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Prediction Of Compressive Strength Of Normal Concrete Using Artificial Neural Network Method

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Abstract: Lombok Island is an archipelago that has a source Natural resources such as sand and gravel are abundant. This material is one of the components of concrete. Concrete is a frequently used material in Indonesia. Compressive strength testing of concrete typically requires a large number of samples and a considerable amount of time. To expedite and simplify this process, researchers employ computer-based intelligence techniques, namely the Artificial Neural Network (ANN) method. This research involved a series of laboratory tests for normal concrete's compressive strength. The obtained data was then processed using MATLAB with the ANN modeling method for training. The research results indicated a Mean Absolute Percentage Error (MAPE) of 0.02% during the training process and 1.54% during testing. This demonstrates that the developed ANN modeling exhibits a high level of accuracy with low error. Therefore, the empirical formula obtained can be used for predicting the compressive strength of normal concrete with a good degree of precision.

Keywords: *prediction, compressive strength, ANN*

1. Introduction

Concrete is a commonly used material in Indonesia. It has advantages such as ease of workability because the components of concrete are readily available, and it is relatively cheaper compared to other materials. Another advantage of concrete is its strong mechanical properties, excellent durability, and a dense microstructure[1]. Additionally, concrete exhibits qualities such as resistance to permeability, water absorption, and sound insulation.[2].

The robust mechanical properties of concrete are particularly evident in its compressive strength. To achieve good compressive strength, several factors must be considered, including the proportion of the concrete's constituent materials. The components influencing concrete's compressive strength include the Water-Cement Ratio, abrasion value, Aggregate-Cement Ratio, and Aggregate Surface Area [3]. Moreover, the age of concrete during compressive strength testing is a crucial factor, requiring adjustment by a concrete age coefficient. Proper concrete mix proportions can significantly affect the construction process. However, compressive strength tests on specimens are typically conducted at 7, 14, and 28 days of age[4]. If the concrete's compressive strength does not meet specifications, the concrete mix design process must be repeated, leading to delays in subsequent construction stages. Early prediction of concrete compressive strength is essential for time and cost savings in construction.

The use of computer-based intelligent techniques, particularly ANN can help expedite and simplify the process.[5]. In addressing complex nonlinear modeling problems, models like ANN have proven capable of analyzing the nonlinear relationship between compressive strength and the constituents of concrete. [6]. Therefore, the author proposes research regarding the utilization of the ANN method for predicting the compressive strength of normal concrete.

2. Method

2.1 Artificial Neural Network (ANN) Method

ANN is an artificial representation of the human brain's neural network system, which continually simulates learning processes, akin to the human brain. "Artificial" implies that neural networks are implemented using computer-based intelligence techniques capable of performing various calculations throughout the learning process.

The research on optimizing the dimensions of office building beams and columns using the Artificial Neural Network method resulted in the discovery of 12 empirical formulas for optimizing these dimensions. The optimization process involved the use of SAP 2000 software to calculate the structural dimensions until an optimal value was achieved. This optimal value was subsequently input into MATLAB to assist in implementing the Artificial Neural Network.[7]

Prasetiawan conducted research on the use of ANN for predicting the dimensions of beams and columns in public facility buildings. The research methodology employed two optimization methods, namely optimizing using the SAP 2000 program. Subsequently, the optimization calculations were continued through ANN modeling.[8]

This method consists of several components, including a series of inputs, layers, and outputs. Inputs can only process numeric data, so if the data consists of graphics, images, or signals, it must first be converted into numeric data. Layers consist of a collection of interconnected neurons grouped into layers. These layers include the input layer, hidden layer, and output layer. Layers can be either single or multilayer. The output provides a solution in the form of numeric data, as depicted in Fig. 1.

