are given in Table 1 as below. PVA fiber proportion is 2% in volume in all mixtures. At first, cement, FA and aggregates as dry components were mixed using a mini mixer as shown in Figure 4 for one minute. To produce the flowable and viscose mortar, water and superplasticizer were added to the dry components and mixed for 4 minutes. Good viscosity of mortar helps the fibers to be dispersed uniformly after adding them to the mortar and mixing about 3 minutes.

After producing standard ECC with two different types of aggregates, the purpose is to evaluate the mechanical properties of seven different ECC mixtures. Total weight of binder is fixed. However, the binder consists of cement and FA in six mixtures.

2. 2. Testing Plan The last purpose of this paper is using IECC, which has high tensile strain and strength, in the strengthening of masonry infill walls. To determine IECC properties, 7-day dog-bone samples were examined under uniaxial tensile forces. The tensile stress-strain curves can be determined based on these tests which show mechanical characteristics of ECC like hardening and cracks. Another important parameter is workability determined using the slump test which is about 35 cm for standard ECC (FA-ST2). Figures 4 and 5 show producing and test set-up of ECC specimens and slump and uniaxial tensile tests results, respectively [15]. The uniaxial tensile tests were done seven days after casting ECC in the dog-bone mold and curing in this period. The displacement control loading rate applied to the specimens was 0.015 mm/s.

TABLE 1. The ratios of the weight of ECC matrix

Mixture	Binder		Aggregates			Superplastisizer
	Cement	FA	Sand	Quartz Powder	Aggregate Type	
FA-ST1	1	2	0.35	0.35	I	0.012
FA-ST2	1	2	0.35	0.35	II	0.012
FA-0.5	1	0.5	0.35	0.35	II	0.012
FA-1	1	1	0.35	0.35	II	0.012
FA-1.5	1	1.5	0.35	0.35	II	0.012
FA-2.5	1	2.5	0.35	0.35	II	0.012
FA-3	1	3	0.35	0.35	II	0.012

Figure 4. Producing and test set-up of ECC specimens [15]

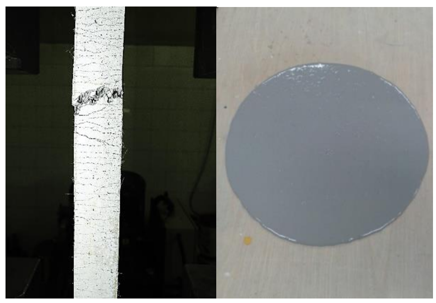
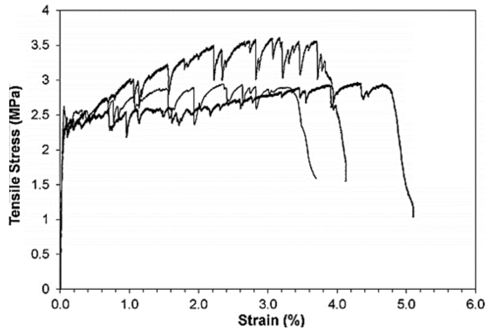


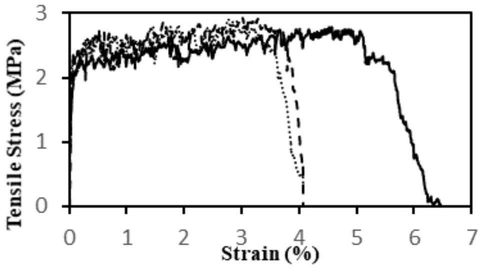
Figure 5. Slump and uniaxial tensile test results [15]

3. RESULTS AND DISCUSSION

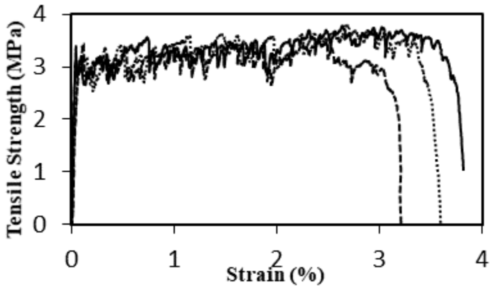
In Figure 6, an extensometer was used in the middle of the specimen to read the relative deformation and calculate the tensile strain. Also, the ratio of average force to the area in the failure zone was utilized for stress determination. Some of these curves consist of the results of the previous work which belongs to the authors [15]; the other new results and the comparisons found in this paper. Each figure shows the tensile stress-strain curves of 3 specimens in experimental studies.



