PREDICTION OF STRENGTH PROPERTIES OF ENGINEERED CEMENTITIOUS COMPOSITES USING ARTIFICIAL NEURAL NETWORK

Shirin Ghatreh Samani, Ali Ehsani Yeganeh and Khandaker M. A. Hossain
Department of Civil Engineering, Ryerson University, Toronto, Ontario, Canada

Abstract: This paper describes the development of Artificial Neural Network (ANN) model for the prediction of compressive strength of the Engineered Cementitious Composite (ECC) based on mix design parameters. A database consisting of large number of ECC mix designs from previous and current research studies are used for training and validation of ANN model. The influence of mix design parameters on the strength properties are evaluated to determine the appropriate input variables for the ANN model with optimized network architecture. The performance of ANN model is found to be good based on various statistical indicators. The ANN model can be used confidently for the optimization of ECC mix design parameters to obtain targeted strength properties.

1 Introduction

For decades, concrete has proven to be a suitable material in infrastructure construction and has been successfully used in numerous projects around the world. Over the last few years, self-consolidating engineered cementitious composite (ECC) has been developed with superior ductility and durability - which translates to speedy construction, reduced maintenance and a longer life span for the structure (Li & Kanda 1998; Wang & Li 2006; Sahmaran et al. 2009). Micromechanical design allows optimization of ECC for high performance, resulting in extreme tensile strain capacity while minimizing the amount of reinforcing fibers, typically less than 2% by volume. Unlike ordinary cement-based materials, ECC strain hardens after first cracking, similar to a ductile metal, and demonstrates a strain capacity of 300 to 500 times greater than that of normal concrete. Even at large imposed deformation, crack width remains below 60 μm. With intrinsically tight crack width and high tensile ductility, ECC represents a new generation of high-performance concrete material that offers significant potential for resolving durability problem of reinforced concrete structures (Li & Kanda 1998; Wang & Li 2006; Sahmaran et al. 2009; Li 2003; Li et al. 2002).

The mechanical property of ECC, specifically strength, depends on type of the fiber and mix design parameters (Pan et al. 2012). The traditional mix design of ECC consists of cement, micro-silica sand, water, Polyvinyl Alcohol (PVA) fiber and water reducing agents. Over the years, there have been modifications in ECC mix designs to improve the mechanical properties and sustainability. Different types of fine aggregates such as iron ore tailing and crushed/mortar sand are used as replacement of expansive micro-silica sand. The aggregates type and strength followed by its dispersion with fibers influences the mechanical properties of the ECC. As a result the aggregate size has to be limited such that strain hardening can be obtained (Huang et al. 2013). Also different supplementary cementitious materials such as fly ash and slag have been incorporated into ECC as percent replacement of cement. Fly ash reduces the matrix toughness and it results in increasing the tensile strength (Mavani 2012). The type and mechanical property of fiber such as fiber's tensile strength, aspect ratio (length over diamerter), and modulus of elasticity (E) have a direct impact on the strength properties (Li & Li 2011; Kong et al. 2003).

The properties of concrete vary with the variation of mix design parameters. Artificial Neural Network (ANN) models have been developed and used as tools for predicting mechanical and durability properties of concrete (Oreta & Kawashima 2003; Sadrmomtazi et al. 2013). ANN models identify the patterns between the input and output. One of the most common methods is the back propagation technique, where the input data are fed into the input layers, then passed through the hidden neurons by assigning certain weight and bias such that the output layer is predicted through a sigmoid transfer function (Tayfur et al. 2013).

In recent years, researchers have successfully used ANN modeling in different civil engineering applications including the prediction of strength of concrete and other materials. Barbuta et al. (2012) used ANN models for predicting the properties such as compressive and flexural strength of polymer concrete with varying fly ash content. Gupta et al (2006) used a number of parameters: concrete mix design, curing techniques, shapes and size of the concrete specimen, curing period and environmental conditions (such as temperature, relative humidity, wind and velocity) to determine the strength of the concrete (Gupta et al. 2006). Also, an ANN model was used to predict the compressive strength of lightweight concrete (Sadrmomtazi et al. 2013).