In this research, data normalization is carried out for both input and output values as a requirement for the data training and testing process. The weighted sum of inputs will be computed by a neuron, then subtracting its threshold from this sum, and transferring this result using a function.[9]. Mathematically, this can be represented by the formula below:

$$Y = Zi.W[i,j] + b[i,j] \tag{1}$$

$$Zi = \frac{1}{1+e^{-Zinj}} \tag{2}$$

$$Zinj = f(Xi.V[i,j] + b[i,j]) \tag{3}$$

- Y = output data
- X = input data
- Zi = hidden layer
- Vij = weight of input
- Wij = weight of layer
- bij = weight of bias

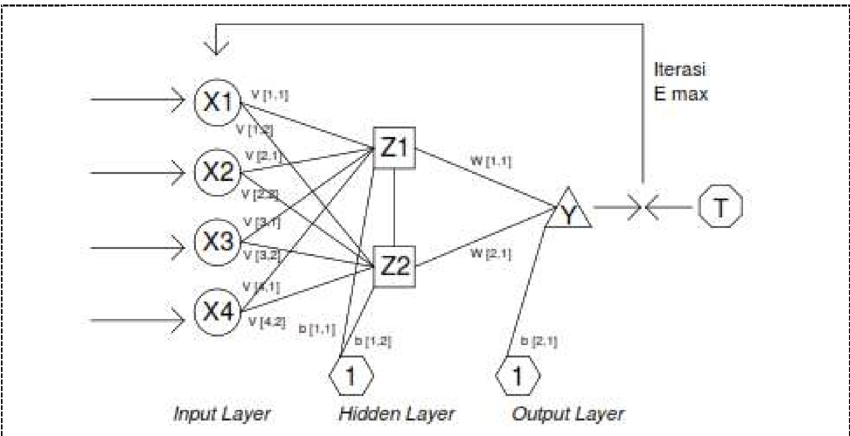

Fig. 1. Sketch of Artificial Neural Network Configuration [10]

2.2 Research Methods

2.2.1 Experimental Data

The experimental data were obtained from laboratory tests. Samples of normal concrete were collected from the compressive strength tests conducted in this laboratory. All samples were prepared following the SNI procedure. The input data included the amount of portland cement, the amount of sand, the quantity of gravel, the amount of water, and the value of FAS. The experimental data served as the actual data and the target data.

2.2.2 Flowchart of ANN Modelling

From the laboratory-acquired data, the data were processed using MATLAB with Artificial Neural Network (ANN) modelling. The modelling steps are as follows:

a. Input data is obtained from normalized results of compressive strength tests on normal concrete in the laboratory. The input components consist of the amount of portland cement, the amount of sand, the quantity of gravel, the amount of water, and the value of FAS, along with the target data for concrete compressive strength.
b. The hidden layer plays a crucial role in the ANN model's ability to generalize patterns. In this research, two hidden layers are used.
c. Incorporating programming language into MATLAB.
d. The data used is divided into several portions, specifically data for the training process and data for the testing process. 80% of the total data is used for the training data, while 20% of the total data is used for testing data.
e. The training data processing.
f. Data interpretation and then getting empirical formula.
g. The testing data processing.
h. calculates the error.
i. The final outcome of this ANN modelling is an empirical formula as the prediction result, measured using accuracy indicators.