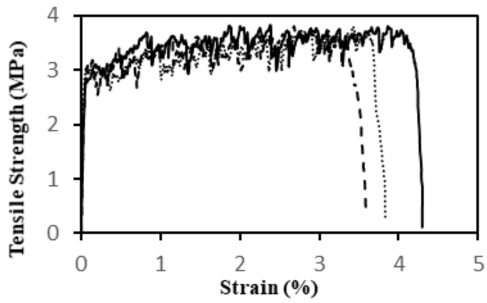
(a) FA-ST1 [6]



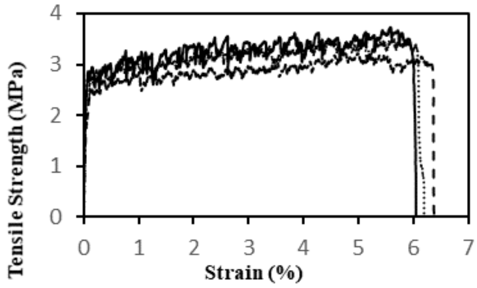
(b) FA-ST2 [15]



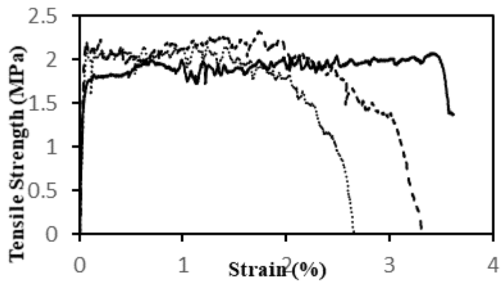
(c) FA-0.5 [15]



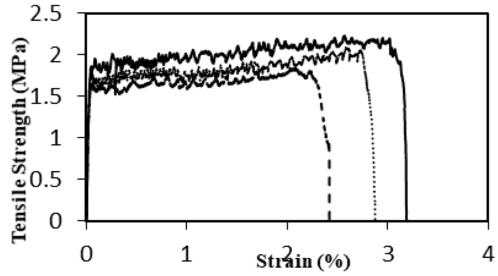
(d) FA-1 [15]



(e) FA-1.5 [15]



(f) FA-2.5 [15]



(g) FA-3 [15]

Figure 6. ECC tensile behavior with different admixtures (a-g)

Some significant mechanical characteristics of ECC which include tensile strength, tensile strain, fracture energy, and toughness index, were calculated to exhibit the comparison of different types of aggregates and binder. The definition of the mechanical properties of ECC is represented in Figure 7.

As seen, the tensile behavior of different mixtures of ECC mentioned in Table 2, were obtained in stress-strain curves to compare the effect of each part which includes FA, SL or aggregates. All strength values in Table 2 are the maximum strength of the specimen before failure, and the ultimate tensile strain is the value before large degradation in the curve. Since the mixture FA-ST2 has better performance than FA-ST1, the other mixtures produced using aggregates type 2 presented above. Among the different ratios of FA, the best tensile behavior of ECC belongs to specimen FA-1.5 which has tensile strength 3.4 MPa and tensile strain of 6.1% averagely. These values are more than standard ECC characteristics which are 2.84 MPa and 4.15%, respectively. Thus, Mixture FA-1.5 is called IECC due

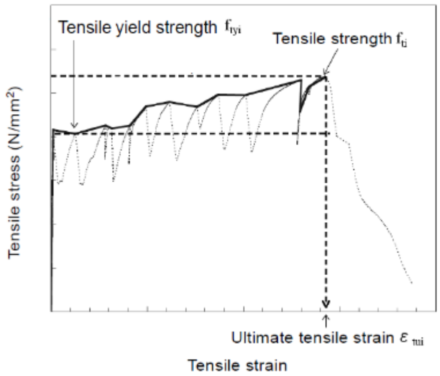


Figure 7. Definition of ECC characteristics

to ductile performance. To compare all tensile properties of specimens, include tensile strength and strain Table 2 and Figures 8 are determined to show mean and standard deviation values of results in bar charts.

Table 2 and Figures 8 show that the amount and the type of admixtures play an important role in material characteristics of ECC. Although FA increases the ductility of ECC and improve tensile behavior, its ratio is so important and effective in these parameters.

