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Comparison of Artificial Neural Network (ANN) and Response Surface Methodology (RSM) in Predicting the Compressive Strength of POFA Concrete

Ahmad Nurfaidhi Rizalman* and Chen Choon Lee

Faculty of Engineering, Universiti Malaysia Sabah, 88999 UMS Kota Kinabalu, Sabah, Malaysia

*Corresponding author: ahmadnurfaidhi@ums.edu.my

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Abstract: This study presents a comparative study between Artificial Neural Network (ANN) and Response Surface Methodology (RSM) in predicting the compressive strength of palm oil fuel ash (POFA) concrete. The comparison was made based on the same experimental datasets. The inputs investigated in this study were percentage of POFA replacement and water-to-cement ratio. The methods employed in ANN and RSM were feedforward neural network and face-centered central composite, correspondingly. The comparison between the two models showed that RSM performed better than ANN with coefficient of determination (R^2) closer to 1 with 0.9959. In addition, all the predicted results by RSM against the experimental results fell within 10% margin. For ANN model, however, three of its predicted results were outside the 10% margin. Percentage of POFA as cement replacement was also found to have greater impacts on the compressive strength of concrete than water-to-cement ratio. Lastly, the optimization of the proportions using RSM predicted that the maximum strength of POFA concrete is 32.19 MPa.

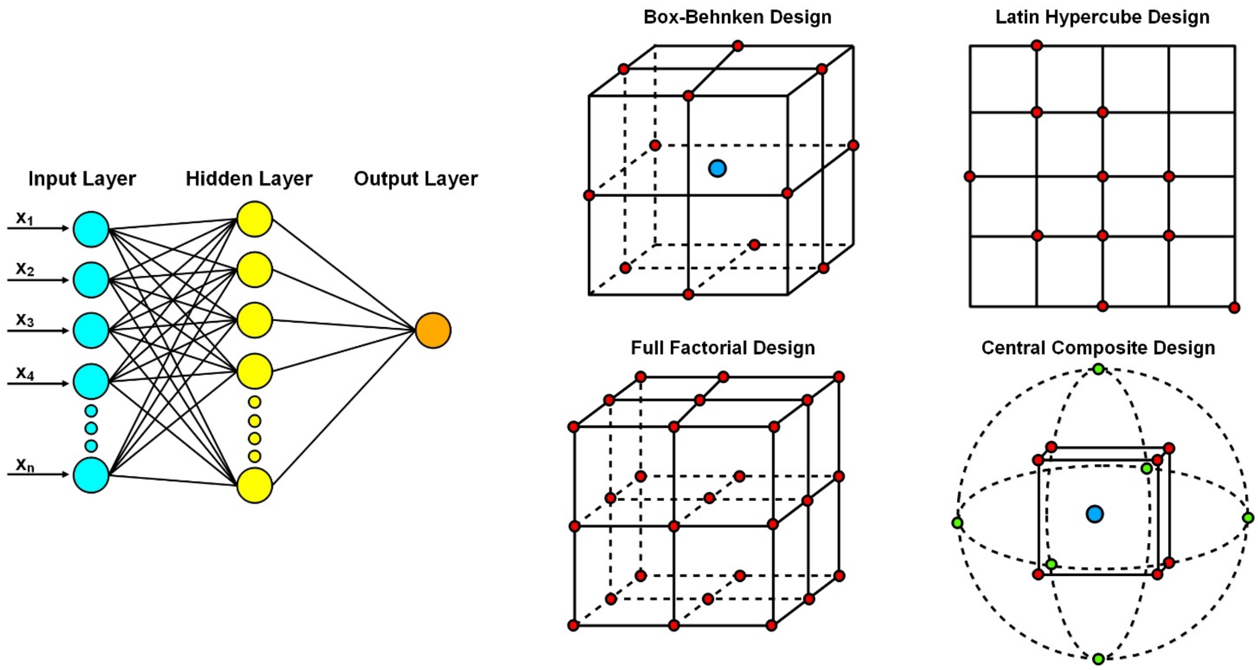
Keywords: Artificial neural network; Compressive strength; Palm oil fuel ash concrete; Response surface methodology; Workability.

