Journal of Construction in Developing Countries, 20(1), 85–98, 2015

Predicting the Significant Characteristics of Concrete Containing Palm Oil Fuel Ash

*Hamed Golizadeh[1] and Saeed Banihashemi Namini[2]

Abstract: Palm Oil Fuel Ash (POFA) is used as a supplementary cementitious material in concrete. Using different percentages of POFA leads to a non-linear variation among the characteristics of concrete. This study aims at developing an empirical model to predict the compressive strength of concrete using POFA as a cement replacement material and other properties of the concrete such as the slump and modulus of elasticity using an artificial neural network. Mixtures of concrete were selected with water-to-binder ratios of 0.50, 0.55 and 0.60, and 10%, 20%, 30% and 40% of the cement content was POFA. The 28-day compressive strength was tested, and the experimental results show that 0%–20% of POFA inclusion in the concrete mixtures has the most positive effects on the compressive strength. Then, a three-layer feed forward-back propagation ANN model with three inputs and three outputs was developed. Finally, the best architecture for the model was trained, tested and validated.

Keyword: Mixture proportioning, Blended cement, Compressive strength, ANN

INTRODUCTION

It is known that carbon dioxide (CO_2) from cement is one of several causes of global warming. Approximately 5% of total CO_2 emission is released into the atmosphere, and approximately 0.7 t–1.1 t of CO_2 is emitted for every ton of produced cement (Bosoaga, Masek and Oakey, 2009). To reduce the amount of CO_2 emission, cement manufactures can help by improving the production process. For concrete production, one solution is the reduction of the cement content in concrete by using supplementary cementitious materials such as fly ash, blast-furnace slag, silica fume, metakaolin, natural pozzolans, and biomass ash to replace cement.

Palm oil is extracted from the fruit and copra of the palm oil tree. After the extraction process, palm oil fibres, shells, and empty fruit brunches as waste products are burnt as biomass fuel to boil water, which generates steam for electricity and the extraction process in palm oil mills. The remaining substance is Palm Oil Fuel Ash (POFA), which is approximately 5% by weight of the solid-waste products. This waste is not used and mostly must be disposed in landfills, which cause some environmental problems (Nochai and Nochai, 2007).

However, many researchers have found that POFA can be used in the construction industry, specifically as a supplementary cementitious material in concrete (Abdul Awal and Mohd. Warid, 1997; Sata, Jaturapitakkul and Kiattikomol, 2004; Sukantapree, Namarak and Jaturapitakkul, 2002; Tay, 1990; Mohd. Warid and Abdul Awal, 1997; Abdul Awal and Mohd. Warid, 2011; Abdul Awal and Shehu, 2013; Chandara et al., 2012; Jaturapitakkul et al., 2011; Johari et al., 2012; Kroehong et al., 2011; Moruf Olalekan et al., 2014a, 2014b). In 1990, Tay

[1]Afzir Co., Tehran, IRAN
[2]Department of Civil Engineering, Universiti Teknologi Malaysia, Johor, MALAYSIA
*Corresponding author: ghamed7@live.utm.my

investigated the use of ash derived from palm oil waste incineration to make blended cement; the results showed that replacing 10%–50% ash by weight of the cementitious material in blended cement had no significant effect on the segregation, shrinkage, water absorption, density, or soundness of concrete.

Mohd. Warid and Abdul Awal (1997) studied the compressive strength of concrete with POFA. The results showed that it was possible to include POFA at a level of 40% without affecting the compressive strength. In addition, Abdul Awal and Mohd. Warid (1997) showed that POFA had a good potential for suppressing expansion because of the alkali-silica reactions.

According to Sumadi and Mohd. Warid (1995), unground POFA, used up to 20% as a cement replacement, has no adverse effect on the strength characteristics and has a durability factor that is at least comparable to that of OPC concrete. Ground POFA provides much higher compressive strength than unground POFA because of significant differences in particle size and fineness. The ground POFA with high fineness is a reactive pozzolanic material and can be used to make high-strength and high-performance concretes (Sata, Jaturapitakkul and Kiattikomol, 2004).

It is well recognised that the prediction of concrete strength is important in in its judgment in modernised concrete construction and engineering (Deepa, Sathiyakumari and Sudha, 2010). Conducting numerous experimental studies to identify the properties of concrete are usually time consuming and require a huge amount of resources and excessive workloads. Although many new prediction methods were developed in the last decade to address this issue by investigating the compressive strength of concrete based on empirical data, there is no prediction model for concretes with POFA as a cement replacement material. However, some previous efforts to develop a predictive model for POFA-containing concrete used linear statistical methods that did not seem sufficiently reliable for different compositions of concrete components.

This study aims at developing an empirical model to predict the significant characteristics of concrete with POFA as a cement replacement material using an artificial neural network.

EXPERIMENTAL STUDIES

To conduct this experimental study, the following steps were considered.

