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Prediction of mechanical properties of engineered cementitious composites using artificial neural network

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ABSTRACT: Engineered cementitious composite (ECC) is a type of cement based material fabricated with various ranges of added-in functional fillers, featuring superior strain hardening, ductility and energy absorption. Proper composition is essential for ECC material design, which may lead various mechanical properties. Artificial neural network (ANN) technique is introduced in this study to predict the mechanical properties of ECC, which contained polyvinyl alcohol (PVA) fibre. The establishment and training of ANN models are based on previous experiment data set. Experimental testing is also carried out to verify the capability of the proposed ANN approach for the prediction of mechanical properties of ECCs.

1 INTRODUCTION

Engineered cementitious composite (ECC) is a special class of high performance fibre-reinforced cement composite (HPFRCC), which usually has a total fibre volume fraction of less than or equal to 2%, and is reinforced with short high performance fibres. It offers significantly improved mechanical properties over regular fibre reinforced concrete (FRC) (Wang and Li, 2005) and is a promising engineering material for protective structures due to its excellent mechanical properties such as high tensile strength, large pseudo-strain-hardening capacity to resist microcracking, and high energy absorption (Fischer and Li, 2007; Li et al, 2001). ECC can be designed by choosing specific composition of the constituents of functional fillers of various types and geometries. There are numerous types of functional fillers such as steel fibre (SF), polypropylene (PP), polyethylene (PE) and polyvinyl alcohol (PVA) fibres, in terms of wide variety of usage of diverse applications in the engineering field. The PVA is considered as one of the most suitable polymeric fibres to be applied as the reinforcement of ECC. A well designed PVA-ECC features high compressive around 70 MPa, tensile strength over 5 MPa, flexural strength around 15 MPa, and greatly improved tensile strain capacity exceeding 3%. It also exhibits excellent freeze-thaw durability compared with normal concrete mix (Wang and Li , 2005).

Artificial neural network (ANN) is propelled by the sophisticated functionality of human brains where many billions of interconnected neurons process data in parallel (Wang, 2003). This approach is an enthralling mathematical tool for solving complicated problems which would be difficult to work out linearly. The neural network technique has been adopted and used to simulate a wide variety of complex problems in both science and engineering fields. In particular, ANN can be used to forecast the mechanical properties of the composite before composition. The ANN model manipulates the past performance of the ECC based on the matrix composition. The database consisted of datasets obtained from past experiments or numerical simulations conducted by researchers. The ANN model is thus trained and validated in order to ensure the robustness in regard to predicting the corresponding mechanical properties. The neural network has been successful in modelling the confined compressive strength and strain of concrete columns (Oreta and Kawashima, 2003) and applying to polymer composites (Zhang and Friedrich, 2003).

In this study, the mechanical performance of ECC with PVA reinforcement will be investigated and several ANN models will be developed in order to predict their mechanical properties such as compressive strength, flexural strength and tensile strength prior to composition. The training database of ANN modelling is based on the literature review of previous studies. The developed ANN models will then be verified by the experimental results.

2 EXPERIMENT

2.1 Materials

In order to test the ANN models, PVA-ECC specimens with different compositions of PVA fibres are prepared. The volume fraction of PVA is 1%, 1.5% and 2% respectively. The PVA fibre applied is REC 15×12 from Kuraray CO., LTD. It is oil coated to deduct the bond strength between the interface of fibres and matrix, so that it can show the pull-out mechanism by which the strain-hardening property is achieved. The cementitious material is normal Portland cement and ASTM class F fly ash, which was added as dispersion material to make the functional fillers distributed and oriented randomly to prevent them from entanglement and close packing. In order to provide best overall performance, the fly ash to cement ratio is set to be 1.2 (Wang and Li, 2005). High range water reducing agent (HRWRA) can help to reduce the water usage by up to 40%, which will enhance the workability of cement as well as the compressive strength. Fine silica sand with an average diameter of 110 μm was used as fine aggregate, which was recommended by Li (2008) for better micro-mechanical properties for ECC mix. The detailed constituents and their mass proportions are shown in Table 1.

Table 1. The composition of ECC mix

ECC mix	Cement	Fly ash	Sand	Water	HRWR plasticizer	PVA (%)
PVA-ECC-1	1.0	1.2	0.8	0.6	0.022	1.75
PVA-ECC-1.5	1.0	1.2	0.8	0.6	0.022	1.75
PVA-ECC-2.0	1.0	1.2	0.8			

2.2 Specimen preparation and test setup

The mix procedure requires a high achievement in even distribution of the filled-in fibers to reach a relative homogeneous cement matrix of expected properties. Following the suggestion by (Han et al, 2015), the latter admixing method was applied for the PVA-ECC. The cementitious materials and silica sand were dry mixed in the Hobart mixer for 2 min firstly. Then one third of the water with super plasticizer was poured into the mixer to wet mix for 1 min. When the workability of mortar was high enough, the rest of water was poured in with the PVA fibres were added gradually in 2 min. Finally, the mix was set in molds and cured with constant temperature of 22 ℃ and 100% relative humidity in the curing chamber for 28 days after de-molding.