1. INTRODUCTION

Design of experiments (DOE) is a systematic approach to determine relationship between input and output of a process. In other words, it is a tool to identify cause-and-effect relationship and interactions between the process inputs. This information can be used to optimize the process outputs. However, a series of experiments is required to investigate numerous input variables that affect the process outputs. Thus, impeccable planning for the experiments is consequential before the process of testing and collecting the data takes place. This, however, requires a huge amount of time, money, and energy. Consequently, many researchers have shifted to mathematical modelling as an alternative to the experiments including in the field of concrete materials. Some of the popular mathematical modellings employed in the fields are Artificial Neural Network (ANN) and Response Surface Methodology (RSM). Both models are said to be capable in optimization with minimal number of experiments [1-2].

ANN is an artificial tool of information processing inspired by biological neural network system such as human brain. ANN is made up of a group of three (3) layers: the input layer, the hidden layer, and the output layer, as illustrated in Figure 1(a)[3]. ANN develops the relationship between inputs and outputs by learning the mapping algorithm of data series. Meanwhile, RSM is a tool used to explore relationships between several independent variables (inputs) and one or more responses (outputs). There are several types of RSM which are governed by the structural configuration and amount of the design points. The most common ones are Box-Behnken Design (BBD), Latin Hypercube Design (LHD), Fractional Factorial Design (FFD) and Central Composite Design (CCD), as shown in Figure 1(b) [4]. Among them, CCD is mostly used in modelling the properties of concrete materials [5-7].

Previous studies have proven the versatility of ANN and RSM models to predict numerous properties of concrete including slump, water absorption, compressive strength, and flexural strength [5-10]. Both ANN and RSM models can also be employed on different types of concrete which include normal concrete [6, 9], fiber-reinforced concrete [2, 7-8], and green concrete [1, 3, 5, 10-11]. These studies indicate a promising future for the models as tools to design and optimize the mix proportions of concrete [12].



(a) (b)

Figure 1. (a) Structure of ANN model and (b) Structural configuration of RSM model

The growing popularity of the ANN and RSM models have spurred interest among researchers to investigate their reliability in predicting the concrete properties [1-2, 12]. The reliability is measured by using coefficient of determination (R^2), in which those that gives value closest to 1 signifies superiority over other models. Thus far, such studies have not been conducted on concrete containing palm oil fuel ash (POFA) although both models have been proven to be capable of predicting its properties [13-17]. Therefore, a comparative study on the reliability between ANN and RSM models in POFA concrete is needed to be investigated.

In this study, the predicting ability of ANN and RSM model on compressive strength of POFA concrete at 28th day are investigated. For this purpose, the effects of input variables such as percentage of POFA as cement replacement and water-to-cement ratio are utilized for this process. The reliability of each model was examined based on the percentage errors between the experimental and predicted strength; and the value of R^2. Then, the equation to predict the strength of POFA is presented and the relationship between the input variables are discussed. Lastly, the mix proportions of POFA concrete is optimized to the maximum compressive strength.

2. METHODOLOGY

2.1 Preparation of Data

In this study, a total of eight (8) experimental datasets by previous researchers were adopted to develop the ANN and RSM prediction models [13]. The data was selected from the same source because to maintain the consistency in the size of materials, mixing method, material preparation and etc. The mix proportions of the POFA concrete are presented in Table 1.