Raw Materials

1. Cement: ordinary Portland cement (Type I) was used.
2. Aggregates: river sand with a fineness modulus of 2.6 and crushed stone with maximum size of 20 mm were used as the fine aggregate and coarse aggregate, respectively.
3. Pozzolanic material: POFA with a specific gravity of 2280 (Kg/m^3) was used. Its fineness was 2.8%, i.e., for every kilogram that passed through sieve no. 325, 28 grams remained (2.8%). Furthermore, the pozzolanic activity index of the ground POFA was 65.3%.

Mixture of Concrete

Mixtures of concrete were selected with water-to-binder (W/B) ratios of 0.5, 0.55 and 0.6 with 10% of sand's weight filler content. This amount of filler is required to modify the standard curve of sand (Gheorghe, Saca and Radu, 2008; Jones, Zheng and Newlands, 2003). Table 1 shows the mixture designs for the given water-to-binder ratios based on the same amounts of fine and coarse aggregate for all specimens. POFA as a percentage of cement was added to the concrete mixtures at 10%, 20%, 30% and 40%.

Table 1. Mix Design of the Specimens

Cement (Kg/m^3)	Gravel (Kg/m^3)	Sand (Kg/m^3)	W/B Ratio
300	1150	800	0.50
300	1150	800	0.05
300	1150	800	0.60

Casting, Curing and Testing of Specimens

Cylindrical specimens of 15×30 cm were used in the experiments. These cylindrical specimens were cast and installed in three steps during the filling of concrete specimens, and each step was vibrated on shaking tables. Then, the specimens were maintained in a 20 °C curing room with 98% relative humidity for 24 hours and subsequently preserved for 6 and 27 days in lime-saturated water. The ASTM code procedure (ASTM C39 / C39M – 09a) was used to test the 7-day and 28-day compressive strengths of the specimens (ASTM C39/C39M-14a, 2014). In addition, the modulus of elasticity of the specimens was tested using the ASTM C469 code procedures (ASTM C469, 2002).

BRIEF DISCUSSION OF EXPERIMENTAL RESULTS

The results of the 28-day compressive strength test based on Figure 1 to Figure 3 indicate that the incorporation of 10% POFA as a cement replacement material with W/B ratios of 0.5, 0.55 and 0.6 enhances the compressive strength by approximately 3%–4% with respect to the specimens without POFA. Similarly, the replacement with 20% POFA increases the compressive strength by 0%–5%. However, further replacement with POFA up to 30% decreased the compressive strength by 3%–7%. According to Mohd. Warid and Abdul Awal (1997), the maximum acceptable incorporation of POFA is 40% of the cement content, i.e., a larger amount reduces the compressive strength of concrete by 13%–18%.