However, no ANN model has been developed for ECC mechanical properties based on the mix design parameters. The purpose of this research is to develop an effective ANN model for prediction of 28-day compressive strength of ECC. The developed ANN model can be used to understand the relationship among various mix design parameters for optimization of ECC strength properties and will serve as a tool for the design of ECC mixtures.

2 Development of artificial neural network model

The process of developing an appropriate ANN model is to construct the effective input parameters by collecting the test results of wide range of ECC mix designs. Next step is to train and test the model with input data to achieve the desirable model output – in this case, 28 days compressive strength. In this research, the Levenberg Marquardt back propagation method from Matlab was used to develop the model. The back propagation of neural networks uses the feed-forward technique where input data are used in one direction to obtain the output (Kshirsagar & Rathod 2012). It is a layered structure with an input layer, hidden layer and an output layer (Hossain et al. 2006). The input should contain all the important parameters such that output will be accurate and reliable (Hossain et al. 2006). Throughout the propagation, the weights associated with each output are adjusted such that the error is minimized. The layers in between input and output are called hidden neurons. The number of hidden neurons are determined through the iterative process such that the Mean Squared Error (MSE) is minimized and the degree of agreement (ξ) approaches to 1 (Hossain et al. 2006). The degree of agreement is calculated from Willmot (1982) as:

$$[1]\ \xi = 1 - \frac{\sum_{m=1}^{n}(P_m - F_m)^2}{\sum_{m=1}^{n}[|P_m - F_{mean}| - |F_m - F_{mean}|]^2}$$

where n is the number of points, F_m is field observation; F_{mean} observed data points and P_m is the predicted data points.

Information on wide range of ECC mixtures with different mix designs were collected from previous research studies. The strength properties of ECC depends on the types/amount of fine aggregates, water to binder ratio, types/percentages of supplementary cementitious materials and types/dosages of superplasticizers (high-range water reducing admixtures). Beside type and dosage of fiber, geometrical (such as aspect ratio, 'L/d'), and mechanical properties (such as modulus of elasticity 'E') influence the 28 days compressive strength (Mavani 2012; Alilou & Teshnehlab 2010). A total of 134 ECC mixtures were selected from extensive literature review of research conducted from 2003 to 2012 (Sahmaran et al. 2009; Yang 2008; Huang et al. 2013; Mavani 2012; Hong et al. 2003; Kan et al. 2010; Kim et al. 2003; Lepech and Li 2008; Lepech et al. 2008; Li & Li 2011; Li et al. 2008; Ozbay et al. 2012; Sahmaran et al. 2012; Sahmaran et al. 2010; Wang & Li 2007; Wang & Li 2003; Yang et al. 2009; Yang et al. 2007; Huang et al. 2013).The ranges of mix design parameters are provided in Table 1.

Table 1: Ranges of Mix Design Data of ANN Model

	PC kg/m^3	Fly Ash F kg/m^3	Fly Ash CI kg/m^3	Micro Silica sand kg/m^3	Light Weight Agg. kg/m^3	Crushed sand kg/m^3	Water kg/m^3	E of PVA MPa	Aspect Ratio of PVA	HRWRA kg/m^3	Strength MPa
Max	851.3	1063	847	845	444.1	447	361	42800	308	22.4	65
Min	131.7	0	0	0	0	0	172.7	42800	205	1.25	11.8

The weight of the Portland cement varied from 131.7 kg/m^3 to 851.3 kg/m^3, depending on the proportion of supplementary cementatious material. The selected fine aggregates for mix designs were fine micro-silica sand, crushed sand and lightweight aggregate including iron ore tail, glass bubbles (S38, S60), polymeric micro-hollow bubbles (MHK) and expanded perlite. The modulus of elasticity for the Polyvinyl Alcohol fiber (PVA) was 42800 MPa. The aspect ratio of PVA fiber varied from 205 to 308.

