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Comparison of Different Weight Optimization Algorithm in Neural Network to Predict Mechanical Properties of AAC Lightweight Brick

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ABSTRACT

This research aims to find the optimal weight optimization algorithm and number of hidden nodes that can be used in Artificial Neural Network to predict mechanical properties (density and compressive strength) of Autoclaved Aerated Concrete (AAC) lightweight brick. The dataset is obtained from secondary source, with a total of 51 data points. From this dataset, the relationship between constituent elements of AAC with its density and compressive strength is modeled using ANN. It was found that the best weight optimization algorithm that can be used for this dataset is the LBFGS (Limited-memory Broyden–Fletcher–Goldfarb–Shanno) algorithm. The optimum hidden layer node is found to be 90 nodes. With this parameters, the ANN can predict density and compressive strength of AAC lightweight brick with accuracy of 93.51% and margin of error around 6.49%. The accuracy of the prediction can be improved by appending the dataset with data points from secondary sources or by doing more experiments and tests.

Keywords: ***Weight Optimization Algorithm, Neural Network, Lightweight Brick, Mechanical Properties***

INTRODUCTION

Lightweight brick is a type of brick with lower density than normal red brick. Red brick usually has a density of 2.2 to 2.4 g/cm^3, while the density of lightweight brick is usually less than 1 g/cm^3. Lightweight bricks are divided into two types: porous (aerated) lightweight bricks and non-porous (non-aerated) lightweight bricks. The difference between aerated and non-aerated lightweight bricks is that aerated lightweight bricks contain pores formed by aeration reaction while non-aerated concrete uses some low density material as aggregate such as synthetic fibers. composite and natural, perlite, etc. Lightweight bricks have a higher economic value than ordinary red bricks. Its low density can reduce the load applied on buildings (Suryani & Munasir, 2015).

One of the most widely used lightweight brick is Autoclaved Aerated Concrete (AAC). The main ingredients for producing AAC bricks are cement, sand, lime (limestone) and aluminum powder which is a foaming agent that will help form voids in AAC bricks. In addition, fly ash, slag, mine waste and some other materials can be used as aggregate in combination with sand. After mixing of ingredients and casting, the brick is then cured in a sealed vessel called autoclave. AAC possess many advantages because of its lower density with higher strength compared to conventional brick. AAC is manufactured from non-biodegradable materials that neither rot nor entice mold, preserving smooth and strong interiors (Kalpana & Mohith, 2020).

In the manufacturing process of lightweight bricks, one of the problems encountered is determining the composition of the raw materials to be used. This is because the raw material composition of lightweight bricks can affect the mechanical properties of lightweight bricks, which is an important quality parameter for lightweight bricks as building materials.

One of the methods to predict relationship between ingredients / components of material with its properties is Artificial Neural Network (ANN). ANN is a series of algorithms inspired by biological neural network which can be used to identify relationships between sets of data. The ANN method was chosen because it can be used as a model to develop lightweight brick compressive strength predictor and can predict nonlinearity and complex interactions between input and output variables (Kifli et al., 2017).

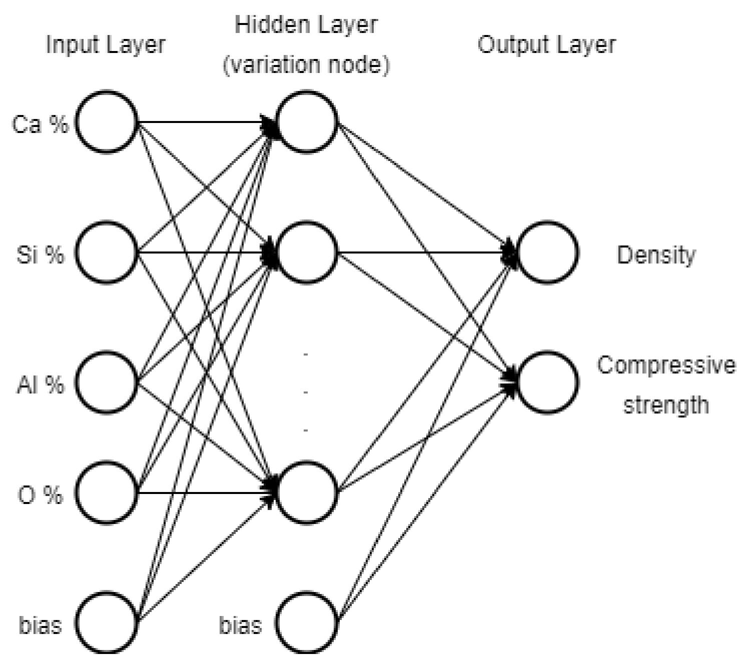
One of the ways to create ANN for prediction is by using Python programming language. Python programming language can be accessed through many environment, one of which via Google Colaboratory, a platform that allows user to write and execute python code through their browser. Google Colaboratory, or Colab for short, has been used to create ANN and shown to be 97% accurate (Gunawan et al., 2020).