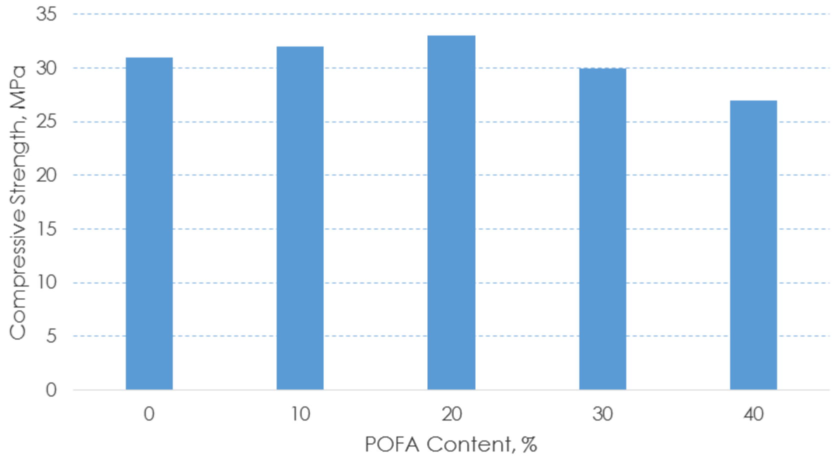

Figure 1. Compressive Strength of POFA Contained Concrete for w/b 0.5

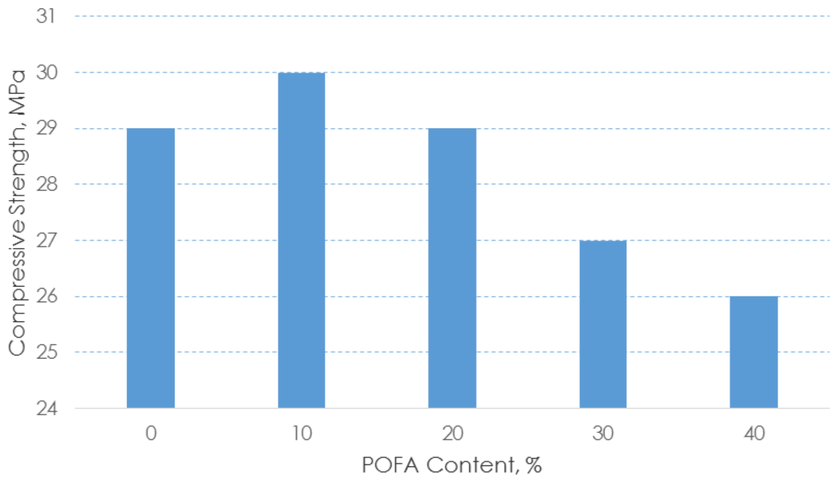

Figure 2. Compressive Strength of POFA Contained Concrete for w/b 0.55

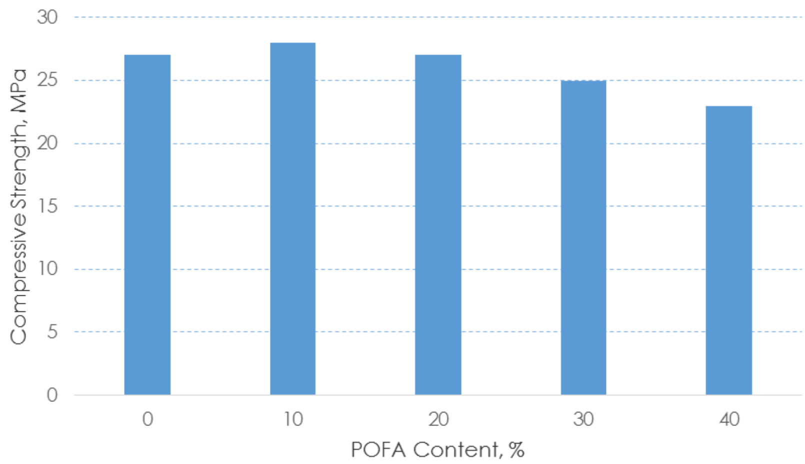

Figure 3. Compressive Strength of POFA Contained Concrete for w/b 0.6

According to Sata et al. (2004), the 10% POFA inclusion has the most positive effect on the compressive strength of concrete. Based on Table 2, the same results are proven for the amount of POFA replacement in this experiment. Figure 4 shows the interactive three-dimensional isoresponse of the 28-day compressive strength of concrete for various W/B ratios and POFA percentages. From this figure, it is observed that the compressive strength of concrete does not significantly vary in the ranges of 0.5–0.55 and 0%–20% of the W/B ratio and POFA replacement, respectively.

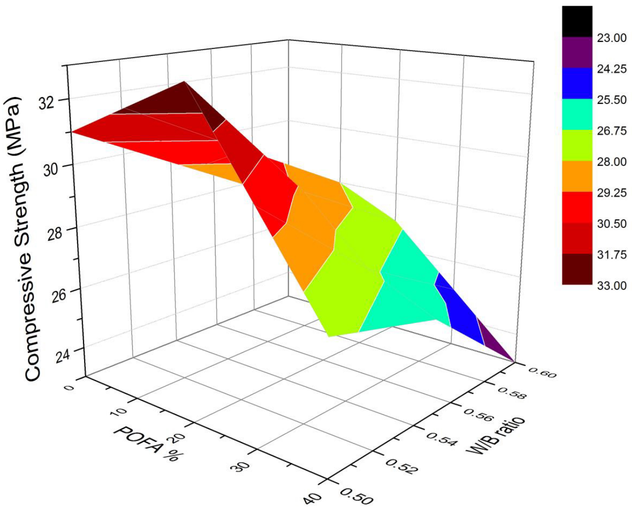

Figure 4. Interactive Three-Dimensional Isoresponse for Different w/b Ratios and POFA Percentages

Table 2. Compressive Strength Test for Different Mix Designs

Mix No.	Total Cementitious Materials (kg/m3)	Cementitious Materials % By Weight		W/B Ratio	Compressive Strength in Seven Days (MPa)	Compressive Strength in 28 Days (MPa)	Slump (mm)	Modulus of Elasticity (GPa)
		Cement	POFA					
1	300	100	0	0.50	22	31	60	26.2
2	300	100	0	0.55	19	29	70	25.3
3	300	100	0	0.60	18	27	95	24.4
4	300	90	10	0.50	21	32	60	29.6
5	300	90	10	0.55	20	30	70	25.7
6	300	90	10	0.60	17	28	85	24.9
7	300	80	20	0.50	21	33	65	27
8	300	80	20	0.55	19	29	65	25.3
9	300	80	20	0.60	16	27	75	24.4
10	300	70	30	0.50	19	30	60	25.7
11	300	70	30	0.55	17	27	70	24.4
12	300	70	30	0.60	14	25	70	23.5
13	300	60	40	0.50	17	27	55	24.4
14	300	60	40	0.55	15	26	60	24
15	300	60	40	0.60	14	23	65	22.5