Table 1. Datasets for ANN and RSM model

Specimen	POFA	w/c ratio	Coarse aggregates	Fine aggregates	Ordinary Portland Cement	Water	POFA	Compressive Strength
	%		kg/m^3	kg/m^3	kg/m^3	kg/m^3	kg/m^3	MPa
1	0.00	0.50	1150.00	800.00	300.00	150.00	0.00	31.00
2	20.00	0.50	1150.00	800.00	240.00	150.00	60.00	33.00
3	40.00	0.50	1150.00	800.00	180.00	150.00	120.00	27.00
4	20.00	0.55	1150.00	800.00	240.00	165.00	60.00	29.00
5	40.00	0.55	1150.00	800.00	180.00	165.00	120.00	26.00
6	0.00	0.60	1150.00	800.00	300.00	180.00	0.00	27.00
7	20.00	0.60	1150.00	800.00	240.00	180.00	60.00	27.00
8	40.00	0.60	1150.00	800.00	180.00	180.00	120.00	23.00

2.2 Development of ANN Prediction Model

The ANN model to predict the compressive strength of POFA concrete was developed by using MATLAB software. It was constructed by adopting feedforward neural network inbuilt in the software. Six (6) inputs were used to develop the model; these are water to cement ratio (w/c), coarse aggregates, fine aggregates, Ordinary Portland cement, water content, and POFA content. Meanwhile, the compressive strength at 28th day was used as the output.

The development of the model was carried out by dividing the datasets into three (3) groups: 60% for the model training, 20% for the model testing, and 20% for the model validation. A linear activation function was used to solve the model. Meanwhile, the number of hidden neurons were decided based on paper in [13]. Several numbers were employed and tested in the software, and it was discovered that four (4) hidden neurons were found to be suitable in this study. Then, the predicted results generated from the ANN model were compared with the experimental results.

2.3 Development of RSM Model

The software used to develop the RSM model was Design-Expert 11. It was constructed based on the face-centered central composite (FCCC) of response surface methodology. The two (2) inputs in this model, the percentage of POFA as cement replacement (%) and water to cement ratio, were coded as A and B as shown in Table 2. They were investigated at three (3) different levels including low, intermediate, and high so that a quadratic relationship between input and output can be developed. Compressive strength at 28th day was selected as the output (or response) of the model.

The details of the inputs are tabulated in Table 3 which consist of the combinations of coded factor levels, the translation of coded factors, and the space type. Then, a quadratic model that represent the experimental datasets was suggested by the program. The model is based on Equation (1) as shown below:

$$Y = \beta_0 + \beta_1 A + \beta_2 B + \beta_{12} AB + \beta_{11} A^2 + \beta_{22} B^2 \tag{1}$$

where Y is a predicted response, β_0 is an intercept, β_1 and β_2 are linear effect coefficients, β_{11} and β_{22} are quadratic effect coefficients, β_{12} is an interaction effect coefficient, and A and B are factors.

Table 2. Factors and factor levels adopted for RSM

Factor	Code	Factor Levels of Code		
		Low	Intermediate	High
		-1	0	1
Percentage of POFA as cement replacement (%)	A	0	20	40
w/c ratio	B	0.50	0.55	0.60

Table 3. Factors combinations as per response surface design

Specimen	Coded Factor Level		Translation of Coded Factor		Space type
	A	B	POFA %	w/c ratio	
1	-1	-1	0.00	0.50	Factorial
2	0	-1	20.00	0.50	Axial
3	1	-1	40.00	0.50	Factorial
4	-1	0	20.00	0.55	Axial
5	0	0	40.00	0.55	Centre
6	-1	1	0.00	0.60	Factorial
7	0	1	20.00	0.60	Axial
8	0	1	40.00	0.60	Axial

3. RESULTS AND DISCUSSION

3.1 Comparison between ANN and RSM models

Table 4 presents the compressive strength of POFA concrete at 28th day predicted by ANN and RSM model. The predicting ability of the models was assessed based on the percentage errors between experimental and predicted strength as tabulated in Table 4. For the ANN model, it was observed that the agreement between the experimental and predicted strength fall within 10% except for specimen 4, 5 and 8. The percentage errors of the three specimens are -7.22%, -11.56%, and 13.04%, respectively. Meanwhile, all predicted strength by RSM fall within 10% agreement. The highest percentage error between experimental and predicted strength was observed in specimen 2 with -3.59% only. This indicates that RSM is a preferred model than ANN.