Multilayer Perceptron (MLP) is one of the most utilized neural network model with applications ranging from classification, pattern recognition, regression, etc. Optimization of the number of hidden nodes in this type of neural network is an important task, to keep the neural network from underfitting and overfitting. Neural network parameters such as weight optimization algorithm and learning rate is also important to create a more accurate neural network prediction (Ramchoun et al., 2016). Hence in this research, MLP ANN models are developed with varying weight optimization algorithm and hidden nodes to create the most accurate ANN to predict the relationship between elemental ingredients of AAC to its mechanical properties.

METHOD

The data used to make the predictions are secondary (Kifli et al., 2017), with a total of 51 data points. From this data, percentages of Calcium (Ca), Silicon (Si), Aluminum (Al), and Oxygen (O) atoms in AAC concrete are used as input for the ANN. The number of nodes in the hidden layer of ANN is varied to achieve lowest error possible. For the output layer, the mechanical properties examined in this research is density and compressive strength. The algorithm to optimize weights for each node connections are varied between three:

LBFGS (Limited-memory Broyden–Fletcher–Goldfarb–Shanno), SGD (Stochastic gradient descent), and Adam (Adaptive moment estimation). Graphical representation of ANN models developed in this research is shown in Figure 1.



From these variations, the ANN model with lowest possible error is selected. The methods for calculating error are as follows:

- Mean Square Error (MSE), given by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

with:

$n =$ number of data points

$Y_i =$ observed values

$\hat{Y}_i =$ predicted values

- Root Mean Square Error (RMSE), given by:

$$RMSE = \sqrt{MSE}$$

- Mean Absolute Error (MAE), given by:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{Y}_i - Y_i\right|$$

with:
$n =$ number of data points

$Y_i =$ observed values

$\hat{Y}_i =$ predicted values

The accuracy of the best ANN model is determined from subtracting Mean Absolute Error to 100% (Harsiti et al., 2022), as shown by equations below.

$$Accuracy = 100\% - Error(\%)$$
$$Accuracy = 100\% - (MAE * 100\%)$$

FINDING AND DISCUSSION

The errors of the ANN models developed in this research are given in Table 1. Generally, ANN with LBFGS solver (weight optimization algorithm) result in lowest errors. This result can be explained by the characteristic of LBFGS algorithm, which is better for smaller dataset (Najafabadi et al., 2017). The number of hidden node which result in lowest mean absolute error is found to be 90. However, the lowest mean square error and root mean square error is found by using 80 hidden nodes.

Table 1: Errors of ANN model developed

NO	Weight Optimization Algorithm	Hidden nodes	MAE	MSE	RMSE
1	Adam	10	0.1776	0.0800	0.2828
2		20	0.1712	0.0668	0.2585
3		30	0.1242	0.0462	0.2150
4		40	0.1310	0.0474	0.2178
5		50	0.1108	0.0402	0.2005
6		60	0.1398	0.0370	0.1924
7		70	0.1170	0.0441	0.2099
8		80	0.1261	0.0506	0.2250
9		90	0.1194	0.0408	0.2019
10		100	0.1251	0.0508	0.2254
11	SGD	10	0.1890	0.0777	0.2787
12		20	0.1659	0.0608	0.2466
13		30	0.1520	0.0594	0.2438
14		40	0.1851	0.0702	0.2650
15		50	0.1484	0.0640	0.2530
16		60	0.1416	0.0401	0.2002
17		70	0.1545	0.0641	0.2533
18		80	0.1687	0.0680	0.2609
19		90	0.1785	0.0637	0.2524
20		100	0.1705	0.0789	0.2808
21	LBFGS	10	0.1146	0.0389	0.1972
22		20	0.1136	0.0323	0.1798
23		30	0.0820	0.0177	0.1329
24		40	0.0668	0.0099	0.0993
25		50	0.0765	0.0128	0.1129
26		60	0.0778	0.0149	0.1220
27		70	0.0717	0.0116	0.1075
28		80	0.0655	0.0089	0.0943
29		90	0.0649	0.0111	0.1053
30		100	0.0774	0.0123	0.1109

