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PREDICTION OF THE COMPRESSIVE STRENGTH OF FOAM CONCRETE USING THE ARTIFICIAL NEURAL NETWORK

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ABSTRACT: Foam concrete experiments require a lot of time and money. Therefore, a brand new modeling system is needed. A system that does not depend on the experiments but can accurately predict the foam concrete's strength. In this study, an Artificial Neural Network (ANN) was used as a solution to predict the compressive strength of foam concrete. The ANN method uses the feed-forward backpropagation architecture and the Levenberg-Marquardt training algorithm it consists of three layers, namely the input layer, hidden layer, and output layer. The input layer consists of cement, sand, water, foam, slum flow, and density, while the output layer consists of the compressive strength of foam concrete. The number of data used in this study was 90 data. The results indicated that the Artificial Neural Network had six input layer neurons, 13 hidden layer neurons, and one output layer neuron, and they had an accuracy rate of 98.7%. It can be concluded that the Artificial Neural Network method can be used to predict the strength of foam concrete with an accuracy level close to 100 percent.

Keywords: Foam concrete, Backpropagation, Artificial Neural Network, Compressive strength, Accuracy rate

1. INTRODUCTION

Foam concrete is a type of lightweight concrete widely used in building construction. The use of foam concrete is the latest innovation in building construction material since foam concrete is lighter and more environmentally friendly, starting from the manufacturing process to its implementation. Foam concrete, one type of lightweight concrete, consists of Portland cement or mortar, which has a hollow structure formed from air bubbles and has a specific gravity of (400 – 1,600) kg/m^2 [1]. Foam concrete is used as a temperature and sound insulation material and is easy to produce. The use of foam concrete in civil building construction should be carefully and effectively planned, as foam concrete must be able to fulfill the required technical specifications [2]. Therefore, a suitable mixture composition must be applied to civil building construction. The design of the foam concrete material mix will significantly affect its weight and strength; thus, it is necessary to test the material's properties and produce test samples in the laboratory [3]. The foam concrete sample is tested using a free compressive strength test. This test requires a large number of test samples, which is not efficient, and it takes a long time. Also, this experimental test cannot describe the relationship between the components of the foam concrete mixture and the compressive strength produced. Therefore, Artificial Neural Network (ANN) can accurately classify complex input-output relationships in foam concrete mixtures. The use of ANN has been researched extensively in recent years to predict lightweight concrete. However, there are not many prediction foam concrete. For instance, the use of ANN on lightweight bricks [4], high-performance foam concrete [5], and porous concrete [3,6] and the research on multivariate adaptive regression splines optimized by water on foamed cellular lightweight concrete (FCLC) [7], the SVM method on lightweight foam concrete (LFC) [8,9] and the use of genetic programming in foam concrete [10,11].

This study predicts the compressive strength of foam concrete with varied constituent materials consisting of mortar and foam, which has a complex impact on foam concrete properties using ANN. This study used ANN to predict the composition of foam concrete constituent materials fulfilling the requirements of a density value. It is smaller than the specific gravity of water, and the compressive strength of foam concrete can be determined before being applied. Although many studies have been devoted to predicting foam concrete, we need to pay more attention to the compressive strength of foam concrete, not its density of foam concrete. The foam concrete has its main advantage, the lightweight. Thus the foam concrete will float if it is immersed in water.

This paper reports the results obtained from predicting the compressive strength of foam concrete using the ANN method, which fulfills the requirements for foam concrete density; thus, it can be applied in fields that require light construction. The benefit of this study is that it can predict the compressive strength of lightweight foam concrete without conducting experimental research that involves a lot of costs and a long time.

2. RESEARCH SIGNIFICANCE

This study predicts the compressive strength of foam concrete with varied constituent materials consisting of mortar and foam, which has a complex impact on the properties of foam concrete using ANN. Based on this research, ANN is a method of predicting the composition of foam concrete constituents that meet the requirements of a density value smaller than the specific gravity of water and the compressive strength of foam concrete, which can be determined before being applied in the field.

