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Prediction of Mechanical Properties of Light Weight Brick Composition Using Artificial Neural Network on Autoclaved Aerated Concrete

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ABSTRACT : In the research domain lightweight brick lifting who qualified mechanical properties. Advantages of light brick AAC low density of about 500 to 650 kg/m^3, more economical, suitable for multi-storey buildings can reduce the weight of 30 to 40 % compared with conventional brick (clay brick). One of the problems found in the fabrication of lightweight brick is how to determine the composition of raw materials used. The composition of materials in lightweight brick can affect its mechanical properties which are an important parameter for building materials. In this research the prediction of the effect of elements composition and density on compressive strength (AAC) using neural network has been done. Furthermore, the simulation on the effect of each element composition and the density on compressive strength also have been done. The best network developed in this research using feed forward back propagation architecture and Levenberg-Marquardt algorithm is to use 8 hidden nodes, with MSE (mean square error) training of 0.001605667 and MSE validation of 0.01455. Simulation results show that composition of Ca, Si, O, and density are all directly proportional to compresssive strentgh, while composition of Al is inversely proportional. The compressive strength prediction results obtained for 4 AAC, and for sample AAC-a = are 4.80 MPa, AAC-b= samples 5.24 MPa, AAC-c=3.23 MPa, and AAC-d= 3.67 MPa. The result of prediction shows that the neural network developed can predict the effect of composition and density on compressive strength of AAC.

Keywords— Prediction, neural network, aac lightweight brick, composition, compressive strength

1. INTRODUCTION

Light brick has a more economical value than conventional brick. Its low density can provide load reduction on the building created and accelerate the implementation process of the construction of a building. It also minimizes the occurrence of remnants of the material used during the construction process. Indonesia with abundant natural resources have the raw material for the manufacture of lightweight brick as limestone, coke, and so scattered in various areas that have not been used up. This provides great opportunities for the development of lightweight brick production scale of domestic and industrial scale [1].

In the fabrication of light brick, one of the problems encountered is the determination of the composition of raw materials which will be used. This is because the composition of the raw material of light brick can affect the mechanical properties of light brick, which is an important parameter of quality for light brick as building material [2] - [5].

Therefore it is necessary to determine the mechanical properties prediction of lightweight brick that will be generated by the composition and temperature of a particular test. Predictions made on this research are using Artificial Neural Network (ANN). ANN method was chosen because this method can be used as a model to develop tools to predict the compressive strength of lightweight brick, and can anticipate the nonlinearity and the complex interactions between input and output variables of light brick [6], [7]. Light brick is a brick that has a lower density than general red brick [8]. Red brick in general has a density of 2.2 to 2.4 g / cm^3, while light brick density is less than 1 g / cm^3 generally. Light brick is divided into two types, porous lightweight brick (aerated) and non-porous (non-aerated). The difference between aerated and non-aerated is, the aerated light brick contained pores which are formed by reaction of aeration, while non aerated concrete using certain materials with low density as aggregates such as synthetic fibers and natural, perlite, etc. [9]. Among the main raw material in the fabrication of lightweight brick AAC is cement, sand, lime (limestone), and aluminum powder as a foaming agent that will help the formation of pores in the brick AAC. In addition, fly ash, slag, mine tailings, and some other materials can be used as aggregate in combination with sand [10].

The main phase in the light brick AAC is the CSH (calcium silicate hydrate), which is formed on the hydration process. While on autoclaving process, the tober morite phase will be formed, wherein phase formation could greatly affect the compressive strength of the bricks [11]. Tobermorite phase is a crystalline phase in AAC. Needle-like tobermorite phase will be mutually adrift with one another (interlock) to form a network. It became one of the main causes of the relatively high compressive strength of AAC compared to non-AAC lightweight brick [12].

