ARTIFICIAL INTELLIGENCE APPROACH FOR PREDICTING COMPRESSIVE STRENGTH OF FOAMED CONCRETE

ỨNG DỤNG TRÍ TUỆ NHÂN TẠO TRONG DỰ ĐOÁN CƯỜNG ĐỘ CHỊU NÉN CỦA BÊ TÔNG BỌT

Nguyen Thi Loc[1], Mai Anh Duc[2]*, Nguyen Cong Luyen[2], Vu Huy Cong[2], Nguyen Van Huong[2]

[1]*Central College of Transport V, Danang, Vietnam*

[2]*The University of Danang - University of Science and Technology, Danang, Vietnam*

*Corresponding author: maduc@dut.udn.vn

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Abstract - Accurately predicting the compressive strength of foamed concrete plays a key role in the wide application of foamed concrete in practice. This study investigates the performance of the six AI models in estimating the compressive strength of foamed concrete. A dataset of 150 samples available in the literature was used for training and testing the AI models. The dry density, cement and sand content, and water-to-cement ratio were employed as input parameters, while the 28-day compressive strength was used as the output parameter. Four statistical indicators were utilized to evaluate the performance of the AI models. The study results reveal that the AI models yield an accurate prediction of the compressive strength of foamed concrete. The best performance model in estimating the compressive strength of foamed concrete is the M5Rules model, while the least accurate model depends on the indicators used to measure the accuracy of the AI models.

Key words - Compressive strength of foamed concrete; Artificial Intelligence models; Prediction of the compressive strength of foamed concrete.

Tóm tắt - Dự đoán chính xác cường độ chịu nén của bê tông bọt đóng vai trò quan trọng trong việc áp dụng rộng rãi bê tông bọt trong các công trình xây dựng. Nghiên cứu này đánh giá độ chính xác của 06 mô hình trí tuệ nhân tạo (MHTTNT) trong dự đoán cường độ chịu nén của bê tông bọt. Bộ dữ liệu gồm 150 mẫu thử được sử dụng để huấn luyện và đánh giá độ chính xác dự báo của MHTTNT, trong đó trọng lượng khô của bê tông bọt, hàm lượng xi măng, hàm lượng cát và tỉ lệ nước trên xi măng là các số liệu đầu vào, cường độ chịu nén ở 28 ngày tuổi là số liệu đầu ra. Độ chính xác dự báo của các MHTTNT được đánh giá thông qua 04 chỉ số thống kê. Kết quả nghiên cứu cho thấy rằng, các MHTTNT dự đoán khá chính xác cường độ chịu nén của bê tông bọt. Mô hình có độ chính xác lớn nhất là mô hình M5Rules, trong khi mô hình có độ chính xác thấp nhất được xác định dựa trên chỉ số thống kê được sử dụng.

Từ khóa - Cường độ chịu nén của bê tông bọt; Mô hình trí tuệ nhân tạo; Dự đoán cường độ chịu nén của bê tông bọt

1. Introduction

Foamed concrete, which is usually composed of cementitious binder, water, foaming agent and fine sand, has been recognized as one of the most commonly used lightweight materials in the construction industry in recent years. The popular use of foamed concrete results from its advantages of lightweight, low thermal conductivity, acoustic absorption and excellent fire resistance. Foamed concrete usually has low density, ranging from 400 to 1600 kg/m^3 [1], which is much lower than traditional concrete with a typical density of 2200 to 2500 kg/m^3 [2]. The low density of foamed concrete is attributed to its pore structures created by the foaming agent. Due to the low density and high porosity, a low compressive strength is inevitable for foamed concrete, which limits the application of foamed concrete for non-load-bearing structural components such as thermal and acoustic insulation systems, lightweight panels and blocks [3].

For a wider application of this lightweight concrete in practice, especially for load-bearing structures, extensive studies have been devoted in attempt to determine the mechanical properties (i.e., elastic modulus and compressive strength) of foamed concrete [4]. As the compressive strength (f'_{co}) of foamed concrete has been considered as one of the most important engineering properties, most of the available studies on foamed concrete paid attention to the prediction of this engineering property.