3. LITERATURE REVIEW

Previous research that has been done to predict foam concrete is in the study [7] on foamed cellular lightweight concrete. The research developed and evaluated the Multivariate Adaptive Regression Splines optimized using Water Cycle Algorithm (MARS-WCA) model. This study has a weakness in modeling optimization, so it takes an artificial intelligence-based method with an algorithm with high-speed convergence. In addition, there is also a lightweight Foamed Concrete (LFC) study with a Support Vector Machine (SVM) [8] which adopts a radial basis function characterized by a minimum mean squared error relative to other equation functions and traditional regression. This study reports having a minimum standard deviation so that the prediction results get high precision values at all points in the data set. The research proposed by previous researchers such as [12–14] all predicts the compressive strength of foam concrete to study quickly and more accurately in improving the performance of methods that indicate the strength of the foam concrete. The compressive strength of foam concrete, without considering the effect of density on foam concrete has not only the targeted compressive strength of foam concrete but also lightweight foam concrete. Therefore, this study offers to explore the use of ANN with the backpropagation (BP) algorithm. The neurons have activation according to formulas Eq. (1) and Eq. (2).

$$net_k = \sum W_{kj} O_j \quad (1)$$

$$Y_k = f\,(net_k) \quad (2)$$

net_k is the activation of k neurons, j sets of neurons in the previous layer W_{kj} of the connection between neuron k and neuron j is the output of neuron j, and y_k is the output that can be calculated in both sigmoid and logistic transfer functions. The ANN structure can be seen in Fig. 1 Artificial neural network architecture with three layers, namely six inputs, 13 hidden nodes, one output

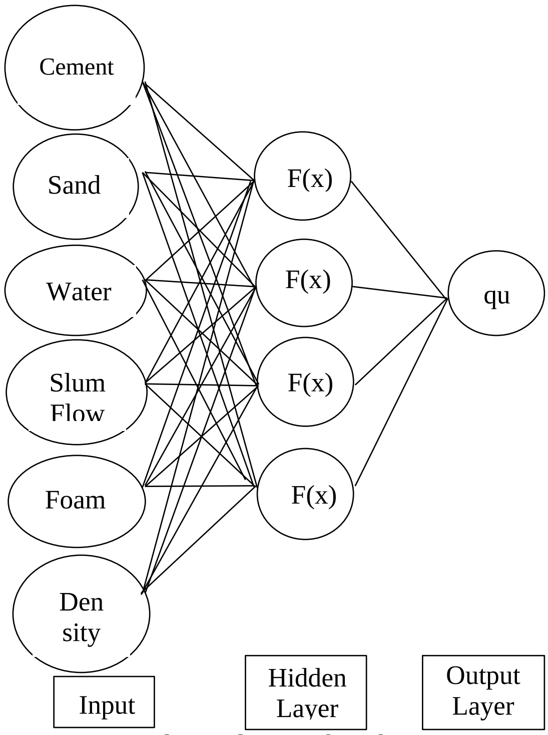

Fig. 1 Artificial neural network architecture

This study also refers to research [7] that uses an artificial neural network model with the Levenberg Marquardt (LM) algorithm used in this study. The LM algorithm can capture complex interactions between input/output variables in a system without prior knowledge of the nature of the interaction and without having to assume a model explicitly. The research describes the existing research data, data selection, network model training process, and validation. The results showed that the compressive strength of porous concrete could be predicted more accurately, efficiently, and quickly from the density of porous concrete, the ratio of sand and cement, and the distribution of sand particle size.

According to [8,15], the neural network method has good performance in overcoming the problem of nonlinear data, but the neural network has limitations in dealing with high noise data. So to solve this problem, a bagging method is needed to reduce data noise in the neural network method. In estimating the compressive strength of the concrete lifted, this study combines bagging and neural network methods to estimate the compressive strength of foam concrete.

4. METHODS

4.1 Foam Concrete Mix Proportion Design

Mix planning is obtained after pre-testing based on analysis from several previous research journals to get the right proportion in the mixed implementation. Mix planning includes the ratio of cement to sand, the water-cement factor, and the amount of foam in the concrete. Reference [16], A pre-study has been carried out to design the proportion of the mixture that will be used in this study. The pre-research was conducted by testing the consistency of the concrete which aims to determine the water-cement factor (FAS) that will be used in this study, with a variation of 0.50. The variable of this research is the comparison of the type of sand used. The sand used in this research is reed terraces sand and ringgit sand. Each type of sand will be examined by comparing the composition of the mixture between foam and sand. From the results of the pre-study with the variation of the water-cement factor, it was found that the minimum average value of the design free compressive strength (UCS) was 1253.73 kPa with a consistency that met the requirements for the value of a = (100 ± 15) % is the water-cement factor of 0.50. So that the ratio for cement: sand: water in a mixture of type N concrete paste is obtained, namely 1 Cement: 3 Sand or known as concrete 1: 3. A foaming agent is used to make foam. Foam is produced from a mixture of foaming agents: water in a ratio of 1: 25. After that, fine aggregate testing, sample making, treatment period, and compressive strength testing were carried out. Smooth, Sludge Content, Agg Sieve Analysis. Smooth, Density & Water Absorption Agg. Smooth, Heavy-Filled Solid & Friable Agg. Smooth, According to Agg Specifications. Smooth, Making JMD Foam Concrete according to concrete specifications, Making Foam Concrete, Mixing Foam Concrete, Testing Slump Flow of Foam Concrete, Printing Concrete Samples, Concrete Curing Process, Testing Concrete Compressive Strength.