TABLE 2. Calculated ECC tensile parameters

ECC Mixture	Tensile Yield Strength (MPa)	Tensile Strength (MPa)	Ultimate Tensile Strain (%)
FA-ST1	2.4 ± 0.1	3.16 ± 0.25	3.92 ± 0.6
FA-ST2	2.3 ± 0.15	2.84 ± 0.23	4.15 ± 0.64
FA-0.5	3.25 ± 0.1	3.65 ± 0.1	3.35 ± 0.4
FA-1	2.95 ± 0.05	3.6 ± 0.08	3.7 ± 0.3
FA-1.5	2.65 ± 0.1	3.4 ± 0.14	6.1 ± 0.13
FA-2.5	1.9 ± 0.12	2.2 ± 0.13	2.7 ± 0.62
FA-3	1.76 ± 0.08	2 ± 0.175	2.67 ± 0.3

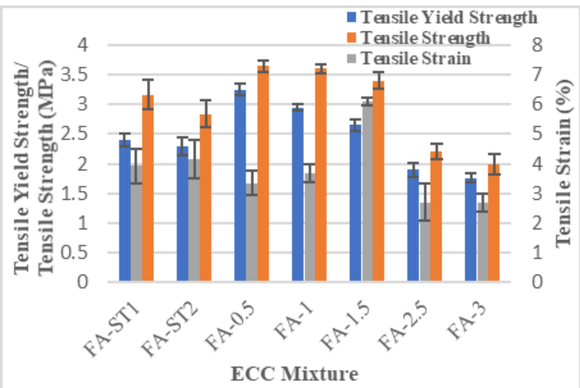


Figure 8. Comparison of ECC tensile behavior

As mentioned above, aggregate type II caused better tensile performance in ECC than aggregate type I. On the basis of Table 3, compared to FA-ST2 as the standard mixture which contains FA, the tensile strain of FA-1.5 was increased 47%, and that of specimens with FA content 0.5, 1, 2.5 and 3 were decreased 19, 11, 35 and 36%, respectively. Also, compared to FA-ST2, the tensile strength of specimens with FA content 0.5, 1 and 1.5 were increased 29, 27 and 20%, respectively and that of FA-2.5 and FA-3 reduce 23 and 30%, respectively.

The results show that the effect of FA on increasing tensile strain was obvious. The comparisons noted above, represent that using FA instead of cement in binder caused increasing tensile strain and de-creasing tensile strength generally. However, in mixture with two materials in the binder, the maximum value of tensile strain and strength belong to FA-0.5 and FA-1.5, respectively.

If FA ratio increases in ECC mixture, sustainability performance will be improved. However, tensile strength and matrix toughness will be decreased. Also, increasing FA content has positive effects on tensile strain of ECC in the specified range. In other words, in FA-0.5, FA-1 and FA-1.5 by increasing FA content, tensile strain is improved. More than FA-1.5 ratio this property is reduced. So, FA effects on tensile strain is not predictable in all conditions. However, numerical models can estimate this influence to predict tensile strain. Using FA decreases tensile yield strength and tensile strength generally. Thus, finding a customized mix proportion based on structural demands by considering these effects is so important in ECC design. In the next section, to predict ECC mechanical properties based on experimental studies, artificial model will be represented.

4. ARTIFICIAL NEURAL NETWORK

Artificial neural network is a method which is inspired by biological neural networks to achieve an estimation of parameters which depend on many inputs. ANNs known as beneficial models to predict parameters and find a solution for complicated tasks [20]. These models learn the performance of tasks using some examples then they find a solution to predict them. As usual, input and output layers in ANN models are one whereas hidden layers are two for the training occurs. The input and hidden layers are allocated to several functions such as tan-sigmoid, pure linear, etc. Different validation approaches are used in validated ANN models like k-fold validation [28].

4. 1. Artificial Neural Network Method As mentioned before, two hidden layers are used in ANN

model to show the relation of parameters adequately. Generally, ANN models have some layers as follows:
one input layer: ip (p=1, 2, …, m)
two hidden layers with j and neurons k
one output layer with os (s=1, 2, …, n).
The relation of the layers calculated as follows is shown in Figure 9 [28, 29].