The available studies on foamed concrete have proven that the f'_{co} of foamed concrete was driven by crucial factors consisting of sand and cement content [5, 6], dry density, binder ratio, water to cement ratio [2], foaming volume, type of additives (i.e., fly ash, silica fume and superplasticizer) [7], curing conditions [5] and void distribution. Some of these studies have been devoted to proposing empirical models for estimating the f'_{co} of foamed concrete. Most prediction models were commonly developed based on three fundamental models consisting of Feret's, Balshin's and Power's models [8]. In Feret's model, the f'_{co} of foamed concrete was determined based on the absolute volume of constitutive materials, while the f'_{co} of foamed concrete in Balshin's model was relied on the porosity and the weight of the constitutive materials [8]. In the Power's models, the f'_{co} of foamed concrete was related to the gel-space ratio [8]. It can be observed from the fundamental compressive strength models that only some parameters were incorporated into the equations used to compute the f'_{co} of foamed concrete [9]. Thus, the empirical model may not be able to reflect the influence of constitutive materials on the f'_{co} of foamed concrete. It should be mentioned that the empirical models were usually calibrated using a test database, resulting in various constants adopted in the empirical models of compressive strength. Adopting multiple constants in the empirical models to describe the nonlinear relationship between the

f'_{co} of foamed concrete and its constituents may yield an unsatisfactory prediction of the f'_{co} of foamed concrete. To overcome this issue, the Artificial intelligence (AI) technique with ability to learn from the experience, adapt to new inputs and undertake human-like tasks may be suitable for accurately capturing the nonlinear and complex correlation between the f'_{co} of foamed concrete and its ingredients.

The AI technique has been widely applied in the construction industry over the last two decades in structural engineering [10-13], geotechnical engineering [14-16] and material sciences [17-19]. The application of the AI technique in prediction problems has been recognized as a reliable and robust computational solution [5]. The application of the AI technique in estimating the engineering properties of foamed concrete has been found in some research studies [5]. Ullah, et al. [5] developed AI-based models for 28-day compressive strength and dry density of foamed concrete using gene expression programming. The proposed models expressed in empirical forms were developed based on a dataset of 191 points available in the literature in which sand and cement content, foam volume and water to cement ratio were used as input parameters while 28-day compressive strength and dry density of foamed concrete were used as output parameters. It was reported that the proposed models obtained high accuracy with the square correlation R^2 of 0.95. Salami, et al. [9] evaluated the accuracy of AI models consisting of gene expression programming (GEP), gradient boosting tree (GBT) and artificial neural network (ANN) in estimating the f'_{co} of foamed concrete. An AI-based model expressed in the empirical equation was also developed by Salami, et al. [9] using GEP. The AI models were developed using a dataset of 232 points in which the water to cement ratio, sand to cement ratio and dry density were utilized as input parameters. It was found that the developed GBT model was superior to the two remaining AI models in estimating the f'_{co} of foamed concrete. Pham, et al. [20] developed a hybrid AI model, which integrated the grey wolf optimization to the least squares support vector regression (LSSVR), to predict the f'_{co} of foamed concrete. The hybrid AI model was trained and tested using a dataset of 150 points in which the density of foamed concrete, cement and sand content, sand to cement ratio, sand size, foaming agent and foam content were used as the input parameters, while the 7-day and 28-day compressive strength of foamed concrete were utilized as the output parameters. The predictive accuracy of the hybrid AI model was evaluated by comparing the performance of the hybrid AI model with that of single AI model. The study results exhibited that the estimated compressive strength agreed well with the actual compressive strength. Also, the hybrid AI model was superior to other AI models in estimating the f'_{co} of foamed concrete. It is obvious that the hybrid model is an advanced computational model, but it could be challenging for design engineers in the practical application. It is observed from Pham, et al. [20] that the cement and sand content were used as input parameters while the sand to cement ratio was also considered as an input parameter. The consideration of the sand to cement ratio may replicate the influence of sand and cement on the f'_{co} of foamed concrete, which was not undertaken in available studies on the application of the AI model in estimating the f'_{co} of foamed concrete. It is also seen that the foam agent was considered in Pham, et al. [20] as an input parameter whereas very limited experimental database on the effect of foam agent on the compressive strength of foam concrete available in the literature, which is attributed to the fact that the database of foam agent used in Pham, et al. [20] had a very small standard deviation.