The results of this experimental data are used as input and output data for the foam concrete prediction program using the artificial neural network method. This experiment was carried out in collaboration with Abdurrab University and Universitas Riau in Indonesia. The data used in this study were 90 samples of foam concrete with variations of cement, sand, and foam, which were used to test the predictive model of the ANN method. The flowchart of this research can be seen in Fig 2.

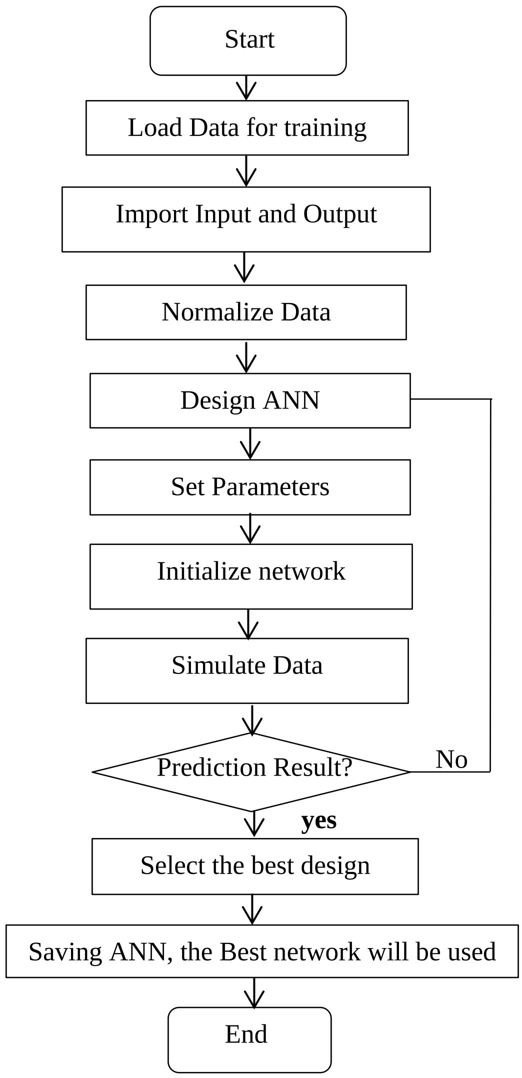

Fig.2 Flowchart prediction of compressive strength of foam concrete using the ANN method

4.2 The Back-propagation algorithm.

This research uses input data: cement, sand, water, slum flow, foam, and density. Meanwhile, the target is the compressive strength of foam concrete. The input and target data are used to train with ANN. Training with ANN is carried out using the MATLAB R2021a software with the following stages: Initialize input and target, normalization of input and target data. The ANN used is feed-forward with a total of 13 hidden layer nodes. The activation function from the input layer to the hidden layer is Tansig and the Levenberg-Marquardt ANN algorithm. The last steps are the determination of training parameters, training process and display of final weight-saving ANN, and conducting the best network will be used.

5. RESULTS AND DISCUSSION

5.1 Experimental and ANN Model

The results of testing the fine aggregate's characteristics, namely the sand-1 sourced from the Teratak Buluh Sand, Kampar Region Indonesia, and sand-2 from Danau Bingkuang Kampar Region Indonesia, are shown in Table 1.

Table 1 Fine Aggregate Inspection Results

Inspection Results	Unit	Sand-1	Sand-2
Specific gravity	gr/cc	2.621	2.694
Specific gravity SSD	gr/cc	2.653	2.722
Apparent specific gravity	gr/cc	2.708	2.771
Absorption percentage	%	1.215	1.031
Bulk density	gr/cc	1.623	1.626
Mud level	%	0.50	3.75

Table 1 shows the results of an examination of the specific gravity and water absorption of fine aggregate obtained from the type of sand are 2.621 and 2.694. The aggregate grain size is smaller than 4.75 mm (No. 4). So the fine aggregate in this study meets the requirements for the density of the concrete mixture testing material. Testing and calculation of the mixed design (job mix design) of foam concrete mixture obtained free compressive strength values of 800 and 2000 KPa, and the foam concrete compressive strength test results are shown in Table 2.