Further examination was carried out to evaluate the fitness of the models by plotting a graph of experimental and predicted strength as illustrated in Figure 2. Then, a best fit regression line was drawn on the scattered points and the closeness of the points to the line was measured which is called as coefficient of determination, R^2. From the figures, it was observed that the R^2 values of ANN and RSM are 0.6328 and 0.9559, correspondingly. Since the R^2 value by RSM is closer to 1, this implies that the predicted strength by RSM have better correlations with experimental strength compared to those obtained from ANN. The finding is similar to the work of [2] which discovered that the prediction by RSM on the properties of concrete containing steel fiber was found to be more accurate than ANN.

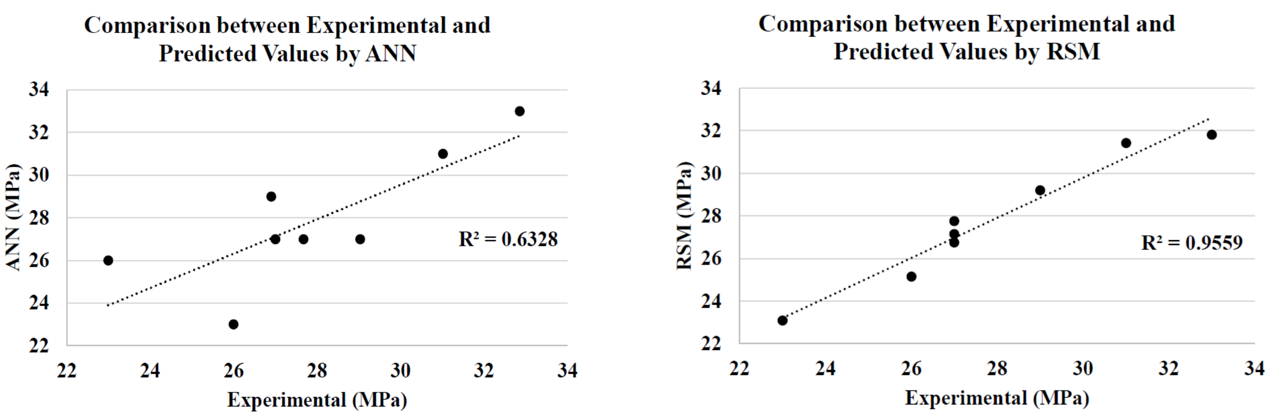
3.2 ANOVA and Quadratic Model Equation of RSM

The interaction between the inputs (percentage of POFA as cement replacement and water-to-cement ratio) and the output (compressive strength at 28th day) was investigated by performing Analysis of Variance (ANOVA) in the RSM. The results are summarized in Table 5. From the table, a large F-value and small p-value of the model of 29.38 and 0.0001, respectively were obtained. This indicates a significant relationship between percentage of POFA as cement replacement and water-to-cement ratio affecting the compressive strength of POFA concrete. It is also observed that the p-value of the model is less than 0.05, thus further confirmed the finding which allow the null hypothesis of the two inputs to be rejected.

From the ANOVA, a quadratic model equation to predict the compressive strength at 28th day of POFA concrete was derived, which is shown in Equation (2).