One of the most studied mechanical properties of lightweight brick is the compressive strength. According to SNI 03-1974-1990 about testing method of compressive strength for concrete, compressive strength is the magnitude of the load per unit area, which causes the concrete specimen to be crushed when loaded with a certain compressive force, which is generated by a press machine. Light brick compressive strength is influenced by many factors, including the density, porosity, lightweight brick age, and method of pore formation, curing methods, and its compositions [10]. Artificial neural network is defined as a computing paradigm mathematically modeled after biological neural system [16]. Artificial neural networks are formed as a generalization of mathematical models of biological neural networks with several assumptions, including [12]:

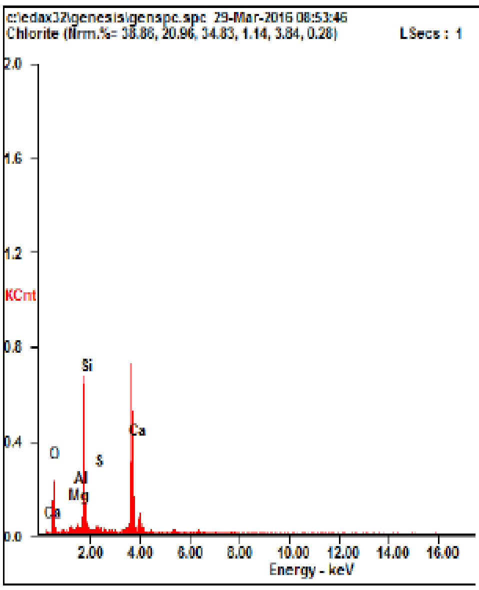
- Processing occurs in a lot of simple elements (neurons)
- Signals transmitted from one neuron to other neurons via connectors
- Connectors between neurons have weights that will strengthen or weaken the signal passing through it.
- To determine the output, each neuron used a particular activation function to changee the input received. The output which is generated then compared to a threshold to determine whether the signal is passed to another neuron or not.

Just as the human brain, neural network also consists of some neurons, and these neurons have connectors. Neurons will transform the information received through the connection and release it to other neurons. In the neural network, this connection is known as weight. Informations about the connection are stored on a particular value in the weights [17]. Information (input) will be sent to the neurons with a specific weight of arrival. This input will be processed by a propagation function that will add up the values of all incoming weights. The result of this sum will then be compared to a threshold value (threshold) given through the activation function of each neuron. If the input passes a certain threshold value, the neuron is activated, otherwise if not, then the neuron will not be activated. When neurons are activated, then the neuron will send output through the weights of its output to all the neurons associated with it, and so on for all other neurons [17].

2. MATERIALS AND METHODS

Primary and Secondary Data Collection, Primary data were taken from the test results of 4 AAC lightweight brick types, namely: AAC-1, AAC-2, AAC-3 and AAC-4. Primary data will be used as input data to a prediction by the neural network. The conducted test were:

2.1. EDX, EDX testing conducted on four samples of light brick AAC, where on each sample, 4 points were taken to be tested. The results of EDX composition test is in the form of AAC light weight brick elemental compositions.



Element	Wt %	At %
O K	29.59	46.67
MgK	00.66	00.69
AlK	01.85	01.73
SiK	29.72	26.70
S K	01.12	00.88
CaK	37.06	23.33

Figure-1 : Sample AAC result of composition test

2.2. Compressive strength

Compressive strength test conducted on four samples of light brick, each sample with a dimension of 10 cm x 10 cm x 10 cm. Compressive strength test was done by giving a certain pressure on the surface of the sample until the sample break, according to the standard method of compressive strength test for concrete (SNI 03 -1974-1990).