Table 2 explains that each composition is made of cube-shaped specimens according to a predetermined age of 28 days. The samples tested were 90 specimens using local sand from the Teratak Buluh area and the Danau Bingkuang Kampar Region in Indonesia. When mixing lightweight foam concrete material, the slump flow value test is carried out. Based on the test results that have been carried out, a minimum flow value of 17 cm and a maximum of 19 cm. The density value in this study was obtained from the comparison of the weight of the test object with the volume of the test object, a minimum of 585 kg/m^3 and a maximum of 785 kg/m^3.

Table 2 Composition of foam concrete and compressive strength of foam concrete

Variable	Unit	Min	Ave.	Max
Input Criteria				
Cement	kg	360	360	420
Slump flow	cm	17	18.15	19
Sand	kg	207	259.8	310.3
Water	kg	180	200	200
Foam	kg	35.4	37.2	39.0
Density	kg/m^3	585	761.3	785.9
Output Criteria				
Compressive Strength	MPa	0.08	0.72	1.48

Testing the compressive strength of foam concrete can be seen in Fig. 3

Fig 3. Unconfined Compression Strength test

The ANN results are compared with the experimental results in Table 3.

Table 3 Comparison of experimental results with testing results obtained from ANN

No.	Experimental	ANN Model
1	0.3185	0.36724
2	0.2831	0.38182
3	0.3008	0.27837
4	0.2477	0.31854
5	0.2035	0.32935
6	0.3274	0.48857
7	0.5203	0.51889
8	0.5311	0.48857
9	0.5221	0.35171
10	0.3362	0.35171
11	0.4690	0.42900
12	0.4644	0.58643
.	.	.
90	0.0707	0.5777

The composition of the foam concrete mixture and the compressive strength of foam concrete is used in the input and output criteria variables. ANN's training results obtained predictions of the compressive strength of foam concrete in Table 3. Table 3 shows that the average error of the ANN training network is 0.1090. This proves that the results obtained are very close to the experimental results, 99.89%. The results of the experiment and ANN can be seen in the graph Fig. 4

Fig 4. shows the prediction results with experimental data using ANN with 13 hidden nodes. It can be seen that the prediction results of the compressive strength of foam concrete using primary data as input, as many as 90 samples, did not deviate too far from the results of the tests carried out. The study shows that the developed ANN can predict the effect of the composition of the constituent elements on the compressive strength of foam concrete with an acceptable level of accuracy.

Fig. 5 shows that for training and validation with ANN using 13 hidden nodes, the R-value (coefficient of determination) is 0.98042 and 0.98131, respectively. This R-value indicates the relationship between the output and the target in the training and validation process.