DEVELOPMENT OF THE ANN MODEL

The variables of the experimental tests were applied to develop a model to predict the compressive strength, slump and modulus of elasticity based on an Artificial Neural Network (ANN) for the specimens. The ANN is a mathematical or computational model that attempts to simulate the structure or functional aspects of biological neural networks (Ukrainczyk and Ukrainczyk, 2008; Yeh, 2009). Neural networks have been applied in the engineering fields to predict the outcome of non-linear statistical problems, model complex relationships between inputs and outputs, and find patterns in datasets (Flores, 2011). Conducting large numbers of experimental tests to analyse and calculate the properties of specimens is complex, which makes ANN a good platform for this purpose. In this form, the network was presented with datasets that were obtained from the experiments, and the weights of the inputs (variables in the experiments) were fed into each neuron or node. Then, the weights were iteratively adjusted using back propagation until suitable outputs were produced. In this case, the suitable outputs (predicted compressive strength, slump and modulus of elasticity) are the closest values to the actual ones. In the back propagation method, the size of the error is fed back into the calculation for the weight changes. To develop and validate the ANN prediction model, MATLAB software was used.

One of the most popular and efficient network structures for an ANN model is the multilayer perceptron (MLP). MLP consists of identical interconnected neurons that are organised in layers. These layers are also connected, where the outputs of one layer act as the inputs of subsequent layers. The data flow starts from the input layer and ends in the output layer. In this journey, the data that pass through one or multiple hidden layers recode or provide a representation for the inputs (Flores, 2011).

To validate the variables for the input layer in the ANN model, the Pearson correlation test for independent variables in the tests was conducted to prevent the multicolinearity phenomenon (Gou and Fyfe, 2004). Based on Table 3, there is no excessive Pearson correlation (more than 0.8) among the independent variables; hence, all variables of the cement weight, POFA weight and W/B ratio were considered the inputs to develop the ANN model, and the compressive strength, slump and modulus of elasticity were the outputs of the ANN model.

Table 3. Pearson Correlation Test for the Inputs of ANN Model

	Cement Weight	**POFA Weight**	**W/B Ratio**
Cement weight	1	0.75	0.35
POFA weight	0.75	1	0.45
W/B ratio	0.35	0.45	1

In this paper, because of the nature of the variables and the non-linearity among them, a multilayer perceptron (MLP) network based on the feed-forward-back-propagation learning method was used to predict the compressive strength of the specimens.

ANN MODEL EVALUATION AND ERROR ANALYSIS

This study constructed a three-layer ANN model of the feed-forward type with three output neurons. There are three neurons in the input layer for the three input variables and three neurons in the output layer for the model. Then, 15 datasets based on 15 conducted experiments were formed and divided into three groups: 70% of the datasets for training, 15% for testing and 15% for validating were randomly selected. When multilayer neural networks are used to solve a problem, the number of neurons in the hidden layers is one of the most important issues. It is known that an insufficient number of neurons in the hidden layers prevents the neural network from solving the problem, but too many neurons leads to over-fitting and decreases the network's generalisation capabilities because the freedom of the network is increased above the required level (Flores, 2011).

Although the selection of the architecture for a neural network requires trial and error, the best number of neurons for the hidden layers depends on the number of input and output neurons, number of training cases, and complexity of the learning function and training algorithm (Panchal et al., 2011; Shariati, Zin and Aghamohammadi, 2011). As a rule of thumb, the following heuristic rules apply:

1. The number of hidden-layer neurons is equal to two times the number of input-layer neurons plus one,
2. The number of hidden-layer neurons is equal to the sum of the number of input-layer neurons and the number of output-layer neurons, or

3. The number of hidden-layer neurons is equal to the sum of the number of input-layer neurons and the number of output-layer neurons divided by two (Shahidehpour, Yamin and Li, 2002).

Therefore, four different numbers, 3, 6, 7 and 10, of neurons for one hidden layer were tested, and the number of 7 neurons was found to be the most optimal number of hidden-layer neurons. The best performance of the model is measured based on the error produced by the ANN model; in this case, the mean absolute percentage error (MAPE) was used as a performance indicator. The MAPE expresses accuracy as a percentage and is defined by the following equation:

$$MAPE = \frac{1}{N_i} \sum_{N_i} \frac{\left| C_p - C_a \right|}{C_a} \times 100 \qquad \text{Eq. 1}$$

where the MAPE is the mean absolute percentage error, C_p is the predicted value, C_a is the actual value obtained from experimental tests, and N is the total number of datasets. It should be noted that in the calculation of the MAPE value, all outputs, which included the compressive strength, slump and modulus of elasticity values, were considered.

The model with 3, 6, 7 and 10 hidden neurons resulted in 6.1%, 0.04%, 0.018% and 0.73% error, respectively. A MAPE value closer to zero indicates a more accurate model. Thus, the optimal number of neurons was 7. The structure of this ANN model is shown in Figure 5.