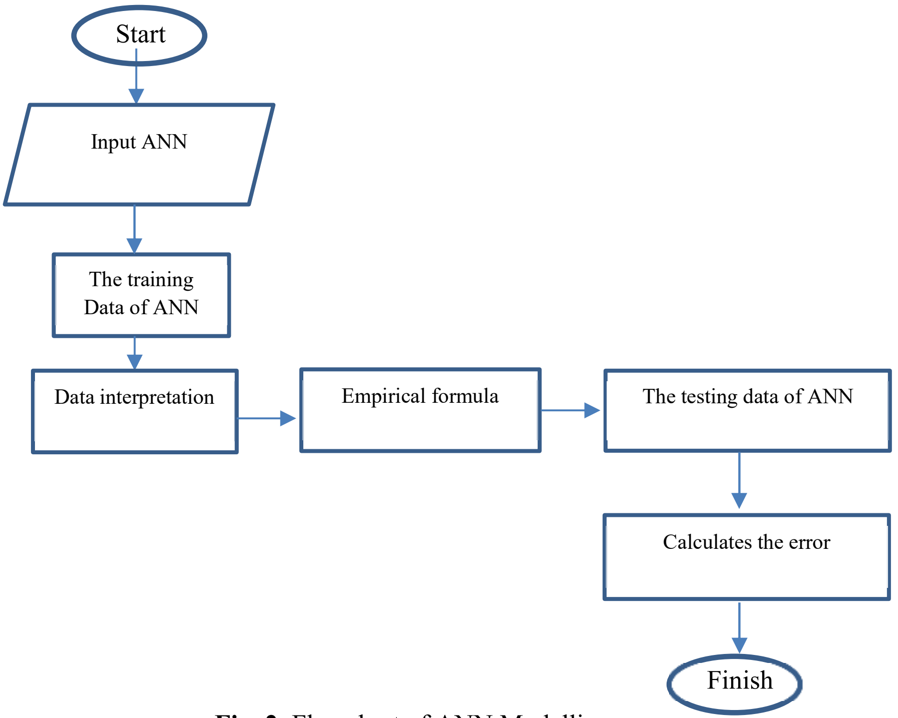

Fig. 2. Flowchart of ANN Modelling

2.2.3 Accuracy Indicators for ANN Modeling

In this research, to measure the accuracy of the method used, the Mean Absolute Percentage Error (MAPE) is employed. The average error is calculated using MAPE (Mean Absolute Percentage Error) by determining the absolute difference between actual data and predicted data. The advantage of MAPE is that the calculation is not affected by the units and the scale of the predicted values and actual values. This makes the calculation for determining the relative differences between models more efficient[11].

$$MAPE = \frac{1}{n}\sum_{1=1}^{n}\left|\frac{y-y\prime}{y}\right| \tag{4}$$

3 Result and Discussion

3.1 Results of ANN Training Data

This study compared the compressive strength test results from the laboratory with the predicted compressive strength using ANN. The target data in this study is the compressive strength, with input data consisting of the amount of portland cement, the amount of sand, the quantity of gravel, the amount of water, and the value of FAS, obtained from laboratory tests. In this ANN modeling, the best training was achieved at the 2530th iteration. Therefore, as indicated in Fig. 3, the automatic data training process will stop.