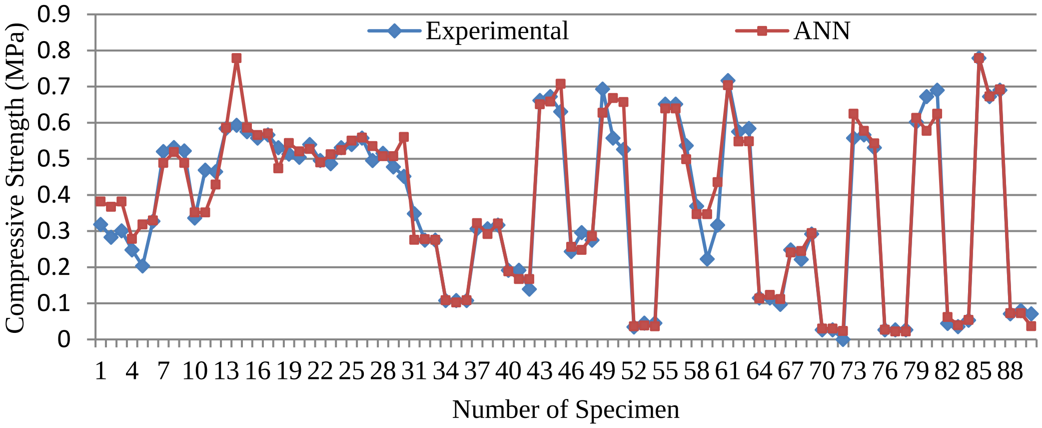

Fig 4. Unconfined Compression Strength test

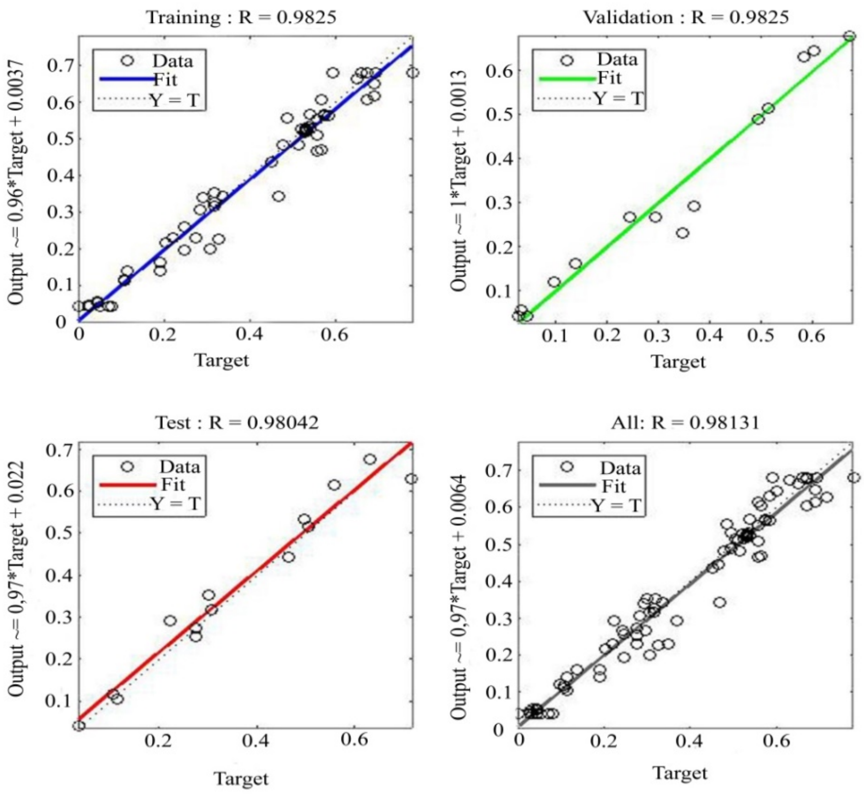

Fig. 5 Training, validation, test and all regression plot in Matlab to predict the compressive strength of foam concrete

An R-value of more than 0.98 means that the amount of training data that has been recognized is large. So it shows that the output data generated in the training and validation is close to the target data entered in the ANN. While the blue and green fit lines close to the dotted line indicate that the Y value (output) is also close to the T value (target).

Fig. 6 shows that ANN's training and data testing results have produced the best error value (Mean Squared Error, MSE) of 4.46×10-5. ANN will be of good value if the MSE value is close to 1. From the training using input data from primary data by varying the hidden node ANN, the mean square error of training and validation results are obtained, as shown in figure 4. It can be seen from the training results that the number of hidden nodes 13 got the smallest validation mean square error, then hidden node 13 had the best training MSE value. Thus ANN can be trained to recognize the compressive strength of foam concrete with this architecture. The architecture of this network is six neurons in the input layer, 13 neurons in the hidden layer, and one neuron in the output layer. Therefore, the network used in this study is a network with 13 hidden nodes.

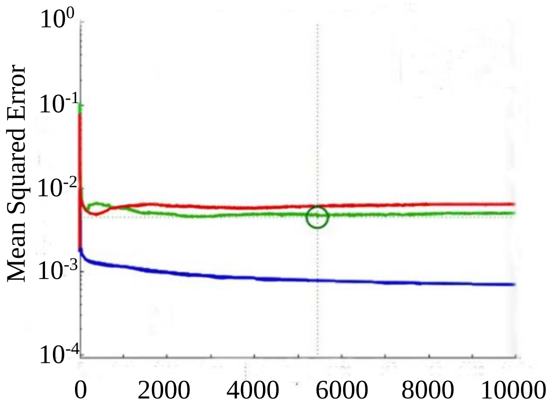

Fig. 6 Error value: Best Validation Performance vs Mean Square Error (MSE)

The input data strongly influence the results of this ANN research, and the target that becomes the learner in ANN training takes a long time to get the best training results. Forecasting research conducted [7], the most recently completed, has limitations regarding the mixture's combination of materials and components. One of the drawbacks of the MARS-WCA model is that its implementation is time-consuming due to the parameter setting of modeling optimization. This study resulted in a small MSE value shown in Fig 4, and the amount of training data successfully recognized was large in Fig 3.