$$\bar{o}_s = F_3\left(\left(\sum_{q=1}^{k}\bar{w}_{q-i}^3 . F_2\left(\left(\sum_{r=1}^{j}\bar{w}_{r-q}^2 . F_1\left(\left(\sum_{p=1}^{m}\bar{w}_{p-r}^1 . i_p\right) + \bar{b}_r^1\right)\right) + \bar{b}_q^2\right)\right) + \bar{b}_i^3\right) \quad (1)$$

where, $\bar{w}_{u-v}^l$ the weight of connection of the uth neuron in the lth layer and the vth neuron in the (l+1)th layer, whereas $\bar{b}_v^l$ and $\bar{ni}_v^l$ are the added bias and the net input in the lth layer for the vth neuron in the (l+1)th layer. It should be mentioned that l=1, 2 and 3. Fl is the function for indicating neurons in different layers [28]. Also, the mean square error function (Er) is reported in literature [28, 29]:

$$E_r = \frac{1}{n}\sum_{s=1}^{n}(\bar{t}_s - \bar{o}_s)^2 \quad (2)$$

where, $\bar{t}_s$: the sth target vector, n: the total nmber of output vectors.

One of the most important part of ANN modeling is the option of neuron numbers that should be appropriate for each result. The rule of neuron numbers was proposed as follows [30]:

$$i = \sqrt{p+q} + B \quad (3)$$

where, i= the numbers of neurons for each processing layer, p= input components, q= output components, B= empirical constant (4-8) which depends on various usages of the model

4. 2. ANN Models and Results To predict the properties, ANN should be trained based on experimental results of ECCs considered as input datasets and output for mechanical properties. In this study six different mixtures were used with different FA content. The results were represented by tensile yield strength and tensile strength and strain. Six uniaxial tensile tests were conducted for each mixture so that 36 results can be used as input datasets corresponding to tensile yield strength and tensile strength and tensile strain. Calculated ECC parameters were shown in Table 2. To design ANN models, Matlab was used in learning, validation and testing. For each mechanical parameter, one ANN model was used to find the relation between the effect of FA ratio and the parameters. In the model learning, 70% of the samples were selected for learning randomly, 15% for validation and 15% for test. The error diagram shown in Figure 10 illustrates the ANN performance, that the bars demonstrate training data, validation and testing data in blue, green and red, respectively.

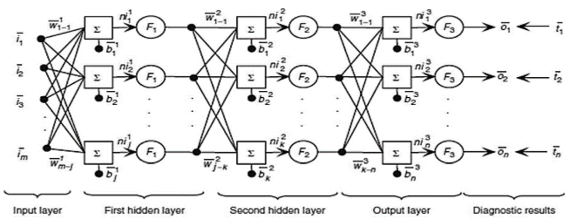


Figure 9. ANN model with one input, two hidden and one output layers [29, 30]

As shown in Figure 10, for tensile yield strength, all errors are between -0.1038 (-10.38%) and 0.1337 (13.37%) illustrate a quite negligible error. Also, the validation and test errors are between -0.07875 (-7.85%) and 0.09625 (9.625%) and -0.07875 (-7.85%) and 0.07125 (7.125%), respectively. The other two networks which are not shown here, also indicated errors like this. Another parameter which represents the performance of ANN model is Mean Square Error (MSE) (Figure 11). This figure represents that the MSE converges to a constant level and the errors were minimized. Thus, it demonstrates that the ANN models were trained well and can be used in forecasting the mechanical properties of ECC accurately. Furthermore, the regressions for all three categories training, validation and test and all of the results are illustrated in Figure 12.