The target values/experimental results for the 28 days compressive strength were trained to create an ANN model using a supervised back-propagation technique. The input parameters (weights of mix designs) were fed into the network and were assigned certain weights and biases such that the outputs were generated. This iterative process was adjusted every round until the outputs had the least errors and constant values with respect to the experimental results (Yao 1999). For this research, the Levenberg Marquardt algotherim was selected because it had the same accuracy, and higher rate of convergence with respect to the other training techniques (Mukherjee & Routroy 2012).

Different tests were performed to determine the optimized number of hidden neurons and to analyze the influence of input parameters on the output. The two tests were completed by the iterative process of removing an input, and observing the effect on the output. Once the input parameters were finalized, the number of the hidden neurons varied by trial and error to determine the optimized neurons with a least error on the output (Chu & Hossain 2013). Based on the training, the optimized model for the 28 days compressive strength was selected. Figure 1 presents the ANN model for the 28 days compressive strength.

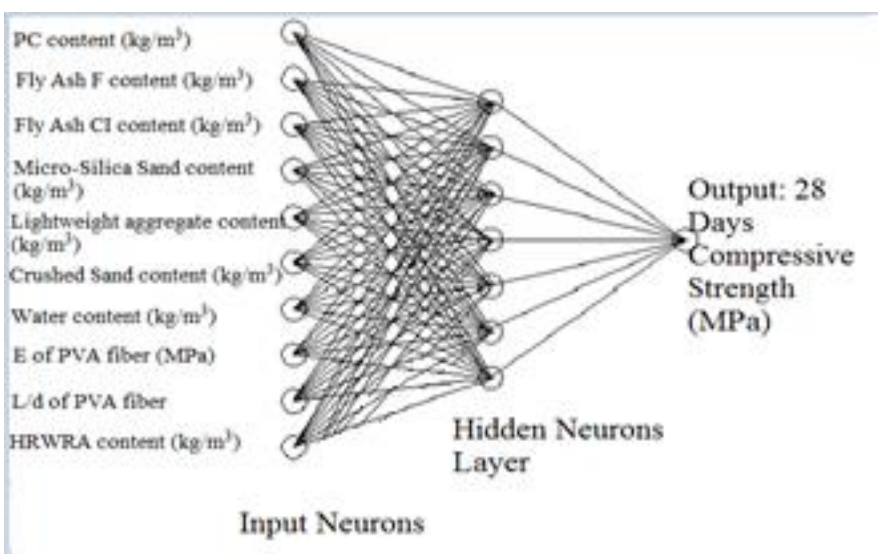

Figure 1: Artificial Neural Network Model

3 Results and performance evaluation for ANN model

The target values for the 28 days compressive strength ANN model was measured using statistical tools including Mean Square Error (MSE), Root Mean Square Error (RMSE), fitting equation of the lines and the degree of agreement (ξ). Additionally, the difference between the target and experimental value for different statistical tools such as average (E_{avg}), standard deviation ($E\sigma$,), coefficient of variance (E_{cv},), maximum range (E_{Max}), and minimum range (E_{Min}) were calculated to determine the optimized ANN model for the 28 days compressive Strength.

3.1 Effect of number of hidden neurons for ANN Models

All input parameters for the 28 days compressive strength were used to determine the appropriate number of hidden neurons. The number of hidden neurons varied from 10 to 3. Using statistical tools the optimized number of hidden neurons for the 28 days compressive model was selected. The effect of changing hidden neurons on predictability of 28 days compressive strength model is shown in Table 2 and Figure 2 respectively.