It can be seen from the review of the literature that available studies on the application of the AI models in estimating the engineering properties of foamed concrete are very limited. Thus, further investigations on the accuracy of the AI model in estimating the f'_{co} of foamed concrete are needed. Furthermore, the accuracy of the single AI model, which is available in many open-source software, in estimating the f'_{co} of foamed concrete should be evaluated to provide alternative computational tools for engineers in designing a foamed concrete mixture of a determined compressive strength. This study investigates the predictive accuracy of the different single AI models consisting of Artificial Neural Network, Support Vector Machine, Random Forest, Random Tree, M5P, M5Rules, Gaussian Process and Linear Regression) in estimating the f'_{co} of foamed concrete.

2. Methodology

2.1. Artificial Neural Networks (ANN)

The ANN model is inspired by the information processing procedure of the human brain, which consists of a set of connected nodes called artificial neurons that mimic the neurons in a biological brain. These neurons are grouped into several layers, the first and last layers being referred to as the input and output layers; respectively, while the middle layers are referred to as hidden layers. The neuron of each layer is connected to other neurons of the successive layers by the connections in which each connection is assigned a weight. A neuron plays a role as a processing unit that performs two functions: collecting the inputs and producing an output. A neuron of the hidden layers receives the signals from the input neurons and computes them using a linear function, as illustrated in Eq. (1), and pastes it to the transfer functions expressed in Eq. (2) before generating the output signal.

$$net_i = \sum w_{i,j}\, x_j + b_i \tag{1}$$

where net_i represents the value of i^{th} net; $w_{i,j}$ represents the weight of the j^{th} input to the i^{th} hidden neuron; x_j represents the value of the j^{th} input neuron; and b_i represents the bias coefficient of the i^{th} hidden neuron.

The transfer function is described by the nonlinear sigmoid function as follows:

$$y_i = f(net_i) = \frac{1}{1 + e^{\gamma net_i}} \tag{2}$$

where y represents the output signal of the i^{th} hidden neuron; and γ represents the adjustment of the function gradient.

The output signals of the hidden layer neurons were sent to all the neurons of the output layer. The neurons of the output layer compute the input signals using linear functions and generate the output signal using the sigmoid function. The training error (e_k) at the output k was determined based on the estimated output (t_k) and the actual output (o_k), as expressed in Eq. (3).

$$e_k = \frac{1}{2}\sum_{k=1}^{n}(t_k - o_k) \tag{3}$$

The procedure of computing the output signal at each artifical neuron is applied to all the pair of the training data and repeated until the training errors obtain the limited values, which are determined by a learning algorithm. The weights and bias parameters of each neuron are updated based on the iterative procedure for minimizing the training errors of each pair of the training data.

2.2. Support Vector Regression (SVR)

The SVR model is one of the most popularly-utilized soft computing tools for regression problems due to its reliability, robustness and accuracy. The SVR first proposed by Vapnik [18] adopts kernel functions to a hyperplane in a high-dimensional space with a maximum epsilon distance (ε) between the hyperplane and closest actual datapoints. The hyperplane in the high-dimentional space is achieved by mapping input variables to a high-dimensional feature space. The hyperplane is expressed as a mathematical equation as illustrated in Eq. (4)

$$f(x) = w^T\varphi(x) + b \tag{4}$$

where w^T is a weight vector in the feature space with l dimension; $\varphi(x)$ is a function that maps x to the feature space; and b is a constant representing the intercept.