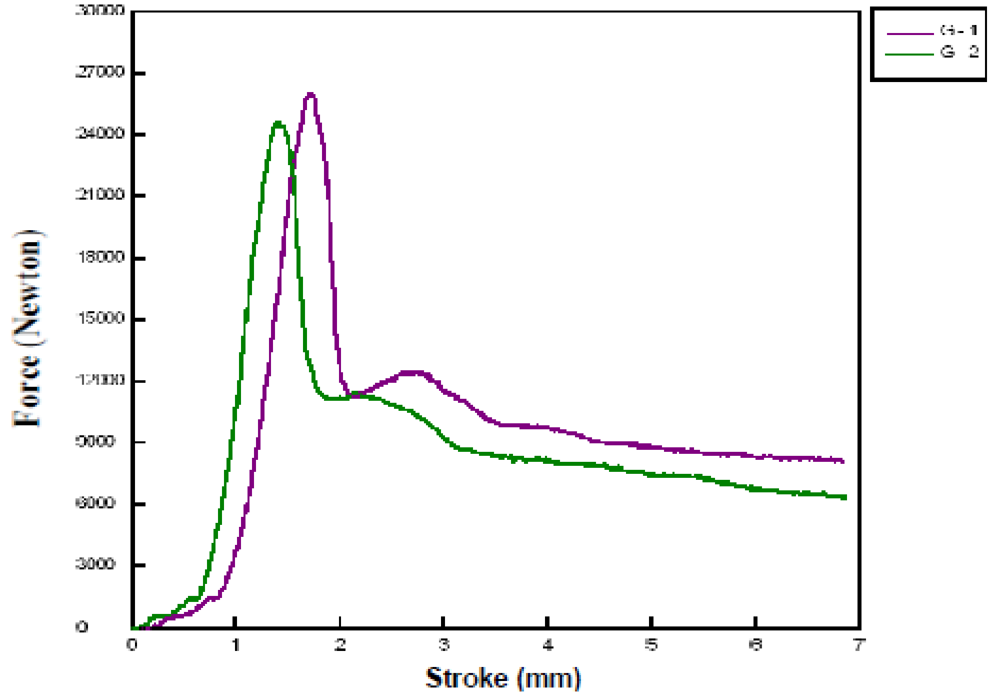


Figure-2 : Sample AAC result of mechanical test

2.3. Measurement of density

Density measurements were done by weighing 4 AAC lightweight brick samples. Each samples with a dimension of 20 cm x 20 cm x 10 cm.

Secondary data were taken from a number of previous studies [20-24] about the effect of composition on compressive strength of AAC. The datas taken from previous research were data on the composition of AAC lightweight bricks, density data, and data compressive strength of AAC lightweight brick. Statistics from secondary data can be seen in Table 1. This secondary data will be used as input data and targets for training the neural network.

Table 1.Secondary data statistics

Input/Target	Data size	min	max	mean	Standard Deviation
wt% Ca	47	10.09	25.09	20.94	2.99
wt% Si	47	12.5	27.21	18.50	3.40
wt% Al	47	1.6	10.32	6.08	2.47
wt% O	47	31.21	46.01	39.28	4.95
Density (kg/m^3)	47	536	1219	665.05	120.98
Compressive Strength (MPa)	47	2.09	13.92	5.26	2.64

2.4. Prediction using ANN

Before starting the prediction, is necessary to determine the number of hidden layer nodes and weights of the ANN which will be used. To determine the matter, ANN training on variation of hidden layer nodes between the nodes 1-10 was conducted to determine the most accurate ANN. The parameters used to determine the best ANN is the mean square error (MSE) training and validation.

Beside that, simulations to see the effect of Ca, Si, Al, O compositions and density on compressive strength were also performed. This was done by varying the input data which is simulated and equate other input data by taking its average value, to simulate the effect of Ca composition of compressive strength, the Ca composition data was varied according to data target, while the input data of Si, Al, and density were equated by taking its average value, such as of figure (3). Simulations also conducted to see the effect of temperature on the compressive strength of the working AAC. The input data used in this simulation is the same data used in the simulation of the effect of the composition and density, except for the added temperature simulation with temperature 25 ^{o}C for each pair of data. This temperature is the temperature of the room in which the AAC tested for compressive strength.

2.5. Training the network

As explained above, the data used for training the neural network is secondary data. With input / target as in the table above, training artificial neural networks performed by the software MATLAB R2012a. The stages of training ANN with MATLAB are as follows:

- Initialization of inputs and targets
- Normalization of input and target
- Initialization of neural network
- Determination of training parameters
- The training process
- View the final weight
- Saving neural network