Three cylinder specimens of 100 mm diameter and 200 mm height were casted for each type of ECC for the compressive test. The test was performed by a 500 kN Baldwin machine (Figure 1) with a loading rate of 157.08 kN/min, in accordance with the ASTM C 39 standard (C39 ASTM, 2001). To test the flexural strength behaviour, three beam specimens of 4000 mm×100 mm ×100 mm dimension for PVA-ECC were prepared for the four point bending test. The test procedure followed the instruction in ASTM

C78 standard (C78 ASTM, 2009) and Baldwin 500kN testing machine with displacement control was used with the loading rate setting as 0.5 mm/min recommended by the standard (Figure 1).

(a) (b)

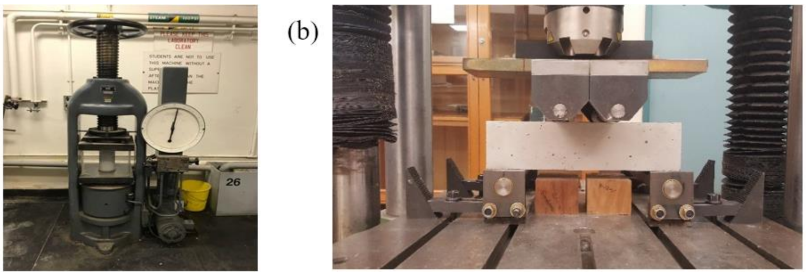

Figure 1. (a) Compressive test set up; (b) Four point bending test set up

3 ARTIFICIAL NEURAL NETWORK

3.1 Feedforward ANN model and backpropagation training

. In general, ANN models feature one input layer with the known value $i_p(p = 1,2, \dots m)$, two processing layers containing j and k neurons respectively, and an output layer with related parameters $o_s(s = 1, \dots\ , n)$, depicted in Figure 2, where the neurons are connected together via the weight matrix and a set of biases. Such kind of ANN models consisting of two processing layers have been demonstrated to be adequate in most structural-related analysis (Lu et al, 2009).

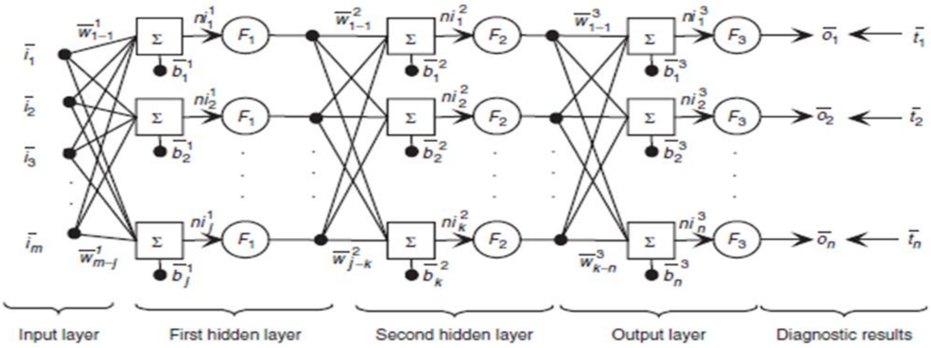

Figure 2. Feedforward ANN model with two processing layers

The output parameters is calculated by the following mathematical expression (Mark H. Beale, 2016):

$$\overline{o_s} = F_3\left(\left(\sum_{q=1}^{k} \overline{w}_{q-i}^{3} \cdot F_2\left(\left(\sum_{r=1}^{j} \overline{w}_{r-q}^{2} \cdot F_1\left(\left(\sum_{p=1}^{m} \overline{w}_{p-r}^{1} \cdot \overline{i}_p\right) + \overline{b}_r^1\right)\right) + \overline{b}_q^2\right)\right) + \overline{b}_i^3\right) \quad (1)$$

where $\overline{w}_{u-v}^{l}(l = 1,2)$ represents the weight connecting the uth neuron in the lth layer and the vth neuron in the $(l + 1)$th layer, while $\overline{b}_v^l$ and 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. $F_l(l = 1,2,3)$ is the transfer function for activating neurons in different layers (Mark H. Beale, 2016).