The SVR problem is formulated by minimizing the function as expressed in Eq. (5).

$$\min_{w,b,e} J(w,b,e) = \frac{1}{2}||w||^2 + \frac{1}{2}C\sum_{k=1}^{l}(\xi_i + \xi_i^*) \tag{5}$$

Subjected to

$$y_i - w^T\varphi(x_i) - b - \xi_i \le \varepsilon, i = 1, \dots, l$$

$$w^T\varphi(x_i) - y_i + b - \xi_i^* \le \varepsilon, i = 1, \dots, l$$

$$\xi_i, \xi_i^* \ge 0$$

where b represents a regulation constant, which is greater than 0; x_i and y_i, respectively, represent input and output variables; ξ_i and ξ_i^* both represent slack variables, which are nonnegative;

The final form of the SVR optimization problem presented in the dual problem comes out as follows:

$$f(x) = \sum_{k=1}^{l}\alpha_k K(x, x_k) + b \tag{6}$$

$$K(x, x_k) = \sum_{k=1}^{l} g_k(x) g_k(x_k) \tag{7}$$

$$K(x, x_k) = e^{-\frac{||x-x_k||^2}{2\sigma^2}} \tag{8}$$

where α_k represents Lagrange multipliers; b represents bias value; $K(x, x_k)$ represents Kenel function; and σ represents Gaussian radial basis function width.

2.3. Gaussian Process Regression (GRP)

The GPR is a non-parametric and probabilistic method for regression problems. In the GPR model, it is assumed that a Gaussian process with a mean function of $w(x)$ and covariance function of $k(x, x')$ generate a function $g(x)$ that correlates the inputs and outputs, as illustrated in Eq. (9).

$$g(x) \sim GP[w(x), k(x, x')], \tag{9}$$

It should be noted that the mean and covariance functions were determined using kernel functions, which are usually employed the squared exponential kernel, as illustrated in Eq. (10).

$$k(x_i, x_j) = e^{-\frac{||x-x_k||^2}{2\sigma^2}} \tag{10}$$

For a given training dataset consisting of N pairs of (x_i, y_i) with $i = 1, 2, \dots N$, the GPR model establishs the following equations to determine the relationship between the given inputs and outputs.

$$w_j = k_j^T[K(X,X) + \sigma_n^2 I]y \tag{11}$$

$$\sigma_j^2 = k(x_j, x_j) - k_j^T[K(X,X) + \sigma_n^2 I]^{-1}k_j \tag{12}$$

where w_j presents a mean value, $K(X,X)$ presents convariance matrix, k_j presents the kernel distance between training and testing data, σ_n^2 presents the noise variance; and y presents the training observation.

For a given input data x_j, the corresponding output data $\bar{f}(x_j)$ can be determined using the following expression:

$$\bar{f}(x_j) = \sum_{k=1}^{s}[K(X,X) + \sigma_n^2 I]^{-1} y k(x_j, x_j) \tag{13}$$

2.4. Multiple linear regression (MLR)

The MLR, which is an extension of linear regression, is able to predict the value of one dependent variable based on two or more independent variables. The correlation between a dependent variable (Y) and independent variables (X_i) is expressed as follows:

$$Y = \sum_{i=1}^{n}\beta_i X_i + \beta_0 + \varepsilon \tag{14}$$

where β_i represent a regression coefficient $(i = 1,2, \dots, n)$, β_0 presents a constant and ε presents an error term.

2.5. M5Rules

M5Rules is a machine learning technique used for classification and prediction problems. The M5Rules establish rules based on the model tree. In the M5Rules, the pruned tree is trained using a tree learner over the training data; then, the elite leaf of the pruned tree is made into a rule while the remaining parts of a tree are discarded. Next, the samples, which are covered by the rule, are removed from the dataset. This iteration is terminated when all the instances belong to at least one rule. By employing the best leaf to achieve the rule, the M5Rules is able to avoid the risk of over-pruning.