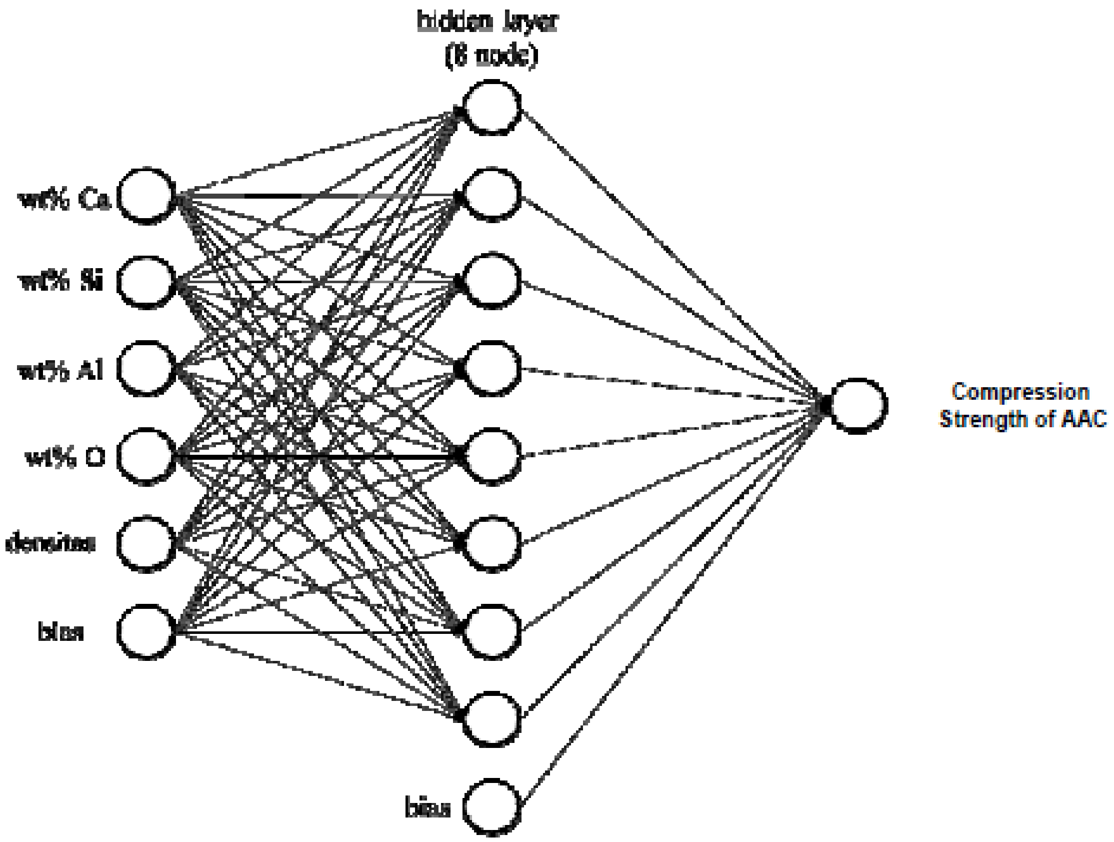


Figure-3. Artificial neural network architecture

3. ANALISYS AND DISCUSION

3.1. Testing Results of AAC Samples

Results of tests performed on lightweight brick can be seen in Table 2. Can be seen from the above table that the sample AAC-3 and AAC-4 does not have a composition of Al. This is most likely due to the expansion agent used on manufacturing process, which is not aluminum powder but other types such as hydrogen peroxide (H_2O_2). In addition, samples of the AAC-3 also has the lowest compressive strength, where the density of the sample is also the lowest. The occurrence of non-linear relationship between the density and compressive strength of AAC can be caused due to environmental conditions in the storage of AAC light brick, with diverse environments where humidity can affect the density of light brick AAC.

Table 2.Testing Results of AAC Samples

AAC Samples	Input				Target	
	Composition (wt %)				Density (kg/m^3)	Compressive Strength (MPa)
	Ca	Si	Al	O		
AAC-1	30.74	27.37	1.67	38.79	592.55	4.95
AAC-2	29.62	25.89	1.69	41.19	606.97	5.59
AAC-3	51.50	5.56	0.00	41.80	508.62	2.61
AAC-4	49.88	10.16	0.00	38.71	631.57	4.88

3.2. Training Results with Hidden Node Variation

Training using input data from secondary data by varying the hidden node ANN, showed mean square error training and validation, as shown in Table 3. It can be seen from the results of the training that the number of hidden nodes 4 and 8 obtained the smallest mean square error of validation. Differences in mean square error of validation at 4 and 8 node is not too significant. However, when both training mean square error was compared, we could see clearly that hidden node 8 has the best mse training value. Therefore, the network used in research is a network with 8 hidden node. The neural network architecture used in this research can be seen in Figure 3.

In the process of training with 8 hidden node, regression plot obtained as in Figure 4. It can be seen that for training and validation by using a neural network with 8 hidden node, R (determination coefficient) obtained were 0.98418 and 0.98571 for training and validation respectively. R shows the relationship between output and target in the training and validation process. R more than 0.93 indicates that the output data generated in the training and validation are a close fit with target data entered in ANN [19].