Table 4. Compressive strength predicted by ANN and RSM model

Specimen	Experimental (MPa)	ANN		RSM	
		Predicted Strength (MPa)	Percentage Error (%)	Predicted Strength (MPa)	Percentage Error (%)
1	31.00	31.02	0.06	31.43	1.37
2	33.00	32.86	-0.43	31.82	-3.59
3	27.00	27.00	0.02	27.76	2.81
4	29.00	26.91	-7.22	29.21	0.71
5	26.00	23.00	-11.56	25.15	-3.27
6	27.00	29.03	7.53	26.76	-0.89
7	27.00	27.68	2.51	27.15	0.55
8	23.00	26.00	13.04	23.09	0.40



(a) (b)

Figure 2. (a) Linear regression analysis by ANN model, and (b) Linear regression analysis by RSM model

$$Compressive\ Strength\ at\ 28th\ day\ (\text{MPa}) = 87.86207 + 0.130747A - 168.04598B + 3.57428e^{-14}AB - 0.005560A^2 + 110.34483B^2 \quad (2)$$

where A is the percentage of POFA as cement replacement (%) and B is water-to-cement ratio (w/c).

Table 5 ANOVA for compressive strength at 28th day of POFA concrete

Source	Sum of Squares	Degree of Freedom	Mean Square	F-Value	p-Value
Model	67.55	5	13.51	29.38	0.0001
A-POFA %	20.17	1	20.17	43.86	0.0003
B-W/C Ratio	32.67	1	32.67	71.05	< 0.0001
AB	0.0000	1	0.0000	0.0000	1.0000
A^2	13.66	1	13.66	29.72	0.0010
B^2	0.2102	1	0.2102	0.4571	0.5207
Residual	3.22	7	0.4598		
Lack of Fit	3.22	3	1.07		
Pure Error	0.0000	4	0.0000		
Model	67.55	5	13.51	29.38	0.0001
A-POFA %	20.17	1	20.17	43.86	0.0003

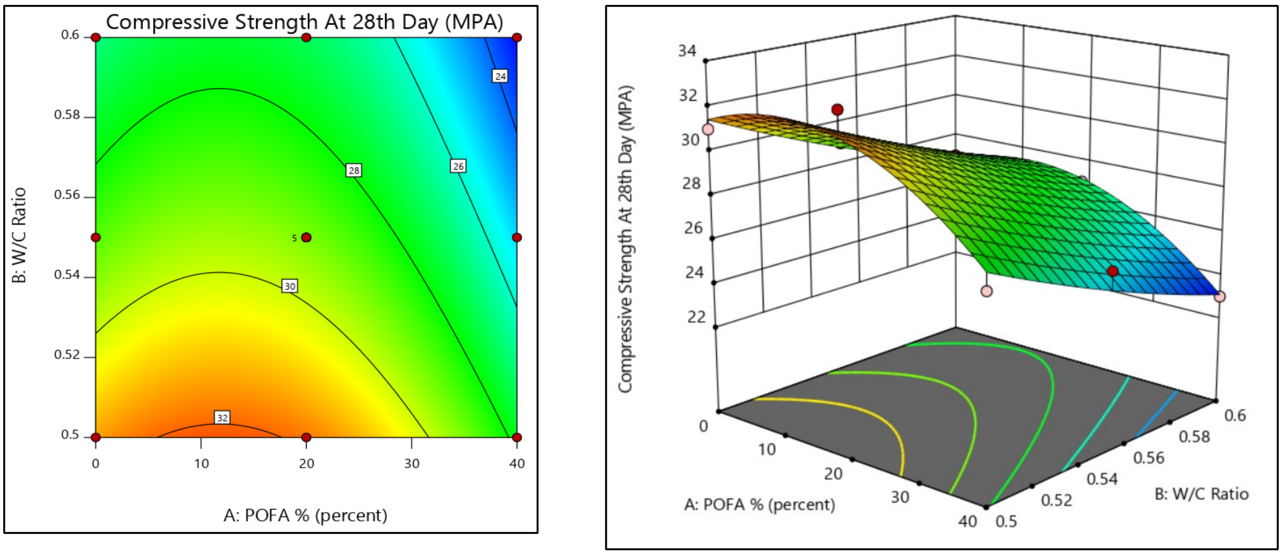
The effect of percentage of POFA as cement replacement and water-to-cement ratio on the compressive strength of POFA concrete can also be seen graphically, as illustrated in Figure 3. The 2D contour plot in Figure 3(a) demonstrates a convex shape that converge close towards the percentage of POFA replacement. This implies that the amount of cement content replaced by POFA has greater impact on the compressive strength of POFA concrete than the amount of water-to-cement ratio.