2.6. Decision Tree

A decision tree, which is a non-parametric supervised learning algorithm, is used for classification and regression problems. The decision trees has hierarchical structures with a root node without incoming edges for the first level, internal nodes with outcoming edges for the next levels and terminal nodes or leaf nodes without outcoming edges for the the last level. The decision tree adopts the internal node to divide the instance space into subspaces using a discrete function of inputs.

In the decision tree, the target fields are symbolized using the Gini method, while the continuous targets are selected using the least-squared deviation method. The Gini index $g(t)$ of the node t is defined using Eq. (15)

$$g(t) = \sum_{j=1}^{n} p(j|t)p(i|t) \tag{15}$$

where $g(t)$ represents the Gini index; i and j are targeting groups.

$$p(j|t) = \frac{p(j,t)}{p(t)} \tag{16}$$

$$p(j,t) = \frac{\pi(j)N_j(t)}{N_j} \tag{17}$$

$$p(t) = \sum_{j} p(j,t) \tag{18}$$

where $\pi(j)$ represents the prior probability value for group j

3. Test database

The test results from an experimental program carried out by Abd and Abd [22] were used for training and testing the AI models. The foamed concrete tested by Abd and Abd [22] was made from four main types of materials consisting of Portland cement, sand, water and foam. The sand utilized in bd and Abd [22] was fine silica sand with three different main sizes of 600 μm, 1.18 and 2 mm. Normal tap water was used for making foamed concrete. The foam was generated by mixing water with foaming agent using a foam generator, which was considered as stable bubbles. The water-to-cement ratio used to develop the mixture was 0.5, 0.45, 0.4 and 0.3, while the sand to cement rato used for the mixture is a constant of 1.0. The density of foamed concrete was 1500, 1750 and 1800 (kg/m^3). The f'_{co} of foamed concrete was measured at seven days and 28 days by testing 150 cubes. In this study, only the f'_{co} of foamed concrete at the 28-day was employed as an output parameter of the database.

For the application of the AI models in estimating the f'_{co} of foamed concrete, the input of the AI models consists of four main parameters, including the density of foamed concrete, cement and sand content, water-to-cement ratio, while the output is the 28-day compressive strength of foamed concrete. The input parameters are symbolized as x_1 to x_4 while the output parameter is symbolized as y. A brief description of the database used for AI models is presented in Table 1.

Table 1. *Descriptive statistics of the input and output parameters used for predicting compressive strength*

$Pa.$	$Sy.$	Unit	Statistics			
			Min	**Max**	**Average**	**Std.**
Density of foamed concrete	x_1	kg/m^3	1406.81	2009.48	1742.77	171.02
Cement content	x_2	kg	1406.81	992.80	727.45	123.68
Sand content	x_3	kg	1406.81	1098.00	733.45	152.40
Water/cement ratio	x_4	-	0.30	0.45	1.06	0.05
28-day compressive strength	y	MPa	3.23	48.88	28.27	11.70

where $Pa.$ is the abbreviation of parameter and $Sy.$is the abbreviation of the symbols

4. Evaluation of models

4.1. Statistical indicators

The predictive accuracy of the AI models is evaluated using four statistical indicators comprising the correlation coefficient (R), main absolute percentage error $(MAPE)$, root mean square error $(RMSE)$, and the mean absolute percentage error $(MAPE)$, which are expressed by Eqs. (19) to (22), respectively.

$$R = \frac{n\sum yy' - (\sum y)(\sum y')}{\left(\sqrt{n(\sum y^2) - (\sum y)^2}\right)\sqrt{n((\sum y'^2) - (\sum y')^2}} \tag{19}$$

$$MAPE = \frac{1}{n}\sum_{1}^{n}\left|\frac{y-y'}{y}\right| \tag{20}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(y-y')^2} \tag{21}$$

$$MAE = \frac{1}{n}\sum_{1}^{n}|y-y'| \tag{22}$$

where y and y' represent the given and estimated results of each data sample, respectively, and n represents the total number of the data samples.