The neural networks can learn their weights and biases using the gradient descent algorithm. The process is carried out until the descent algorithm reaches the desired value. However, there was a gap where the gradient of the function can be hard to obtain (Nielsen, 2016). As a result, an algorithm known as backpropagation is taken place in order to provide a fast algorithm for computing such gradient. The backpropagation is associated with a stochastic steepest descent algorithm for ANN training within a required error tolerance (Lu et al, 2009). The mean square error function (MSE) E_r is defined as (Mark H. Beale, 2016):

$$E_r = \frac{1}{n}\sum_{s=1}^{n}(\overline{t_s} - \overline{o_s})^2 \quad (2)$$

where t_s is the sth target vector and n is the total number of output vectors. In the training process, the weight and bias values were modified based on the steepest descent method in order to minimise the mean square error, E_r (Suh et al, 2000).

The neural network training was accomplished utilising the "Neural Network Toolbox – MATLAB" (R2016b). The transfer functions have been selected to be Tan-sigmoid and Log-sigmoid for the processing layer 1 and 2 respectively. The transfer function is set to be pure linear between the second processing layer and the output layer to prevent the output values to be limited to a small range.

3.2 Artificial neural network setup

In the present research, the data for the proportion of the constituents of PVA-ECC were collected by a comprehensive literature review. However, some of the data in the references were blemished and thus they were missing or zeroed. Therefore, after tailoring and regrouping the relevant data, there are 24, 44, 47 and 54 sets corresponding to compressive strength, tensile strength, flexural strength and failure strain capacity (FSC) respectively. Each set contains 9 aforementioned input parameters that constitute PVA-ECC, i.e. weight of cement, class F and CI fly ash, silica sand, coarse aggregates, crush sand, water, HRWR, volume fraction of PVA. Therefore, the total number of input would be 216, 396, 423 and 486 respectively, and that of the target data would be 24, 44, 47 and 54, corresponding to each parameters respectively. Consequently, there are in total four ANN models developed for PVA-ECC in this case, i.e. ANN_c, ANN_t, ANN_f and ANN_s, corresponding to compressive strength, tensile strength, flexural strength and failure strain capacity, respectively. The input and target data were normalised within each parameter into the range of [0, 1], and the weight and bias values were randomly initialised. The determination of the number of neurons follows the rule of thumb. . These four ANN models were configured with respective neuron numbers tabulated in Table 2.

Table 2. Number of neurons used in training for ANN models for PVA-ECC

	Available sets of data for ANN training	Number of neurons in first processing layer	Number of neurons in second processing layer
ANN_c	24	23	6
ANN_t	44	34	9
ANN_f	47	34	9
ANN_s	54	35	10

The designated ANN models were put into training using the MATLAB toolbox. The trainings first initialised the weight and bias values, and then those values were put into neurons at different layers. The outcomes were then generated and compared against with the target values. After that, backpropagation was taken place in order to achieve an accurate and efficient ANN model. Eventually, the ANN models were tested and validated with the built-in function to ensure their robustness.

4 RESULT

4.1 ANN models

Each ANN model for PVA-ECC was trained with the total number of datasets minus one which will be used for validation. This process was carried out for three times with new test data being replaced and each process is performed for 6 times and the averaged values were examined against with the target value. The outcomes were tabulated in the Tables 3-4. It can be noted that the differences between the actual values and the predicted ones are reasonable for the PVA-ECC ANN models.

Table 3. ANN model for compressive strength and flexural strength of PVA-ECC

	Compressive Strength (MPa)	Compressive Strength (MPa)	Compressive Strength (MPa)	Flexural Strength (MPa)	Flexural Strength (MPa)	Flexural Strength (MPa)
Prediction	ANN_{c1}	ANN_{c2}	ANN_{c3}	ANN_{f1}	ANN_{f2}	ANN_{f3}
Average	67.71	67.10	69.59	11.97	12.98	12.46
Target	67.7	69	67	11	12	12.68
Difference (%)	0%	3%	4%	9%	8%	2%

Table 4. ANN model for tensile strength and failure strain capacity of PVA-ECC

	Tensile Strength (MPa)	Tensile Strength (MPa)	Tensile Strength (MPa)	FSC	FSC	FSC
Prediction	ANN_{t1}	ANN_{t2}	ANN_{t3}	ANN_{s1}	ANN_{s2}	ANN_{s3}
Average	5.40	4.24	4.05	3.48	3.24	3.64
Target	5.93	4.25	3.73	3	3	4
Difference (%)	9%	0%	9%	16%	8%	9%

In the model training, for instance the ANN_c, 70% of the samples are used for training, 15% for validation and 15% for testing. The error histogram is produced to demonstrate the network performance. As illustrated in Figure 3(a), the blue, green and red bars represent training data, validation data and testing data. The error histogram gives an indication of outliers, which are data points where the fit is significantly worse than the majority of data (Mark H. Beale, 2016). In the ANN_c, all errors fall between -0.06415 and 0.1102, indicating a trivial error. The other three networks showed only marginal errors as well as the compressive strength model. The networks are therefore proven to be accurate to predict the mechanical properties of PVA-ECC. Furthermore, the performance of the ANN models for the failure strain capacity is plotted in Figure 3(b), where the mean square error was converged, indicating that the errors have been minimised.