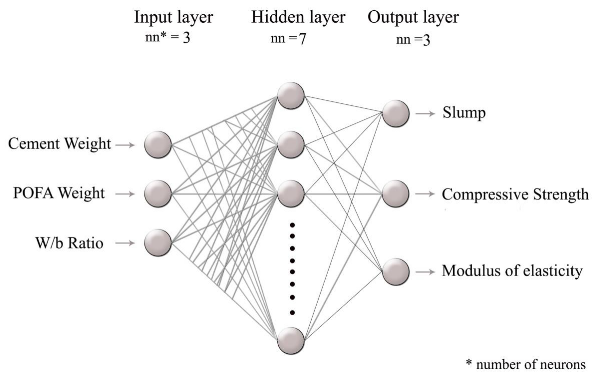

Figure 5. The Structure of the Developed ANN Model

The information flow starts at the input layer, passes through the hidden layer and ends in the output layer. The Levenberg-Marquardt Back propagation algorithm was used to fit the weights during the learning process, which started at the output layer and passed through the input layer (Flores, 2011). The hyperbolic tangent function was the selected activation function for the input layer, and a sigmoid transfer function was used between the hidden layer and the output layer. Then, the program was instructed to run for 2,000 iterations, and the error for each run of iteration was measured. To avoid overtraining, it was specified that training had to be stopped when the error remained unchanged for 10 continuous iterations. To find the optimal percentage of cases to be trained, tested and validated, Test 1 with 60% training, 20% testing and 20% validating, Test 2 with 70% training, 15% testing and 15% validating and Test 3 with 90% training, 5% testing and 5% validating were performed.

To estimate the quantitative performance of these three tests based on the different numbers of cases for training, testing and validating, the statistical performance criteria, root mean square error (RMSE) and graphical performance correlation coefficient (R) were used. The RMSE can quantitatively indicate the model error in terms of a dimensional quantity (Shariati, Zin and Aghamohammadi, 2011). An RMSE of zero indicates a perfect match between the observed and predicted values and is calculated using the following equation:

$$RMSE = \left[\frac{\sum_{i=1}^{N}(C_p - C_a)^2}{N}\right]^{1/2} \qquad \text{Eq. 2}$$

where C_p is the predicted value, C_a is the actual value, and N is the total number of datasets (Shariati, Zin and Aghamohammadi, 2011).

Different numbers of cases were used for training, testing and validating; based on the results, the lowest RMSE for training, testing and validating with the values of 0.006, 0.008 and 0.02 were achieved using Test 2, where 70, 15 and 15% of the cases were used for the training, testing and validating, respectively (Figure 6).

The predicted values that were obtained using the ANN model for the compressive strength, slump and modulus of elasticity of different ranges of Test 1 (60% training, 20% testing and 20% validating), Test 2 (70% training, 15% testing and 15% validating) and Test 3 (90% training, 5% testing and 5% validating) were plotted against their respective experimentally obtained values, as shown in Figure 7 to Figure 9. The efficiency of the developed ANN model for Test 2 can be inferred from these figures according to its better consistency with the drawn equality lines.

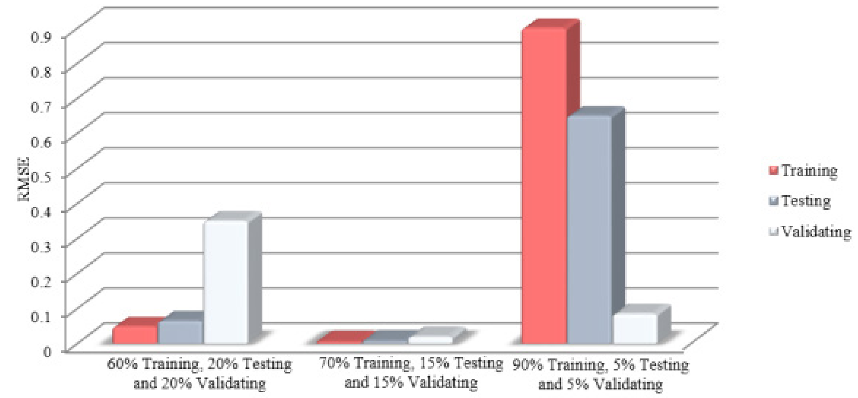

Figure 6. Comparison of RMSE of the Model for Different Training, Testing and Validating Ratios