4.2. Accuracy of AI models

The performance of the AI models is evaluated using a 10-fold cross-validation method in which the AI models are evaluated ten times by dividing the test database into 10-fold for model evaluation. The f'_{co} of foamed concrete estimated by the AI model compared to the actual results is shown in Figure 1.

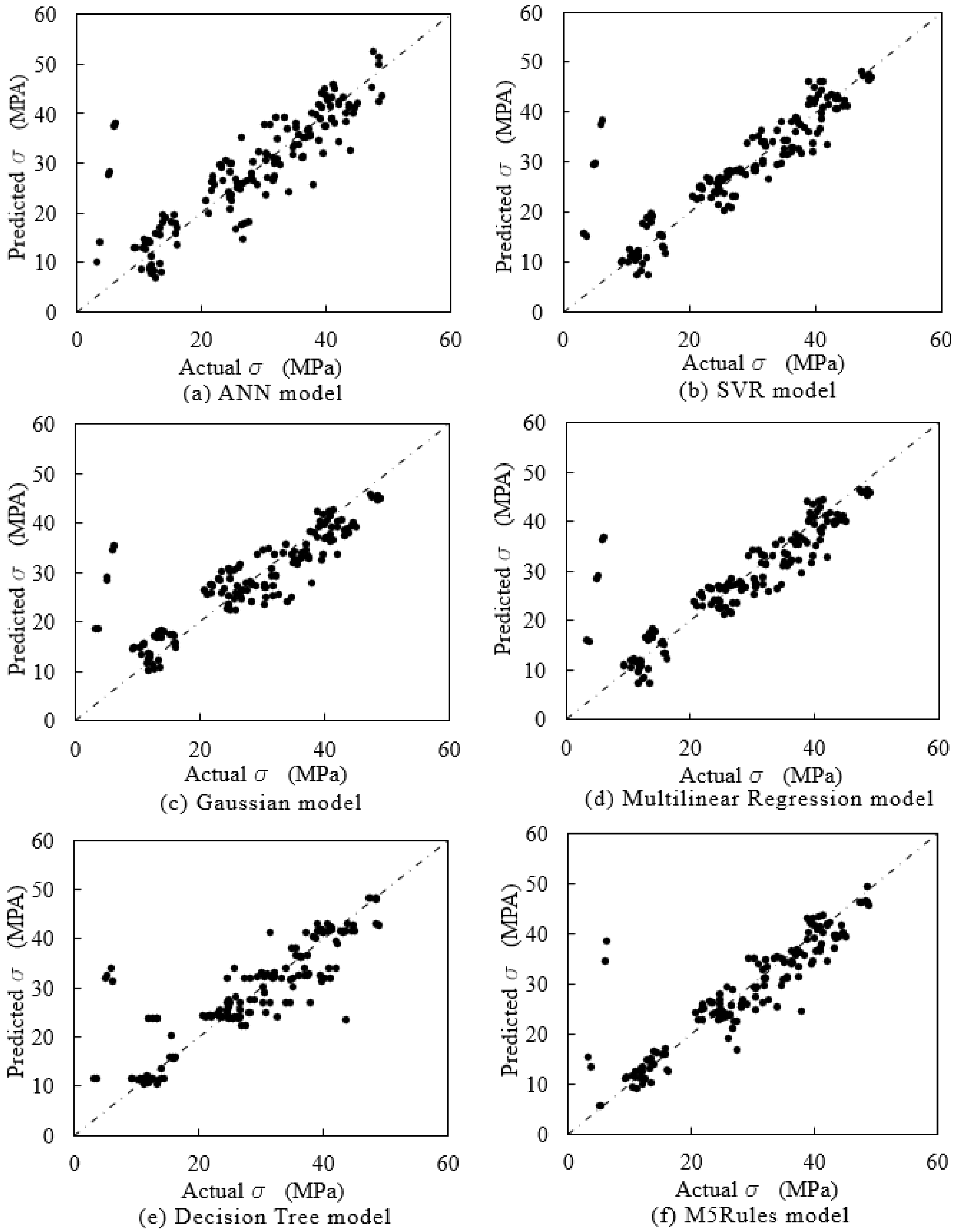

Figure 1. *The estimated compressive strength versus the actual compressive strength of foamed concrete*

The statistical indicators of the AI models are presented in Table 2 and the comparison of these models using three statistic indicators of MAPE, RMSE and MAE is plotted in Figures 2-4.