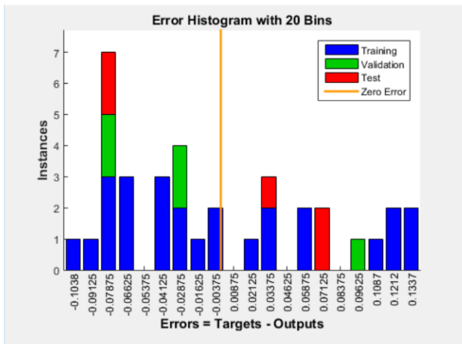


Figure 10. Error histogram with 20 Bins for tensile yield strength

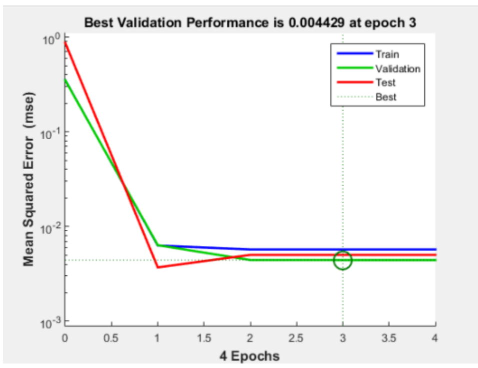


Figure 11. ANN training Performance

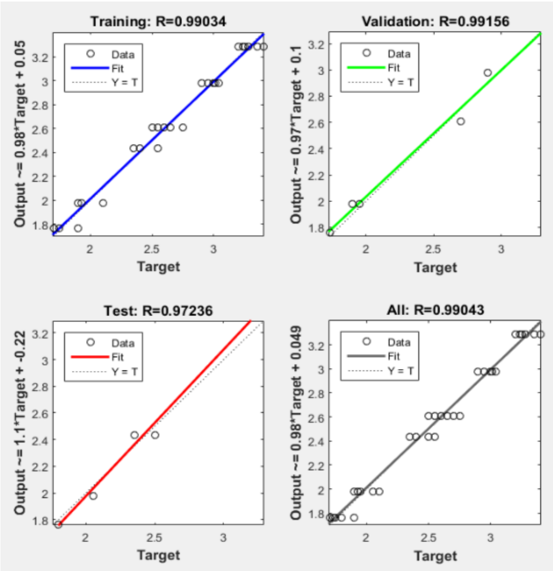


Figure 12. Regression of Neural Network model

As seen in Figure 11, MSE of train, validation and test were minimized at epoch 3 so that the best validation performance was 0.00443. It means that MSE converges in low values with a good accuracy. The regression of experimental results and the ANN model shows that this model is strong and predict the results very well. Training and validation regression is 99% and the test regression is 97% so that the regression of all results is 99%. These values confirm that the model is useful and applicable in ECC mechanical properties prediction.

4. 3. ANN Model Verification To verify tensile yield strength ANN models developed before, the results of previous study by the author [6] were used for training and test. The comparison of experimental results and ANN prediction model are shown in Table 3. The highest and lowest difference between experimental values and prediction results were around 8.29 and 3.61%, respectively.

It can be noticed that the number of neurons affects on the accuracy of the model. Using appropriate range for the option of neuron numbers prevents poor training performance. Another important parameter in ANN models is the size of database. The smaller database makes ANN modeling less accurate. However, using complete and sufficient database in ANN models shows perfect prediction of multiple properties with better accuracy. In this way, gathering all dataset from literature and doing more experimental studies can cause achieve this aim. Also, controlled different types of material can show better results. In other words, different types of admixtures, aggregates and superplasticizers represent various mechanical properties of ECC which can be used in ANN model and predict them using well trained and validated data. The ANN model shows that the regression between experimental and numerical study is strong. Since experimental study is always expensive to use in ECC design to use in structural components, using this model with good accuracy and fitness is economic and applicable in engineering design.

TABLE 3. Calculated ECC tensile parameters

Mechanical Property	Experimental average	Prediction average	Difference (%)
Tensile Yield Strength (MPa)	2.3	2.383	3.61
Tensile Strength (MPa)	2.84	2.913	2.57
Ultimate Tensile Strain (%)	4.15	4.494	8.29

5. CONCLUSION

ANN model provides an appropriate tool for structural designers to find the best design properties of ECC in structural components. In this study, a type of neural network was developed to foresee the main properties of ECC which consist of tensile yield strength, tensile strength and tensile strain for various mixtures. All datasets, used in ANN modeling, were conducted by the authors in experimental studies. The main results are summarized as follows:

- Two different types of aggregates in experimental studies showed that fine aggregates reduced tensile strength and increase tensile strain.
- The best mixture called IECC was FA-1.5 with FA: C=1.5:1 ratio. The tensile strength and tensile strain of this IECC were 3.4MPa and 6.1%, respectively.
- FA-0.5 has the highest tensile strength with 3.65 MPa value averagely.
- ANN models show a good prediction with good accuracy of mechanical properties of ECC based on error histogram, validation performance and regression analysis between the model and experimental results.
- The small difference between the prediction ANN model and experimental values shows that this model is reliable and beneficial in ECC design with favorable properties.

6. ACKNOWLEDGMENT

The authors thank International Institute of Earthquake Engineering and Technology (IIEES) for the funds in experimental and numerical studies. The authors would also appreciate Dr. Ayoub Dehghani for his invaluable helps in carrying out the experiments.