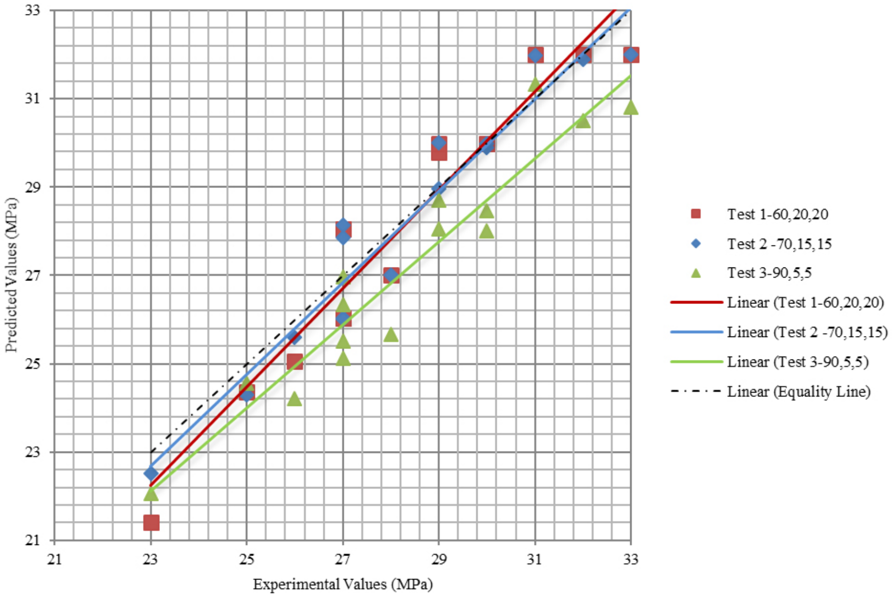

Figure 7. The Predicted Compressive Strength Values Obtained for Three Tests against Experimental Values

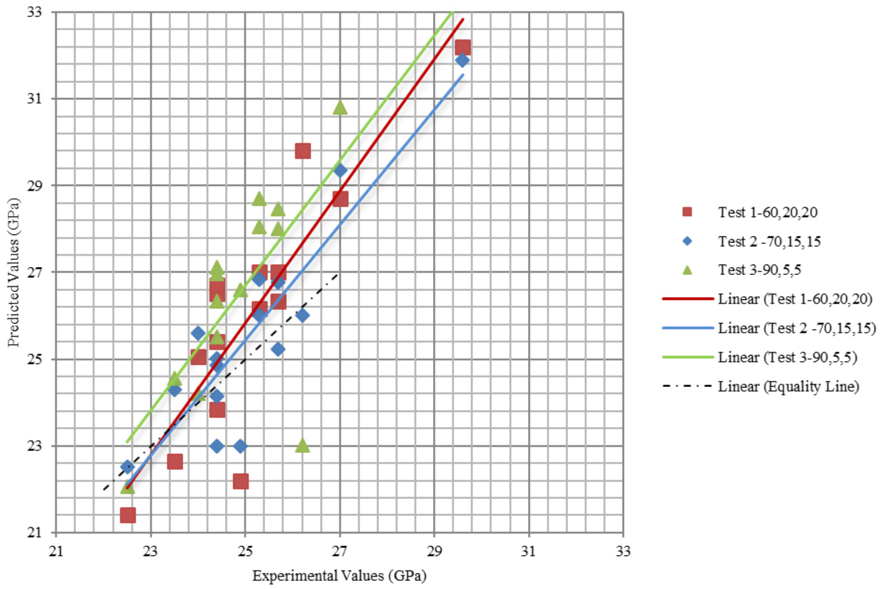

Figure 8. The Predicted Modulus of Elasticity Values Obtained for Three Tests against Experimental Values

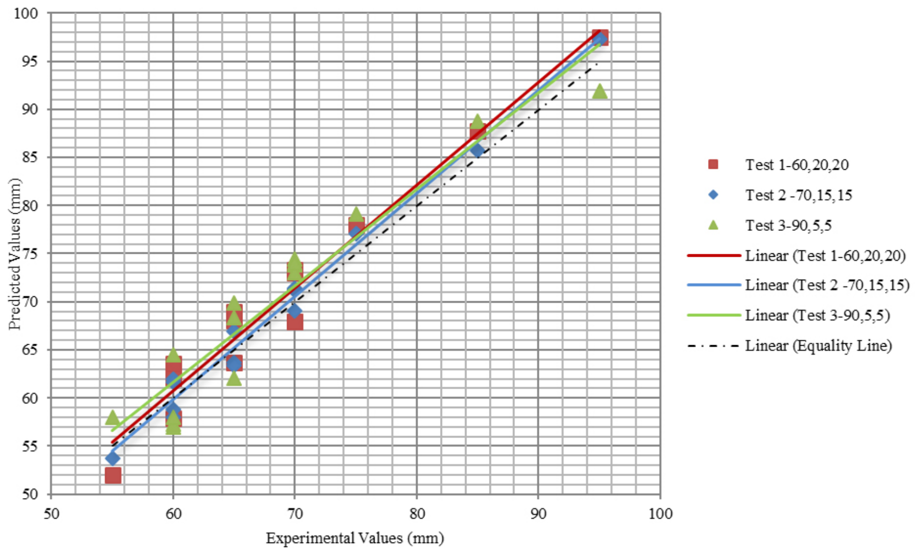

Figure 9. The Predicted Slump Values Obtained for Three Tests against Experimental Values

The correlation coefficient (R) indicates how closely the predicted compressive strength fits the actual compressive strength. A higher R value shows that the predicted values are closer to the actual results (Shariati, Zin and Aghamohammadi, 2011). The R values of Tests 1, 2 and 3 are shown in Table 4. Test 2 with the highest correlation coefficients of 0.98 0.98, and 0.99 for training, testing and validating, respectively, had the best match of predicted values with actual values.