Table 2: Constant Input Varying Hidden Neurons

# of Hidden Neurons	$\frac{P_p}{P_e}$	ξ	MSE	RMSE	E_{avg}	E_σ	E_{CV}	E_{max}	E_{min}
10	1.01	0.83	36.8	6.06	0.08	2.85	0.06	8.74	2.75
9	1.02	0.87	27.8	5.28	0.34	-8.65	-0.18	1.43	6.39
8	1.03	0.89	23.5	4.85	0.40	-6.30	-0.17	0.82	3.09
7	1.01	0.96	9.0	3.00	0.03	-3.42	-0.07	0.02	1.10
6	0.98	0.66	73.0	8.54	1.45	5.05	0.21	0.14	12.9
5	0.99	0.64	72.4	8.51	2.37	-23.0	-0.41	6.58	4.60
4	1.05	0.74	54.7	7.39	0.19	-18.3	-0.42	0.01	10.9
3	1.05	0.66	72.4	8.51	0.24	-18.1	-0.41	7.26	10.7

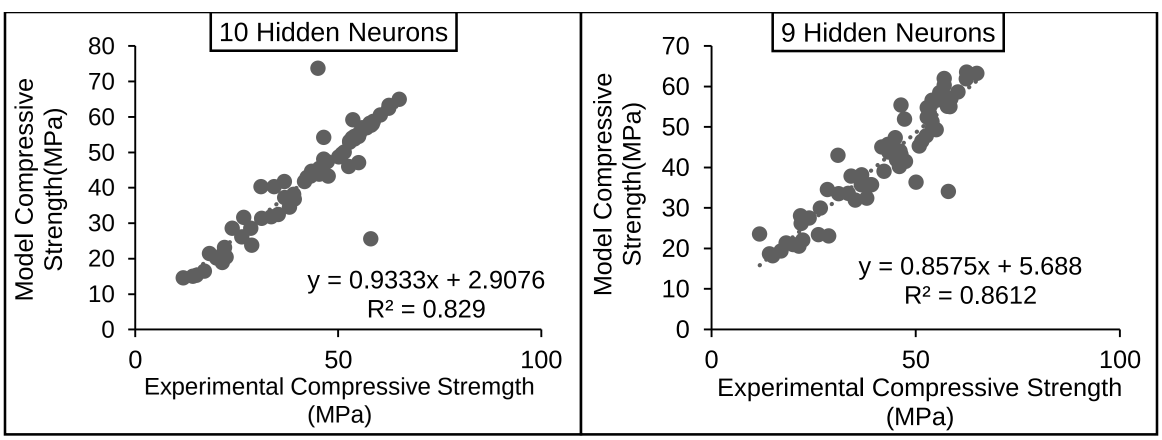

Figure 2: Influence of Hidden Neurons with Constant Input

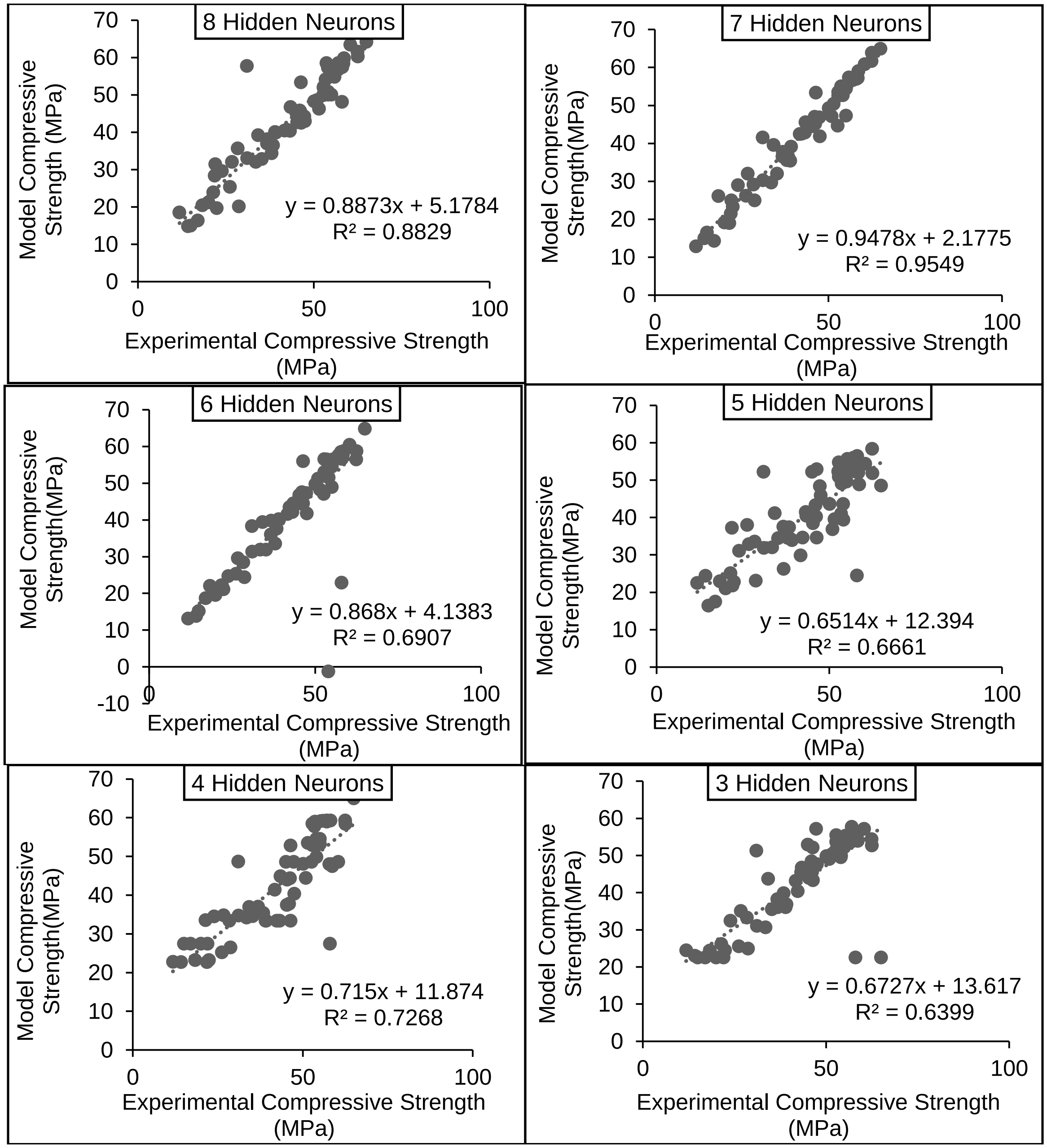

Figure 2 (contd.): Influence of Hidden Neurons with Constant Input

As it is evidenced from statistical tools and comparative graphs (Table 2 and Figure 2), the optimized number of hidden neurons for the 28 days compressive strength ANN model is 7. The seven hidden neurons has a good degree of agreement of 0.957, close to 1, smallest Mean Squared Error of 9.027, and RMSE of 3.005. The equation of the line shown in Figure 2 indicates that the experimental and model outputs are very close to each other, since the slope of the line is close to 1 and the y intercept is very small, close to 0. This indicates that there is a high correlation between the experimental and model outputs for the 28 days compressive strength.

3.2 Effect of the number of input parameters

Different combination of input parameters with constant hidden neurons of 7 was used to obtain the optimal input parameters for 28 days compressive strength ANN model. One input parameter was eliminated and the ANN model was trained to obtain an output of 28 days compressive strength. Figure 3, as well as Table 3 illustrates the results for removing different input parameters for the 28 days compressive strength.