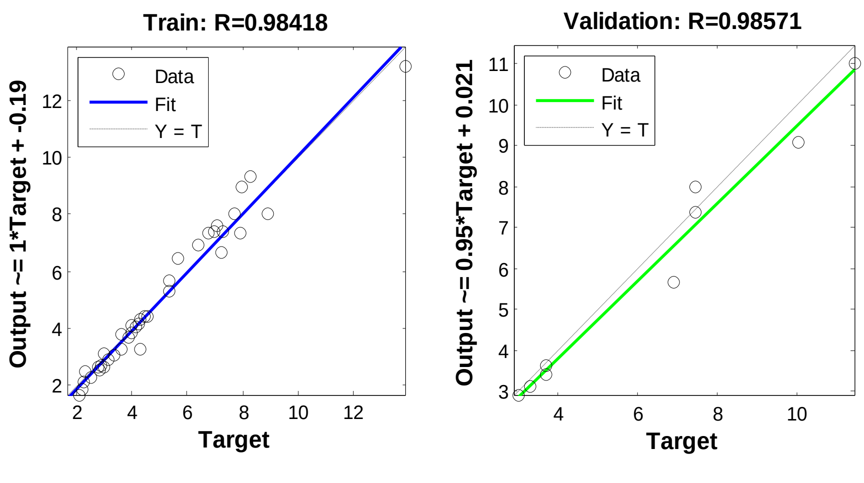


Figure 4. Regression plot of training and validation

Table 3.Training Results with Hidden Node Variation

Hidden node variation	MSE training	MSE validation
1 node	0.008196667	0.02213
2 node	0.02491	0.015293
3 node	0.003757	0.024276667
4 node	0.006014333	0.014428333
5 node	0.003374333	0.019144333
6 node	0.001591767	0.026366
7 node	0.0022111	0.04877
8 node	0.001605667	0.01455
9 node	0.001826333	0.140697333
10 node	0.001190367	0.041153333

In Table 4 the results of prediction using neural networks with hidden node 8 are shown. It can be seen that the compressive strength prediction results using primary data as input did not deviate too far from the results of tests performed. This shows that artificial neural networks can be developed to predict the effect of the composition of the constituent elements on compressive strength of AAC.

Table 4.Prediction Results Strength and Prediction Test

Samples	Compressive Strength Test (MPa)	Compressive Strength Prediction (MPa)
AAC-1	4.95469	4.802
AAC-2	5.5875	5.2389
AAC-3	2.60781	3.2298
AAC-4	4.88281	3.6663

Furthermore, in Figure 5 to Figure 9 the results of simulation of the effect of composition and density on compressive strength of lightweight brick AAC are shown. From these figures it can be seen that the overall composition of Ca, Si, and O of AAC have positive effects on compressive strength, albeit with different trends. The higher the composition of Ca, Si, O, as well as the density of AAC light brick, its compressive strength will get higher as well. This is possibly because Ca, Si and O are key elements of AAC lightweight brick. Ca, Si, O are elements forming the main phase in AAC, which is tobermorite. The existence and extent of the tobermorite phase itself heavily affects the compressive strength of AAC.

The composition of Al is inversely proportional to the compressive strength of AAC. The higher the Al composition, the lower the compressive strength of AAC. It is because Al is an element that is used as an expansion agent in the manufacture process of AAC. So with the increasing number of expansion agent used in the fabrication process, there will be more and more pores in the light brick AAC. This causes the porosity of the AAC to rise, and with a growing number of pores formed the density of the AAC will reduce, and as described above, AAC density is proportional to its compressive strength. The higher the density, compressive strength is also higher and vice versa. It can also be seen from the results of the simulation effect of density on the compressive strength.

If the value of compressive strength resulting from the simulation observed, it was found that the compressive strength is generated were not too far away from the range of minimum and maximum compressive strength data is used as the target, ie from 2.09 to 13.92 MPa. It also shows that the simulation is quite accurate because the input data used in this simulation is essentially the same as the input data in the training process, except that the input data here varied one, and another equated to its average.