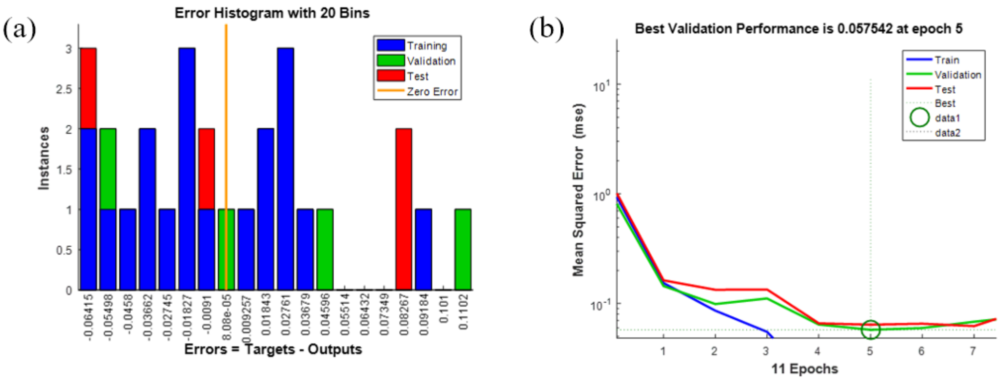

Figure 3. (a)Error histogram with 20 Bins - ANN_c; (b) Convergence history of ANN training

4.2 *Experimental results*

In order to verify the performance of the well-trained ANN models, three cylinders with different volume fraction each for the PVA-ECC have been tested to determine the respective compressive strength. The compressive strength for all samples appeared to be smaller compared to the well-designed PVA-ECC compressive strength, i.e. more than 70 MPa in (Li, 2003). That is mainly attributable to the larger water cement ratio used in the experiment, which is reasonable for a better workability for practical in-situ use. The average compression strength for the PVA-ECC fabricated with 1%, 1.5% and 2% volume fraction PVA are 58.94 MPa, 62.83 MPa and 57.4 MPa. The comparison of the experimental compressive strengths of the PVA-ECC with the ANN predictions is listed in Table 5. It is obvious that the results are quite close to the prediction results from ANN, varying from 0.84% to 2.15%, which verified the feasibility of the proposed ANN model to predict the property of ECCs.

In parallel, beam specimens have been tested to verify the flexural and tensile strength. The moduli of rupture of PVA-ECC ranged from 8.91 to 10.04 MPa for 1% volume fraction PVA-ECC, 9.99 to 12.04 MPa for 1.5% volume fraction PVA-ECC and 8.89 to 10.69 MPa for 2% volume fraction PVA-ECC. The predictions of the flexural strength of the PVA-ECC obtained from the ANN_f models are also depicted in Table 5 together with the experimental results, which shows great consistency. Table 5 also compares the predictions and experimental results of tensile strength, where the difference is even smaller, showing a more reliable prediction.

Table 5. Experiment validation for PVA-ECC

		Prediction Average	Experiment Average	Difference (%)
Compressive strength (MPa)	ANN_{c-1}	58.94	60.23	2.15%
	$ANN_{c-1.5}$	62.83	63.74	1.43%
	ANN_{c-2}	57.40	57.89	0.84%
Tensile strength (MPa)	ANN_{t-1}	3.86	3.98	3.02%
	$ANN_{t-1.5}$	4.47	4.524	1.19%
	ANN_{t-2}	3.97	4.076	2.60%
Flexural strength (MPa)	ANN_{f-1}	9.41	9.95	5.46%
	$ANN_{f-1.5}$	11.01	11.31	2.62%
	ANN_{f-2}	9.85	10.19	3.30%

5 CONCLUSION

Prediction of mechanical properties of ECC prior to composition was developed in this study by virtue of the ANN technique. The ANN models were established and tested based on the available literature while the small differences in the predictions and target values with experimental verification indicated that the estimation of the mechanical properties can be achieved with good accuracy.

It is worth noted that the diagnostic performance and precision of the ANN models were highly dependent on the neural network configurations and structure. A total of six ANN models were developed due to the lack of sufficient data. There is still room to improve the overall performance. One of the suggestions for the future work is to carry out a number of experimental works for more reliable data collection. In this case, the artificial neural network could be updated and therefore capable of predicting all required mechanical properties in one model.

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