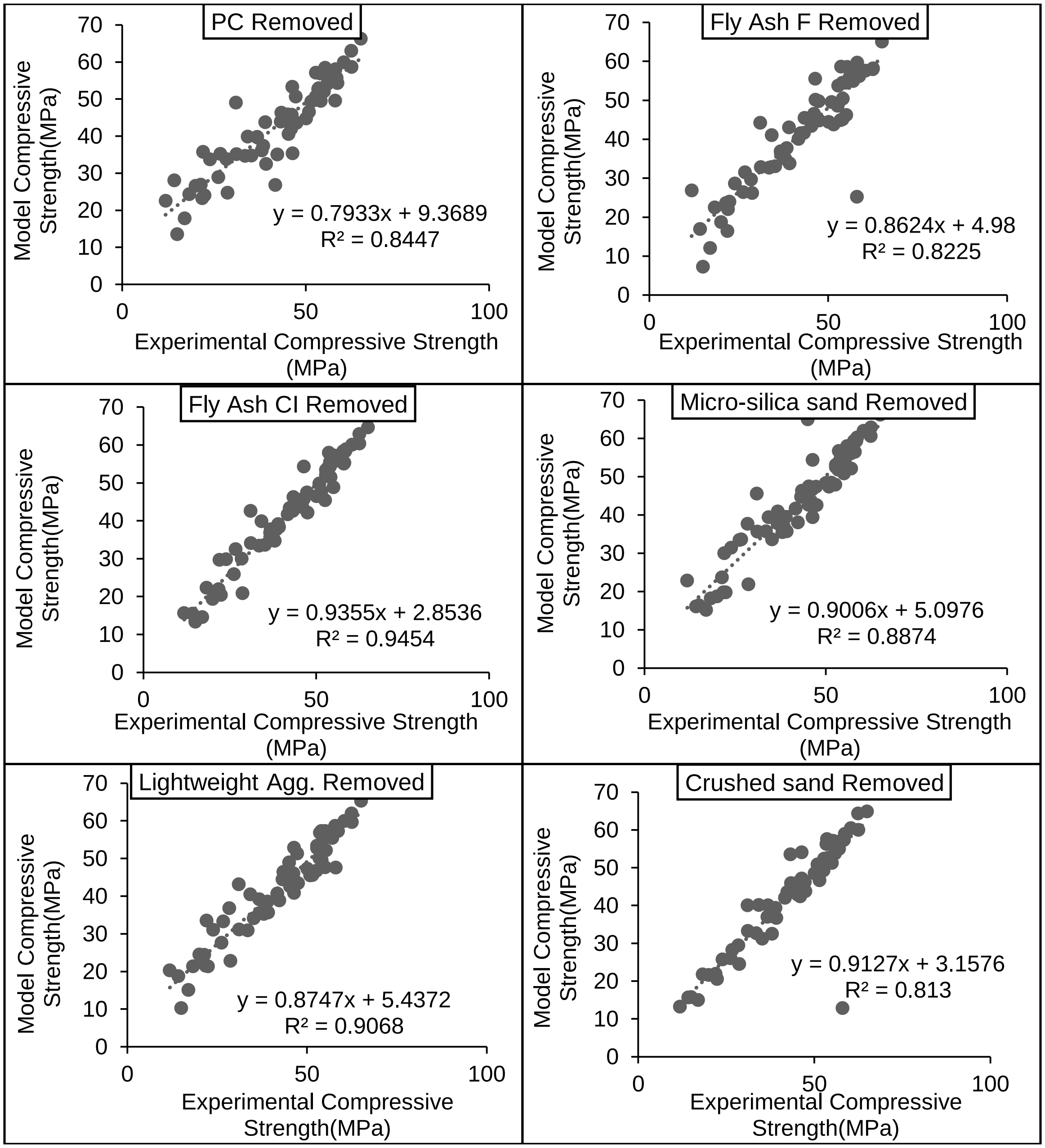

Figure 3: Influence of Varying Input Parameters with Constant Hidden Neuron of 7

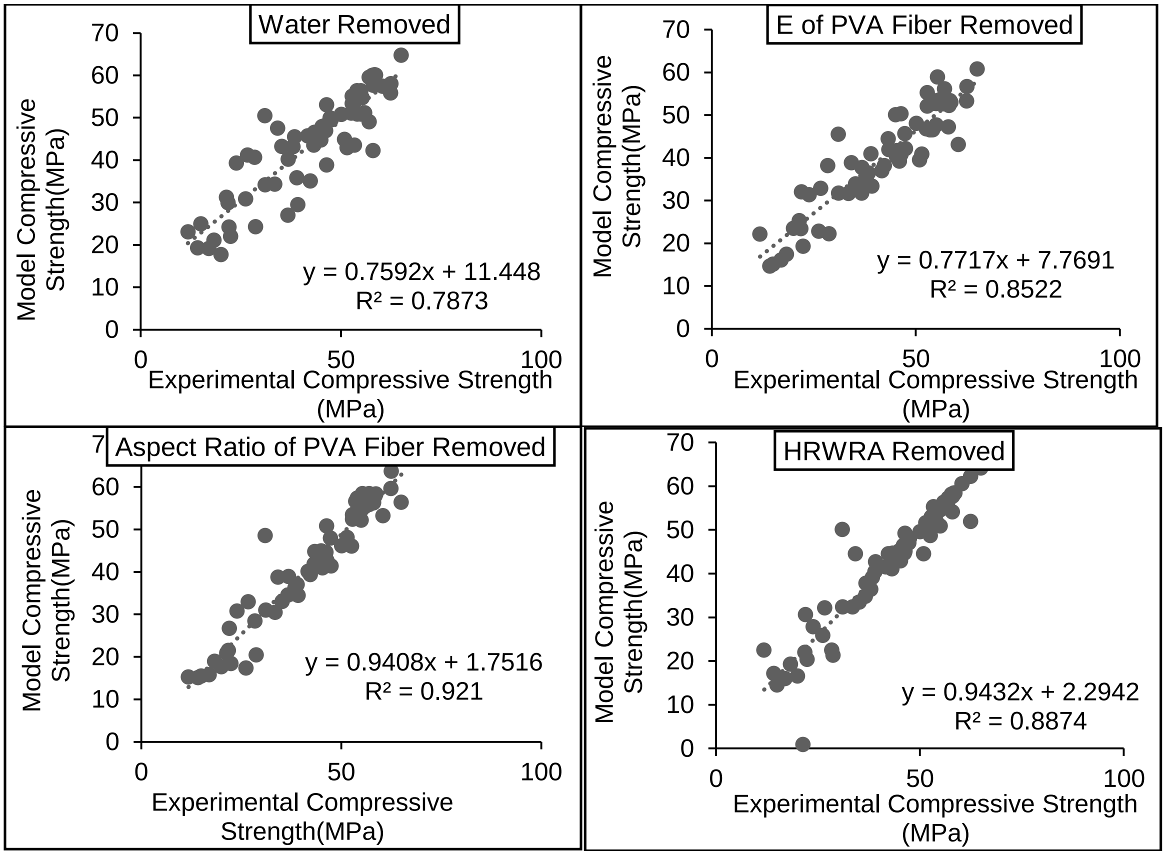

Figure 3 (contd.): Influence of Varying Input Parameters with Constant Hidden Neuron of 7

Table 3: Varying Input, Constant Hidden Neurons

Input Excluded	$\frac{P_p}{P_e}$	ξ	MSE	RMSE	E_{avg}	E_{σ}	E_{CV}	E_{max}	E_{min}
PC	1.06	0.84	32.0	5.66	0.61	15.6	0.40	1.24	1.74
Fly Ash F	1.00	0.82	36.6	6.05	0.89	5.60	0.08	0.08	4.55
Fly Ash CI	1.01	0.94	10.9	3.30	0.12	4.31	0.10	0.38	1.55
Micro-silica sand	1.04	0.89	23.3	4.83	0.88	5.01	0.17	1.13	3.35
Lightweight Agg.	1.20	0.91	18.8	4.34	0.13	9..28	0.22	0.29	1.54
Crushed sand	0.99	0.81	40.1	6.33	0.54	1.39	0.06	0.14	1.01
Water	1.07	0.78	44.3	6.65	1.24	16.4	0.45	0.20	5.92
E of PVA	0.98	0.83	34.7	5.89	1.90	18.7	0.33	4.21	2.84
Aspect ratio of PVA fiber	0.99	0.92	16.4	4.50	0.75	2.24	0.01	1.27	3.32
HRWRA	1.00	0.89	23.2	4.82	0.11	0.14	0.01	0.83	10.9

As it is evidenced from Figure 3 and Table 3, no input parameters can be eliminated for the 28 days compressive strength model. Based on the provided analysis (for both tests) the optimized ANN model for predicting the 28 days compressive strength of ECC is 10:7:1.