Table 4. R Values of Different Training, Testing and Validating Ratios

	R Values of Training	**R Values of Testing**	**R Values of Validating**
Test 1	0.96	0.98	0.95
Test 2	0.98	0.98	0.99
Test 3	0.93	0.95	0.96

The ultimate goal of each neural network is to provide an optimal generalisation performance. After a network is trained, it should perform well on examples that are not included in the training set. There are various techniques described in the literature that attempt to accomplish this task. One of the most popular techniques is early stopping. The basic idea of early stopping is to terminate training when some estimate of the generalisation error begins to increase. If the training is not stopped early and continues to convergence, then there is a danger that the network will over-fit its training data and not generalise well to new and unseen examples. In this paper, to avoid the over-training problem, the early-stopping principle to develop an alternative interpretation of learning was used, as illustrated in Figure 10. As depicted, the best validation performance occurred in epoch 1.

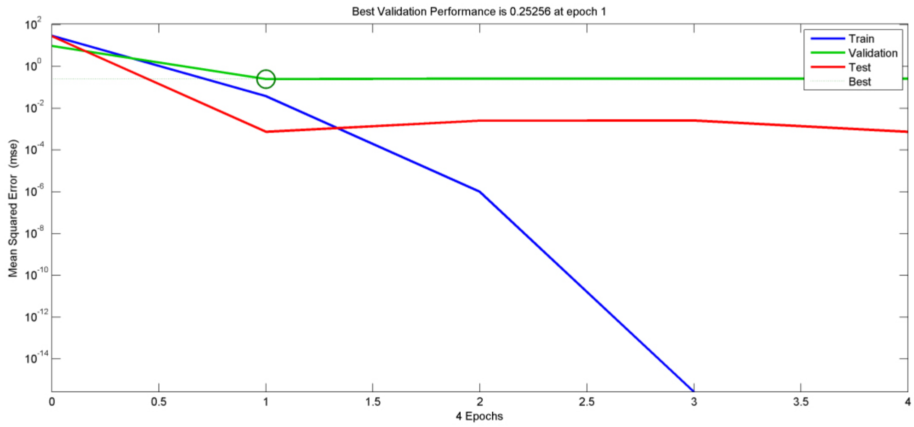

Figure 10. Best Validation Performance Evaluation

CONCLUSION

It was concluded that the POFA incorporation of up to 20% as a cementitious material enhanced the compressive strength of concrete compared to the specimens without POFA in their compositions. This result, which was obtained from the experimental investigation, is consistent with the previously published results in the literature. The compressive strength is not significantly affected by reducing the water-binder ratio in the range of 0.5–0.6.

The best architecture for the ANN models was achieved when seven neurons were placed in one hidden layer. The measured value of the MAPE test was 0.018%. The ANN model with 70% of the data for training, 15% for testing and 15% for validating provided the statistical test results with RMSEs of 0.006, 0.008 and 0.02 and R values of 0.98 0.98, and 0.99, respectively, which indicates an excellent predictive performance of the model.

With this model, from the concept of concrete mix details, the compressive strength, slump and modulus of elasticity of arbitrary concrete with POFA can be efficiently determined. This method does not require extraneous statistical equations, which are usually used in traditional prediction models such as linear regression.

REFERENCES

Abdul Awal, A.S.M. and Mohd. Warid Hussin. (2011). Effect of palm oil fuel ash in controlling heat of hydration of concrete. *Procedia Engineering*, 14: 2650–2657.

———. (1997). The effectiveness of palm oil fuel ash in preventing expansion due to alkali-silica reaction. *Cement and Concrete Composites*, 19(4): 367–372.

Abdul Awal, A.S.M. and Shehu, I. (2013). Evaluation of heat of hydration of concrete containing high volume palm oil fuel ash. *Fuel*, 105: 728–731.

ASTM C39/C39M-14a. (2014). Standard Test Method for Compressive Strength of Cylindrical Concrete Specimens. ASTM International, West Conshohocken, PA. Available at: www.astm.org. DOI: 10.1520/C0039_C0039M-14A.

ASTM C469. (2002). Standard Test Method for Static Modulus of Elasticity and Poisson's Ratio of Concrete in Compression. ASTM International, Volume 04.02. West Conshohocken, PA.