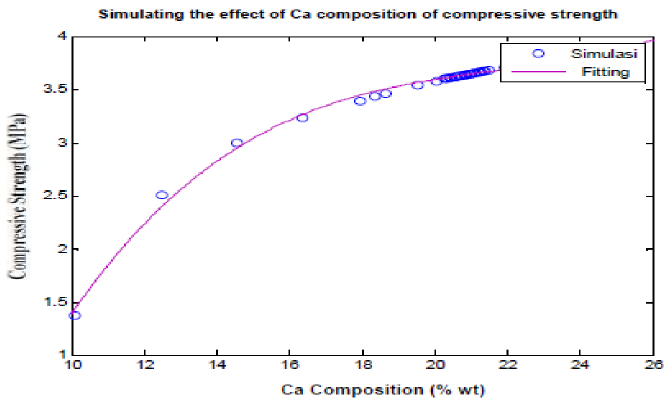


Figure 5. Simulation results of the effect of wt% Ca on compressive strength

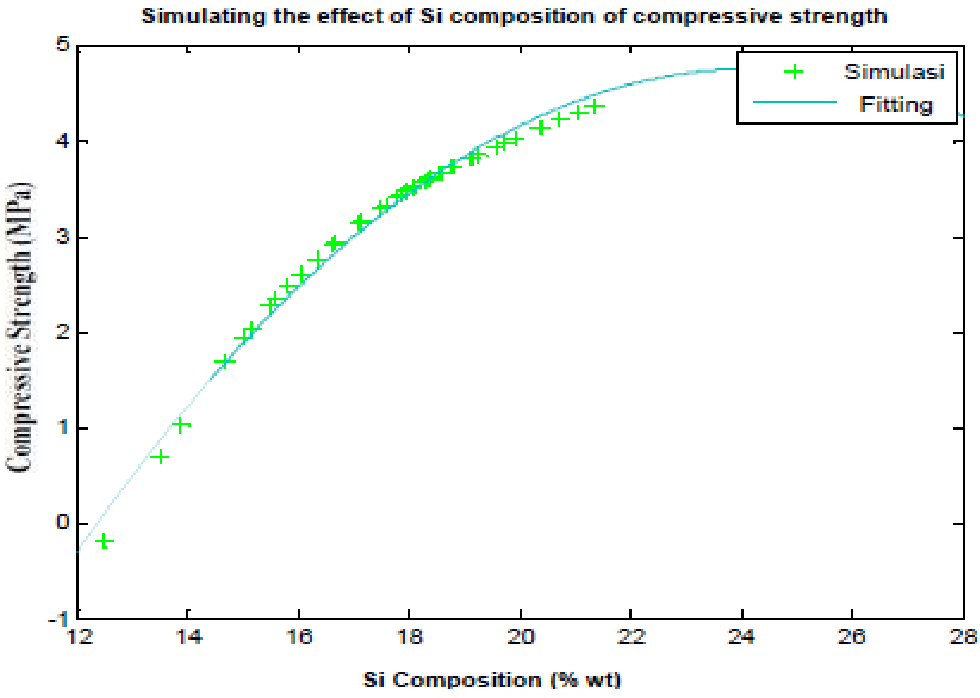


Figure 6. Simulation results of the effect of wt% Si on compressive strength

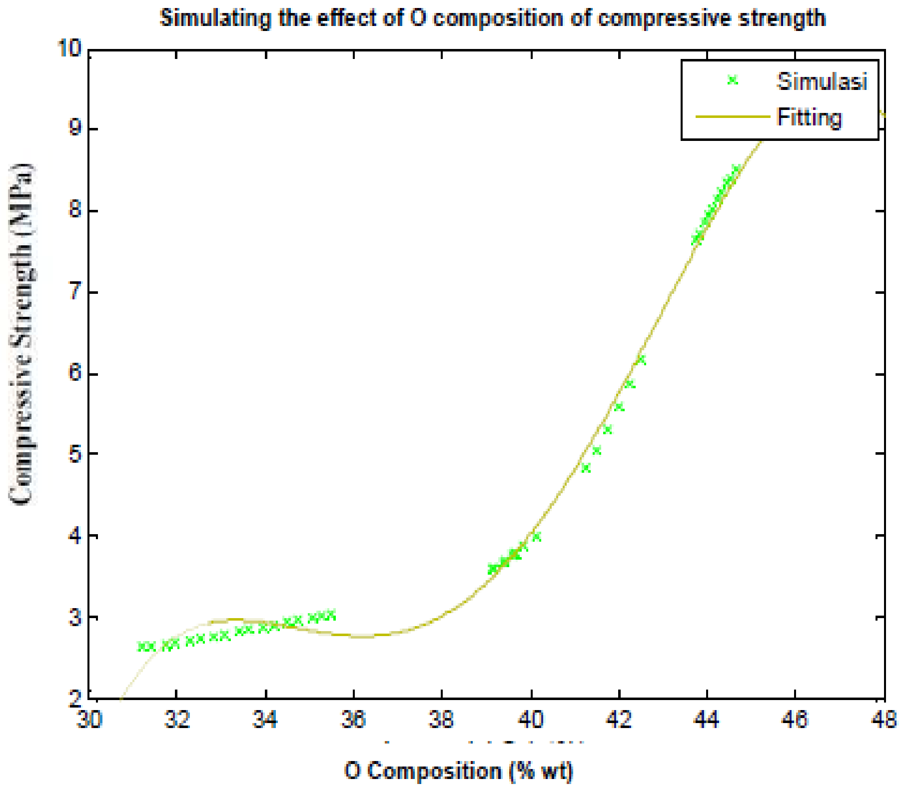


Figure 7. Simulation results of the effect of wt% O on compressive strength

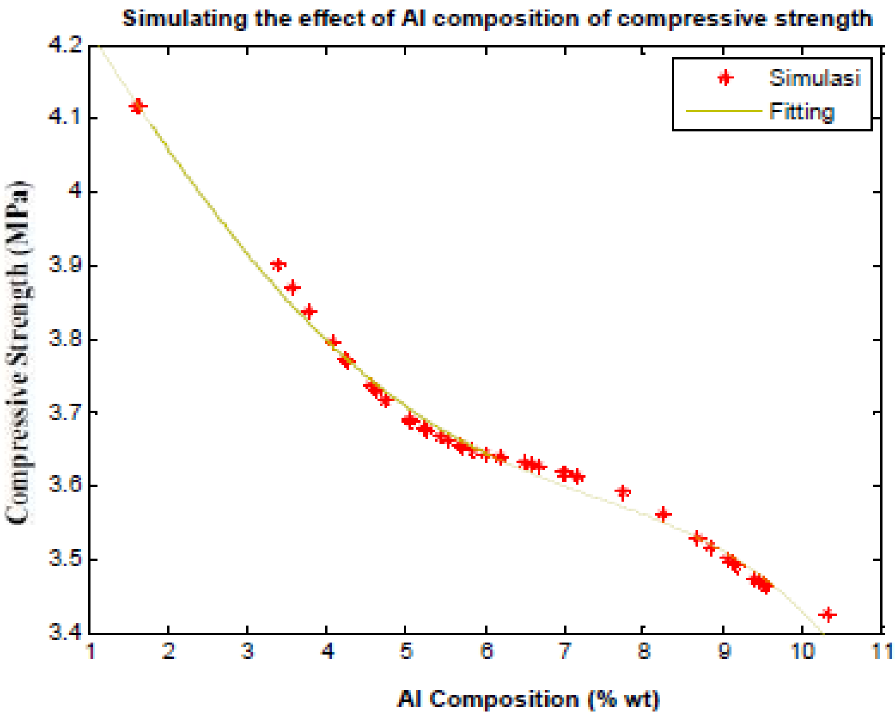


Figure 8. Simulation results of the effect of wt% Al on compressive strength

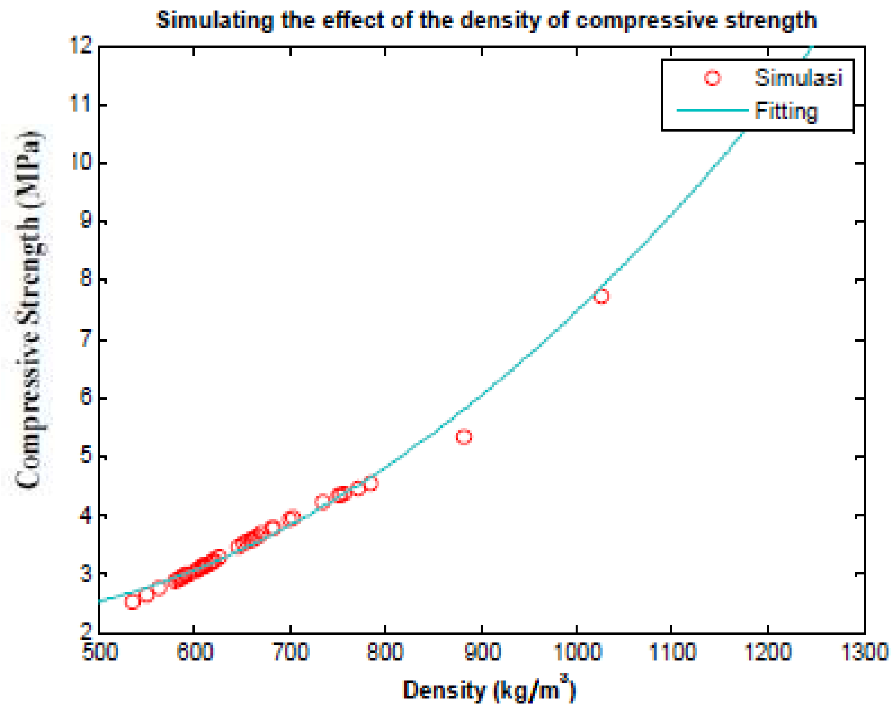


Figure 9. Simulation results of the effect of density on compressive strength