It should be noted that the formulae of RMSE and MAE indications used in this study are similar to those employed in Nguyen, et al. [8], which estimated the f'_{co} of foamed concrete using deep-neutral network. Thus the values of these two indicators obtained in this study are compared to those obtained in Nguyen, et al. [8] to examine the accuracy of the AI models in estimating the f'_{co} of foamed concrete. It was found that the RMSE and MAE indicators of the AI models in this study varied from 4.92 MPa to 6.22 MPa and from 2.98 MPa to 4.11 MPa, respectively, while these indicators of the conventional ANN model employed in Nguyen, et al. [8] varied from 2.58 MPa to 12.79 MPa and from 2.25 MPa to 11.36 MPa, respectively. The smaller RMSE and MAE indicators in this study in comparison to the RMSE and MAE indicators in Nguyen, et al. [8] indicated that the f'_{co} of foamed concrete estimated by the AI models is in good agreement with the actual values, indicating that the AI models predict the f'_{co} of foamed concrete well. Figures 2-4 and Table 2 also show that the M5Rules model has the smallest values when three indicators of MAPE, RMSE and MAE are used, while the M5Rules has the largest value when the indicator of R is used. This indicates that the M5Rules model is the most accurate model for predicting the f'_{co} of foamed concrete.

It is also observed from the Figs. 2-4 that the SVR and Linear Regression models also provide a good correlation between the estimated and actual values of the f'_{co} of foamed concrete. However, it is interesting to note that using different statistical indicators leads to different degrees of accuracy in the AI models.

Table 2. *Performance evaluation of the AI models*

Model	Indicator			
	R	MAPE (%)	RMSE (MPa)	MAE (MPa)
ANN	0.852	29.9	6.223	4.106
SVR	0.877	27.6	5.700	3.279
Gaussian	0.864	31.0	5.992	3.933
MLR	0.876	27.7	5.639	3.396
Decision Tree	0.855	27.2	6.090	3.602
M5Rules	0.908	20.2	4.924	2.980

As revealed in Table 2, by using R as a statistical indicator, the second most accurate model in estimating the f'_{co} of foamed concrete is the SVR model, which has 3.5% less accuracy than the M5Rules model. The least accurate model in estimating the f'_{co} of foamed concrete is the ANN, which is 6.5% less accurate than the M5Rules model. It should be noted that for the use of the MAPE indicator, the most accurate model is still M5Rules, which is followed by the Decision Tree model. The least accurate model is the Gaussian model. The Decision Tree and Gaussian models are 25.7% and 34.8% less accurate than the best model, which is M5Rules. For the use of the RMSE indicator, the second most accurate model is the SVR, which is 13.6% less accurate than the most accurate model of M5Rules. The least accurate model is the Decision Tree, which is 19.1% less accurate than the M5Rules model. Based on the MAE indicator, the second most accurate model is the SVR, while the least accurate model is the ANN. The SVR and ANN models are, respectively, 9.1% and 27.4% less accurate than the M5Rules model.

Overall, the use of the AI models in estimating the f'_{co} of foamed concrete yields a good correlation between the estimated and actual values. The R indicator of the AI models varies from 0.852 to 0.908, while the MAPE indicator of the AI models varies from 20.2% to 31.1%. The RMSE and MAE indicators of the AI models vary; respectively, from 4.92 MPa to 6.22 MPa and from 2.98 MPa to 4.11 MPa.