6. CONCLUSIONS

Based on the research and observations that have been carried out on the ANN system for predicting the compressive strength of concrete using feed-forward backpropagation architecture and the Levenberg-Marquardt training algorithm, the best is obtained at hidden node 13 with a validation MSE of 4.4992×10-7. The study can conclude that the ANN method can be used to predict the compressive strength of foam concrete based on the input amount of the foam concrete-forming mixture. So that costs in planning the formation of foam concrete can be minimized because they no longer depend on concrete experts who offer services at high prices. The ANN in this study showed that the accuracy of the 90 training data tested reached 98.7%, indicating that the amount of training data that was successfully recognized was large. However, further research is needed to optimize the prediction results of lightweight foam concrete and the required compressive strength of foam concrete.

7. ACKNOWLEDGMENTS

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8. REFERENCES

[1] Mydin MAO, Wang YC. Mechanical properties of foamed concrete exposed to high temperatures. Constr Build Mater, Vol. 26, 2012, pp. 38–54.

[2] Suryanita R, Firzal Y, Maizir H, Mustafa I, Arshad MF Bin. Experimental study on the performance of cellular lightweight concrete due to exposure to high temperature. Identity, Vol. 10, 2021, pp. 12–4.

[3] Maizir H, Suryanita R, Arditama R. Study on performance of lightweight concrete bricks with a ratio of sand and cement composition. IOP Conf. Ser. Mater. Sci. Eng., IOP Publishing, Vol. 615, 2019, pp.12105.

[4] Alshihri MM, Azmy AM, El-Bisy MS. Neural networks for predicting compressive strength of structural light weight concrete. Constr Build Mater, Vol. 23, 2009, pp. 2214–9.

[5] Nguyen T, Kashani A, Ngo T, Bordas S. Deep neural network with high-order neuron for the prediction of foamed concrete strength. Comput Civ Infrastruct Eng, Vol. 34, Issue 3, 2019, pp. 16–32.

[6] Bayuaji R, Biyanto TR. Model Jaringan

Saraf Tiruan Kuat Tekan Beton Porus dengan Material Pengisi Pasir. J Civ Eng, Vol. 20, 2013, pp. 23–32.
[7] Ashrafian A, Shokri F, Amiri MJT, Yaseen ZM, Rezaie-Balf M. Compressive strength of Foamed Cellular Lightweight Concrete simulation: New development of hybrid artificial intelligence model. Constr Build Mater, Vol. 230, 2020, pp. 117048.
[8] Abd AM, Abd SM. Case Studies in Construction Materials Modelling the strength of lightweight foamed concrete using support vector machine (SVM). Case Stud Constr Mater, Vol. 6, 2017, pp. 8–15.
[9] Yaseen ZM, Deo RC, Hilal A, Abd AM, Bueno LC, Salcedo-Sanz S, et al. Predicting compressive strength of lightweight foamed concrete using extreme learning machine model. Adv Eng Softw, Vol. 115, 2018, pp.112–25.
[10] Journal D. Support vector machine (svm) for modeling, 2015, pp. 29–36.
[11] Kiani B, Gandomi AH, Sajedi S, Liang RY. New formulation of compressive strength of preformed-foam cellular concrete: an evolutionary approach. J Mater Civ Eng 2016;28:4016092.
[12] Dao D Van, Ly H-B, Vu H-LT, Le T-T, Pham BT. Investigation and optimization of the C-ANN structure in predicting the compressive strength of foamed concrete. Materials (Basel), Vol. 13, 2020, pp. 1072.
[13] Yoon JY, Kim H, Lee Y-J, Sim S-H. Prediction model for mechanical properties of lightweight aggregate concrete using artificial neural network. Materials (Basel), Vol. 12, 2019, pp. 2678.
[14] Naderpour H, Rafiean AH, Fakharian P. Compressive strength prediction of environmentally friendly concrete using artificial neural networks. J Build Eng, Vol. 16, 2018, pp. 213–9.
[15] Behnood A, Golafshani EM. Predicting the compressive strength of silica fume concrete using hybrid artificial neural network with multi-objective grey wolves. J Clean Prod, Vol. 202, 2018, pp. 54–64.
[16] Aciu C, Ilutiu-Varvara D-A, Manea D-L, Orban Y-A, Babota F. Recycling of plastic waste materials in the composition of ecological mortars. Procedia Manuf, Vol. 22, 2018, pp. 274–9.