Figure 10 shows a simulation of the effect of temperature on the compressive strength of the AAC light brick. At a temperature range of 26-37 ^{o}C of constant compressive strength of 3.37 MPa, as well as in the 38-44 ^{o}C temperature range the constant compressive strength decreases to 3.17 MPa. In accordance with the theory the higher the temperature of compressive strength testing, the compressive strength of the AAC brick is lower

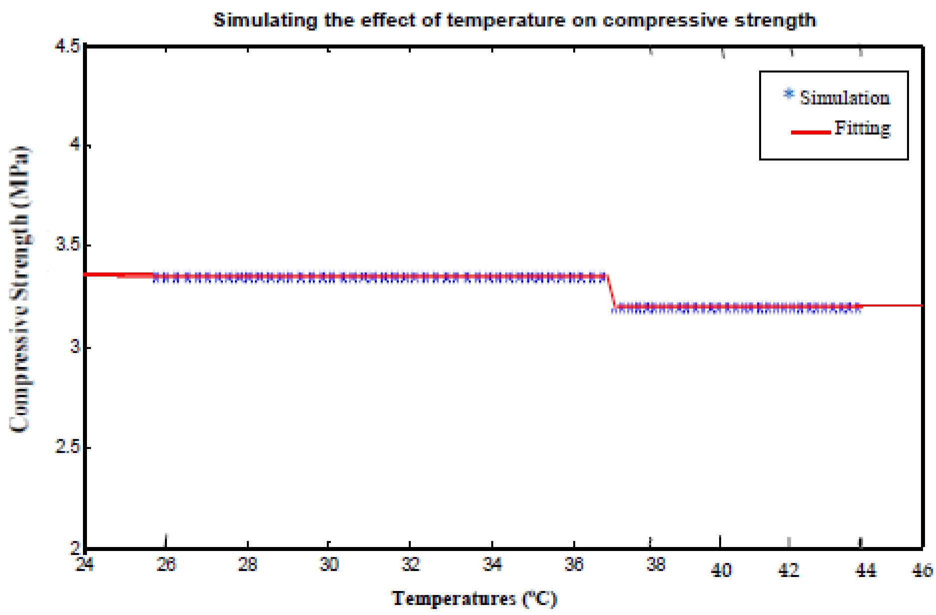


Figure 10. Simulation results of the effect of temperature on compressive strength

4. CONCLUSION

From the simulation of composition and density influence on the compressive strength of AAC lightweight brick, it can be concluded that the composition of Ca, Si, O and the density is proportional to the compressive strength of AAC, while the composition of Al is inversely proportional to the compressive strength of AAC. Compressive strength prediction results obtained for 4 samples AAC-1= 4.80 MPa, AAC-2= , 5.24 MPa, AAC-3= 3.23 MPa, and AAC-4= 3.67 MPa. respectively or Average value of the compressive strength is 4.235 MPa. Artificial neural network with feed forward back propagation architecture and Levenberg-Marquardt training algorithm that is best found in the hidden node 8, with MSE training of 0.001605667 and MSE validation of 0.01455.

5. ACKNOWLEDGEMENT

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