4 Predicting ability of Artificial Neural Network Model

The optimized 28 days compressive strength ANN model was tested and validated on new sets of data within the same ranges of the model. The testing data were collected from Ryerson University laboratory and other scholars. The ranges of new data set are provided in Table 4 (Huang et al. 2013; Mavani 2012; Sahmaran et al. 2009).

Table 4: Ranges of Testing Data for Validation of Model

	PC kg/m^3	Fly Ash F kg/m^3	Fly Ash CI kg/m^3	Micro silica sand kg/m^3	Light Weight Agg. kg/m^3	Crushed sand kg/m^3	Water kg/m^3	E of PVA MPa	Aspect ratio of PVA	HRWRA kg/m^3	Strength MPa
Max	570	999.7	847	455	448.7	446	331	42800	308	5.7	62
Min	227.2	0	0	0	0	0	319	42800	205	4.2	27.9

The results for validation of the 28 days compressive strength ANN model is provided in Table 5, and Figure 4.

Table 5: Evaluating Predicted Values for ANN Model

Validation of compressive strength			
P_p/P_e	ξ	MSE	RMSE
0.993	0.989	1.156	1.075

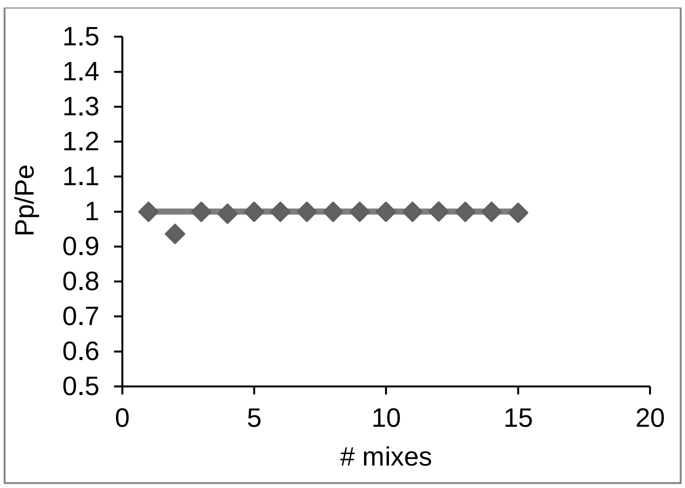

Figure 4: Validation of ANN model based on P_p/P_e factor

As it is observed from Table 5 and Figure 4 both degree of agreement ξ and the ratio between the model (P_p) and experimental (P_e) outputs are close to 1 (acceptable range) for testing and validating the 28 days compressive strength ANN model of 10:7:1. These statistical tools justify the validation for the 28 days compressive strength ANN model of 10:7:1 within the same ranges of data set.

5 Conclusion

An artificial neural network (ANN) model for the prediction of the 28 days compressive strength of engineered cementitious composite (ECC) is developed by using mix design parameters as input variables. Optimized network architecture of the model is determined based on parametric studies considering the influence of ECC mix design parameters and hidden neuron layers. A 10:7:1 ANN model is found to be good in predicting the 28 days compressive strength of ECC. The model is trained band developed by using large number of data sets gathered from previous research studies and its performance is validated based on the new data sets. The developed ANN model is found to predict the 28 days compressive strength of ECC mixture with excellent accuracy. This model can be used as a tool for the design of ECC mixture for desired or prediction of the 28 days compressive strength of a given ECC mixture within the same ranges of data set.

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