Similar observation was made on the 3D representation of response surface of compressive strength of POFA concrete shown in Figure 3(b). It is clear from the figure that increasing the POFA content decreases the compressive strength at 28th day of POFA concrete. The gradients on the graph also show that the influence of amount of POFA replacing cement on compressive strength is more significant than the water-to-cement ratio.

3.3 OPTIMIZATION BY RSM

The optimization of the mix proportions of POFA concrete was carried out by using the optimization tool in the software. In the tool setting, there are several options available for optimization including maximize, minimize, or attain a specific target. To investigate the mix proportions of POFA concrete with a highest strength, the compressive strength of POFA concrete was set at maximum.

The result shows that the maximum compressive strength of POFA concrete at 28th day predicted by RSM is 32.19 MPa. From this strength, there are thirteen (13) possible combinations of the percentage of POFA replacement and water-to-cement ratio. A visual example of one of the combinations is shown in Figure 4. From the figure, the suggested percentage of POFA as cement replacement is 11.75% and the water cement ratio is 0.5.



(a) (b)

Figure 3. (a) 2D Contour plot of the compressive strength, and (b) 3D representation of response surface of the compressive strength

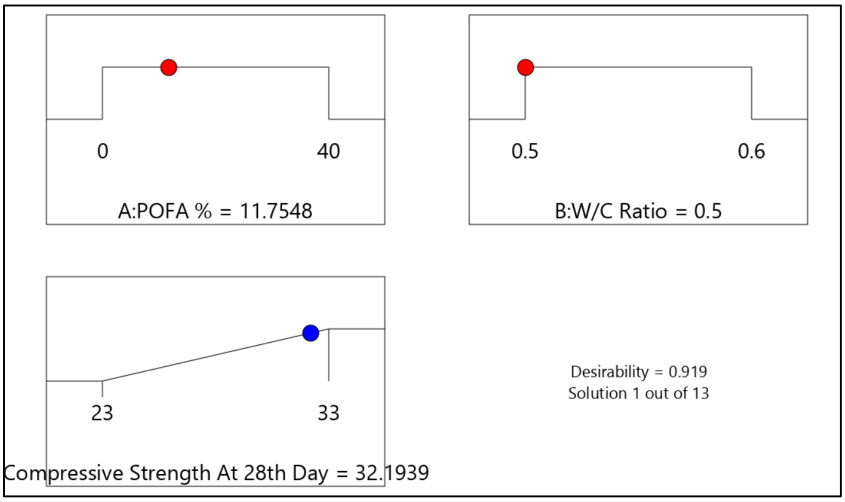


Figure 4. Percentage of POFA as cement replacement and water-to-cement ratio for maximum strength of POFA concrete

4. CONCLUSION

In this study, comparison between ANN and RSM in predicting the compressive strength of POFA concrete was carried out. The input variables investigated in this study were the percentage of POFA as cement replacement and water-to-cement ratio. The followings are the conclusions from this study:

a) The comparison between the two models showed that RSM performed better than ANN with coefficient of determination (R^2) closer to 1 with 0.9959. In addition, all the predicted results by RSM against the experimental results fell within 10% margin. For ANN model, however, three of its predicted results were outside the 10% margin.
b) Percentage of POFA as cement replacement has greater impacts on the compressive strength of concrete than water-to-cement ratio.
c) The optimization of the proportions using RSM predicted that the maximum strength of POFA concrete is 32.19 MPa.

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