7. REFERENCES

1. Li, V.C., "From micromechanics to structural engineering-the design of cementitous composites for civil engineering applications", ***Journal of Structure Mechanical Earthquake Engineering***, Vol. 10, No. 2 (1993), 37-48.
2. Weimann, M.B. and Li, V.C., "Hygral behavior of engineered cementitious composites (ECC)", ***International Journal for Restoration of Buildings and Monuments***, Vol. 9, No. 5, (2003): 513-534. https://doi.org/10.1515/rbm-2003-5791.
3. Leung, C., "Theory of steady state and multiple cracking of random discontinuous fiber reinforced brittle matrix composites", ***ASCE Journal of Engineering. Mechanics***, Vol. 118, (1992), 2246-2264.
4. Hung, C.-C. and Chen, Y.-S., "Innovative ecc jacketing for retrofitting shear-deficient rc members", ***Construction and Building Materials***, Vol. 111, (2016), 408-418.
5. Dehghani, A., Fischer, G. and Alahi, F.N., "Strengthening masonry infill panels using engineered cementitious composites", ***Materials and Structures***, Vol. 48, No. 1-2, (2015), 185-204.
6. Dehghani, A., Nateghi-Alahi, F. and Fischer, G., "Engineered cementitious composites for strengthening masonry infilled reinforced concrete frames", ***Engineering Structures***, Vol. 105, (2015), 197-208.
7. De Koker, D. and Van Zijl, G., "Extrusion of engineered cement-based composite material", ***Proceedings of BEFIB***, Fibre-Reinforced Concretes; Proc. 6th RILEM Symposium on FRC (BEFIB 2004), Varenna, Italy, (2004),1301- 1310..
8. Torigoe, S.-i., Horikoshi, T., Ogawa, A., Saito, T. and Hamada, T., "Study on evaluation method for pva fiber distribution in engineered cementitious composite", ***Journal of Advanced Concrete Technology***, Vol. 1, No. 3, (2003), 265-268.
9. Lepech, M.D. and Li, V.C., "Large-scale processing of engineered cementitious composites", ***ACI Materials Journal***, Vol. 105, No. 4, (2008), 358-366.
10. FISCHER, G. and Shuxin, W., Design of engineered cementitious composites (ECC) for processing and workability requirements, in Brittle matrix composites 7. (2003), Elsevier, 29-36.
11. Şahmaran, M. and Li, V.C., "Engineered cementitious composites: Can composites be accepted as crack-free concrete?", ***Transportation Research Record***, Vol. 2164, No. 1, (2010), 1-8.
12. Tosun-Felekoğlu, K., Gödek, E., Keskinateş, M. and Felekoğlu, B., "Utilization and selection of proper fly ash in cost effective green htpp-ecc design", ***Journal of Cleaner Production***, Vol. 149, (2017), 557-568.
13. Zhu Y., Yingzi Y., Xiaojian G., Hongwei D., Yan Y., "Mechanical properties of engineered cementitious composites with high volume fly ash", ***Journal of Wuhan University Technology*** Vol. 24, No. S1, (2009), 166-170.
14. Li, W., Zhou, X. and Li, N., "Research on the effect of fly ash content on the tensile properties of pva-ecc", in 2015 Asia-Pacific Energy Equipment Engineering Research Conference, Atlantis Press., (2015).
15. Nateghi-A, F., Ahmadi, M.H. and Dehghani, A., "Experimental study on improved engineered cementitious composite using local material", ***Materials Sciences and Applications***, Vol. 9, No. 03, (2018), 315-329.
16. Yang, E.-H., Yang, Y. and Li, V.C., "Use of high volumes of fly ash to improve ecc mechanical properties and material greenness", ***ACI Materials Journal***, Vol. 104, No. 6, (2007), 303-311.
17. Zhu, Y., Yang, Y.Z. and Yao, Y., "Effect of high volumes of fly ash on flowability and drying shrinkage of engineered cementitious composites", in Materials Science Forum, Trans Tech Publ. Vol. 675, (2011), 61-64.
18. Bilim, C., Atiş, C.D., Tanyildizi, H. and Karahan, O., "Predicting the compressive strength of ground granulated blast furnace slag concrete using artificial neural network", ***Advances in Engineering Software***, Vol. 40, No. 5, (2009), 334-340.
19. Demir, F., "Prediction of elastic modulus of normal and high strength concrete by artificial neural networks", ***Construction and Building Materials***, Vol. 22, No. 7, (2008), 1428-1435.
20. Griinke, T.J., "Development of an artificial neural network (ann) for predicting tribological properties of kenaf fibre reinforced epoxy composites (KFRE)", University of Southern Queensland, Australia (2013).
21. Lee, S.-C., "Prediction of concrete strength using artificial neural networks", ***Engineering Structures***, Vol. 25, No. 7, (2003), 849-857.
22. Nehdi, M., El Chabib, H. and El Naggar, M.H., "Predicting performance of self-compacting concrete mixtures using artificial neural networks", ***Materials Journal***, Vol. 98, No. 5, (2001), 394-401.
23. Oreta, A.W. and Kawashima, K., "Neural network modeling of confined compressive strength and strain of circular concrete columns", ***Journal of Structural Engineering***, Vol. 129, No. 4, (2003), 554-561.
24. Shi, Z.-Q. and Chung, D., "Carbon fiber-reinforced concrete for traffic monitoring and weighing in motion", ***Cement and Concrete Research***, Vol. 29, No. 3, (1999), 435-439.
25. Topcu, I.B. and Sarıdemir, M., "Prediction of properties of waste aac aggregate concrete using artificial neural network", ***Computational Materials Science***, Vol. 41, No. 1, (2007), 117-125.
26. Wang, S.-C., Artificial neural network, in Interdisciplinary computing in java programming. 2003, Springer, 81-100.
27. Zhang, Z. and Friedrich, K., "Artificial neural networks applied to polymer composites: A review", ***Composites Science and Technology***, Vol. 63, No. 14, (2003), 2029-2044.
28. Shi, L., Lin, S., Lu, Y., Ye, L. and Zhang, Y., "Artificial neural network based mechanical and electrical property prediction of engineered cementitious composites", ***Construction and Building Materials***, Vol. 174, (2018), 667-674.
29. Beale, M.H., Hagan, M.T. and Demuth, H.B., "Neural network toolbox", ***User's Guide, MathWorks***, Vol. 2, (2010), 77-81.
30. Su, Z. and Ye, L., "Lamb wave propagation-based damage identification for quasi-isotropic cf/ep composite laminates using artificial neural algorithm: Part i-methodology and database development", ***Journal of Intelligent Material Systems and Structures***, Vol. 16, No. 2, (2005), 97-111.