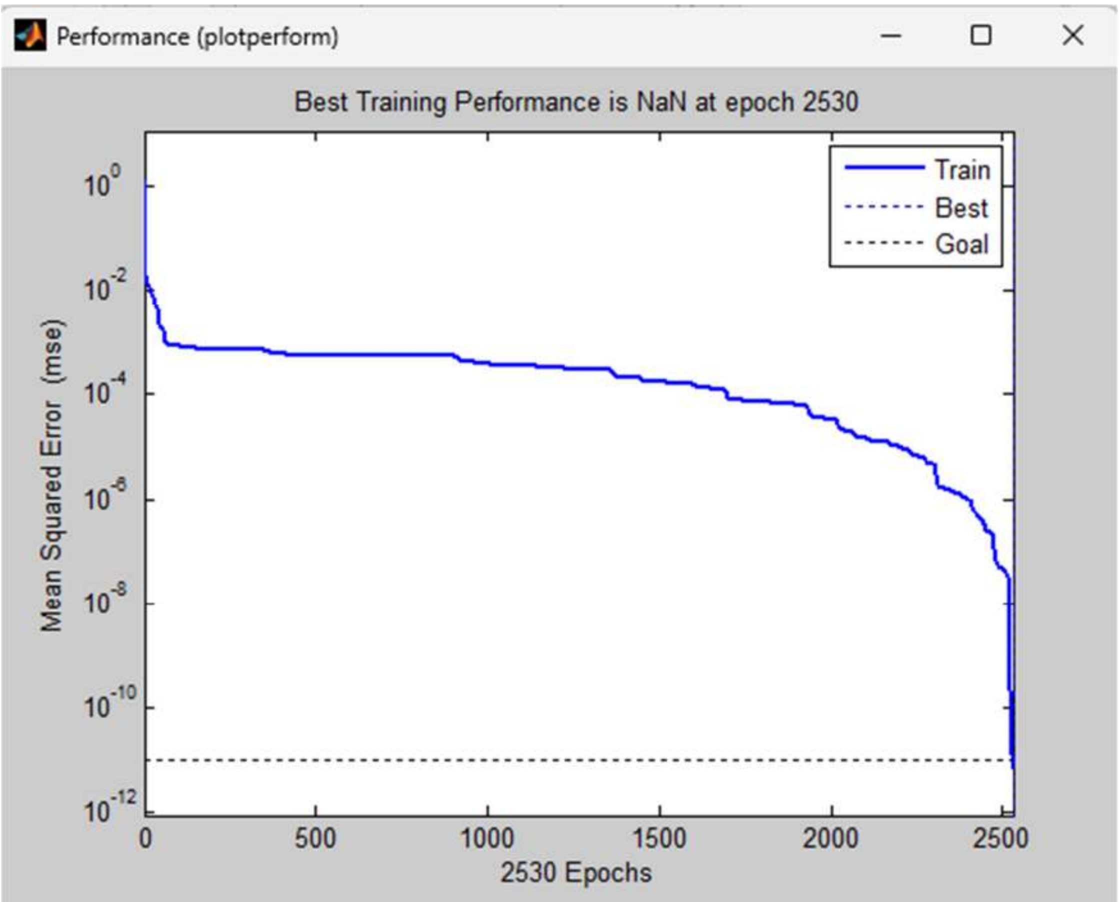

Fig. 3. Training performance

The outcome of the training data conducted is an empirical formula for predicting normal concrete compressive strength in accordance with the architecture of the ANN that has been constructed. From the modelling conducted, the equation obtained is as follows:

Table 1. The value of Z_{inj}

	$b_{i,j}$	$V_{i,j} \cdot X_1$	$V_{i,j} \cdot X_2$	$V_{i,j} \cdot X_3$	$V_{i,j} \cdot X_4$	$V_{i,j} \cdot X_5$
Z_{in1}	57.925	4.218	-30.094	-28.992	14.766	-15.871
Z_{in2}	-13.693	0.516	-11.216	17.782	14.668	-8.700

From the equation above we get an empirical formula like this:

$$Y = 3.002 + (-2.779) Z_1 + 1.034 Z_2 \tag{5}$$

The next step involves calculating the difference between the laboratory research results and the compressive strength calculated using the empirical formula derived from ANN modelling. The MAPE value for training is found to be 0.02%.

3.2 Results of ANN Testing Data

Following the previous ANN network modelling, the next step is the testing process using input data that is distinct from the training data. Data from the laboratory is compared with the compressive strength calculated using the empirical formula. Based on these results, the difference (error) between the compressive strength obtained from laboratory testing and the compressive strength from ANN modeling is calculated. The MAPE value for testing is found to be 1.54%.

3.3 Discussion

Based on the training performance graph in Fig. 2, it is evident that the best training occurred at epoch 2530, indicating that the best performance has been achieved. This suggests that the ANN modelling conducted is capable of recognizing patterns based on the learned input, output, and hidden layers.

The MAPE value obtained in the ANN modelling is 0.02%, signifying that the ANN has successfully assessed the relationship between input and output. Meanwhile, during the testing data process, the MAPE value obtained is 1.54%. Although the error value increases slightly, it remains very small. The variation in error values is due to the smaller amount of data input. A low MAPE value indicates that the prediction errors of the ANN model are minimal. Consequently, the empirical formula derived from the ANN modelling to predict normal concrete compressive strength can be used with a high level of accuracy.

4 Conclusion and recommendations

4.1 Conclusion

Based on the previous discussion, it can be concluded that the developed ANN modeling results can be effectively used as a method for predicting the compressive strength of normal concrete. This is evident from the low error values. The highest error value during the training process is 0.02%, while during the testing process, it is 1.54%. This indicates that the constructed ANN model exhibits a high level of accuracy with minimal errors. Therefore, the empirical formula obtained can be employed to predict normal concrete compressive strength with a high degree of precision.

4.2 Recommendations

Research on ANN modeling for concrete prediction can be further diversified by incorporating commonly used concrete additives. Additionally, the inclusion of local materials in concrete mix designs can also serve as input variations for future ANN modeling studies.

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