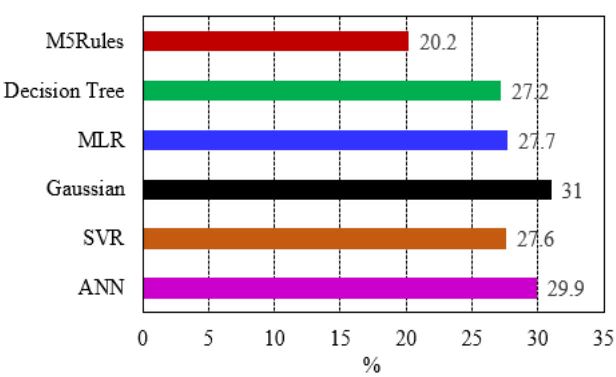

Figure 2. *Comparison of the AI models using MAPE indicator*

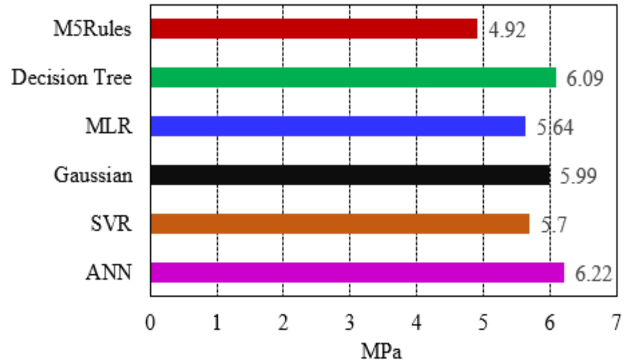

Figure 3. *Comparison of the AI models using RMSE indicator*

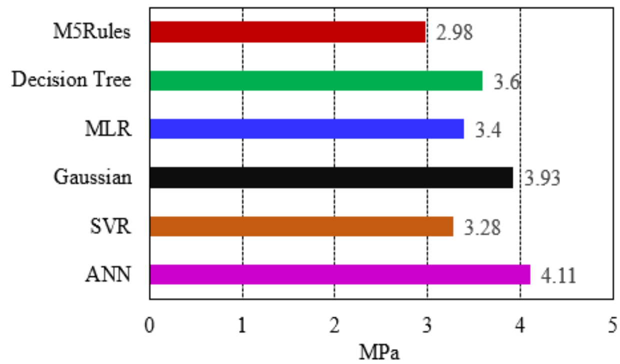

Figure 4. *Comparison of the AI models using MAE indicator*

5. Conclusions

The f'_{co} of foamed concrete was estimated using six single AI models consisting of ANN, SVR, Gaussian, Multilinear Regression, Decision Tree and M5Rules. The input parameters of the AI models consisted of the dry density of foamed concrete, the cement and sand content and the water-to-cement ratio, while the output parameter was the compressive strength. The AI models were evaluated using 10-fold cross-validation.

The performance of the AI models in estimating the f'_{co} of foamed concrete has been examined using four main statistical indicators, including the correlation coefficient (R), mean absolute percentage error $(MAPE)$, root mean square error $(RMSE)$, and the mean absolute percentage error $(MAPE)$. Based on the performance of the AI models, the following conclusions can be given:

(1) The AI models have provided a good estimation for the f'_{co} of foamed concrete as the graphical correlation of the estimated and actual compressive strength closely distributes along the diagonal line.

(2) Although various indicators were employed to evaluate the performance of the AI model in estimating the f'_{co} of foamed concrete, the M5Rules model has obtained the highest accuracy in estimating the f'_{co} of foamed concrete compared to the other AI models. The M5Rules obtains the R of 0.908 and the MAPE of 29.9%.

(3) Based on the R and MAE indicators, the second most accurate model in estimating the f'_{co} of foamed concrete was the SVR, followed by the MLR model, while the least accurate model is the ANN model. Based on the MAPE indicator, the second most accurate model is the

Decision Tree and the least accurate model is the Gaussian. Based on the RMSE indicator, the second most accurate model is the MLR and the least accurate model is the ANN.

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