Bosoaga, A., Masek, O. and Oakey, J. E. (2009). CO_2 capture technologies for cement industry. *Energy Procedia*, 1(1): 133–140.

Chandara, C., Khairun Azizi Mohd Azizli, Zainal Arifin Ahmad, Syed Fuad Saiyid Hashim and Sakai, E. (2012). Heat of hydration of blended cement containing treated ground palm oil fuel ash. *Construction and Building Materials*, 27(1): 78–81.

Deepa, C., Sathiyakumari, K. and Sudha, V.P. (2010). Prediction of the compressive strength of high performance concrete mix using tree based modeling. *International Journal of Computer Applications*, 6(5): 18–24.

Flores, J.A. (2011). *Focus on Artificial Neural Network*. New York: Nova Science Publishers.

Gheorghe, M., Saca, N. and Radu, L. (2008). The fillers influence on the self compacted concrete properties. *Revista Romana de Materiale-Romanian Journal of Materials*, 38: 212–223.

Gou, Z. and Fyfe, C. (2004). A canonical correlation neural network for multicollinearity and functional data. *Neural Networks*, 17(2): 285–293.

Jaturapitakkul, C., Tangpagasit, J., Songmue, S. and Kiattikomol, K. (2011). Filler effect and pozzolanic reaction of ground palm oil fuel ash. *Construction and Building Materials*, 25(11): 4287–4293.

Johari, M., Zeyad, A., Muhamad Bunnori, N. and Ariffin, K. (2012). Engineering and transport properties of high-strength green concrete containing high volume of ultrafine palm oil fuel ash. *Construction and Building Materials*, 30: 281–288.

Jones, M., Zheng, L. and Newlands, M. (2003). Estimation of the filler content required to minimise voids ratio in concrete. *Magazine of Concrete Research*, 55(2): 193–202.

Kroehong, W., Sinsiri, T., Jaturapitakkul, C. and Chindaprasirt, P. (2011). Effect of palm oil fuel ash fineness on the microstructure of blended cement paste. *Construction and Building Materials*, 25(11): 4095–4104.

Mohd. Warid Hussin and Abdul Awal, A.S.M. (1997). Palm oil fuel ash: A potential pozzolanic material in concrete construction. *Journal of Ferrocement*, 27(4): 321–327.

Moruf Olalekan Yusuf, Megat Azmi Megat Johari, Zainal Arifin Ahmad and Mohammad Maslehuddin. (2014a). Evolution of alkaline activated ground blast furnace slag–ultrafine palm oil fuel ash based concrete. *Materials and Design*, 55: 387–393.

______. (2014b). Strength and microstructure of alkali-activated binary blended binder containing palm oil fuel ash and ground blast-furnace slag. *Construction and Building Materials*, 52: 504–510.

Nochai, R. and Nochai, T. (2007). Price transmission in Thai palm oil industry. *International Conference on Business and Information*. Tokyo, Japan, 10–13 July.

Panchal, G., Ganatra, A., Kosta, Y. and Panchal, D. (2011). Behaviour analysis of multilayer perceptrons with multiple hidden neurons and hidden layers. *International Journal of Computer Theory and Engineering*, 3(2): 332–337.

Sata, V., Jaturapitakkul, C. and Kiattikomol, K. (2004). Utilization of palm oil fuel ash in high-strength concrete. *Journal of Materials in Civil Engineering*, 16: 623–628.

Shahidehpour, M., Yamin, H. and Li, Z. (2002). Frontmatter and index. In *Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management*, i-xiv. New York: John Wiley & Sons, Inc.

Shariati, O., Zin, A.M. and Aghamohammadi, M. (2011). Application of neural network observer for on-line estimation of salient-pole synchronous generators' dynamic parameters using the operating data. *4th International Conference on Modeling, Simulation and Applied Optimization*. Universiti Teknologi Malaysia, 19–21 April.

Sukantapree, S., Namarak, C. and Jaturapitakkul, C. (2002). Use of calcium carbide residue and palm oil fuel ash in concrete. *Proceedings: 2002 Annual Conference of the Engineering Institute of Thailand*. Bangkok, Thailand, 20-23 June, 191–199.

Sumadi, S.R. and Mohd Warid Hussin. (1995). Palm oil fuel ash (POFA) as a future partial cement replacement material in housing construction. *Journal of Ferrocement*, 25(1): 25–34.

Tay, J.-H. (1990). Ash from oil-palm waste as a concrete material. *Journal of Materials in Civil Engineering*, 2(2): 94–105.

Ukrainczyk, N. and Ukrainczyk, V. (2008). A neural network method for analysing concrete durability. *Magazine of Concrete Research*, 60(7): 475–486.

Yeh, I.-C. (2009). Simulation of concrete slump using neural networks. *Proceedings of the ICE-Construction Materials*, 162(1): 11–18.