Prediction of Engineered Cementitious Composite Material Properties Using Artificial Neural Network

F. Nateghi-A., M. H. Ahmadi

International Institute of Earthquake Engineering and Seismology, Tehran, Iran

P A P E R I N F O

Paper history:
Received 20 July 2019
Received in revised form 13 September 2019
Accepted 14 September 2019

Keywords:
Engineered Cementitious Composites
Experimental Study
Artificial Neural Network
Local Admixtures
Mechanical Properties

چکیده

استفاده از مصالح کامپوزیتی سیمانی نظیر کامپوزیت های سیمانی مهندسی (ECC) در مقاوم سازی سازه ها به دلیل مقاومت و کرنش کششی بالای آنها کاربرد فراوانی دارد. در این مقاله پس از یافتن بهترین طرح اختلاط کامپوزیت های سیمانی مهندسی براساس مقاومت و ظرفیت کرنش کششی آنها، رابطه بین این دو پارامتر محاسبه خواهد شد. از آنجاییکه مشخصات این مصالح به نسبت طرح اختلاط وابسته است، ٦ طرح اختلاط متفاوت که دارای نسبت های مختلف خاکستر بادی (FA) و نوع سنگدانه متفاوت هستند در نظر گرفته شده است تا بهترین طرح تعیین گردد. بهترین طرح اختلاط پس از انجام آزمایش ها کامپوزیت های سیمانی مهندسی بهبود یافته (IECC) نامگذاری خواهد شد. به منظور پیش بینی خصوصیات مکانیکی ECC از شبکه عصبی مصنوعی استفاده شده است. آموزش و اعتبار سنجی مدل پیشنهادی با استفاده از ٣٦ آزمایش انجام شده برروی این مصالح صورت گرفته است. نتایج نشان می دهد که تاثیر خاکستر بادی و سنگدانه ها قابل ملاحظه هستند. همچنین مدل پیشنهادی، می تواند مقاومت و کرنش کششی ECC را با دقت مناسبی پیش بینی کند. به علاوه این مدل می تواند مشخصات مکانیکی مصالح ECC آزمایش های قبلی را تخمین بزند.

***doi**: 10.5829/ije.2019.32.11b.04*