Comparison between density and compressive strength predicted with density and compressive strength observed from the data is shown in Figure 2. Here, 11 data points from testing phase is plotted to show the difference between observed data from secondary source and the data from ANN prediction. It can be seen that for 90 hidden nodes, the ANN model can predict the density of AAC with minimal error and quite a high accuracy. However, the result for prediction of compressive strength is considerably worse with higher error and lower accuracy. This result can be attributed to small dataset which can make it harder for ANN to recognize the relationship between constituent elements of AAC with its compressive strength (Kifli et al., 2017).

The accuracy of the ANN model used for prediction, as described above, can be calculated by:

$$Accuracy = 100\% - (MAE * 100\%)$$
$$Accuracy = 100\% - 6.49\%$$
$$Accuracy = 93.51\%$$

With the accuracy of 93.51%, it can be said that this ANN model can predict mechanical properties of AAC lightweight brick quite accurately with the margin of error around 6.49%.

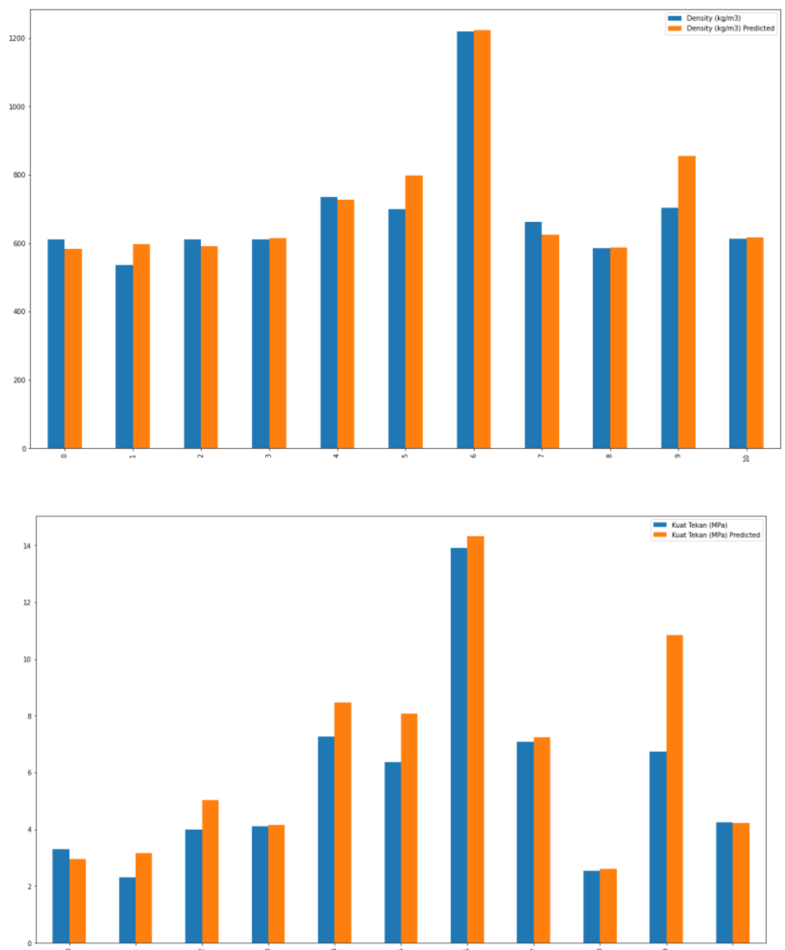


Figure 2: Comparison between density and compressive strength observed (blue) vs predicted (orange)

CONCLUSION

It was found that the best weight optimization method for ANN to predict AAC mechanical properties is LBFGS (Limited-memory Broyden–Fletcher–Goldfarb–Shanno). The optimum number of hidden layer nodes which result in lowest mean absolute error is 90. With these parameters, the ANN can predict density and compressive strength of AAC with around 6.49% margin of error, or in other words with 93.51% accuracy. The comparison between predicted density and compressive strength with observed density and compressive strength is plotted. The plot for compressive strength is shown to be relatively worse, with higher errors. This can be attributed to small size of dataset. Hence, the dataset need to be appended, be it from secondary sources or by doing more experiments and tests.

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