Prediction Model of Concrete Compressive Strength Using Artificial Neural Networks with Backpropagation Algorithm

Zhia Unnahar[1, a)], Agustinus Agus Setiawan[2, b)] and Rufman Iman Akbar E. [3, c)]

[1]*Student Civil Engineering Department, Universitas Pembangunan Jaya, Indonesia.*

[2]*Civil Engineering Department, Universitas Pembangunan Jaya, Indonesia.*

[3]*Information System Department, Universitas Pembangunan Jaya, Indonesia.*

[a)]*unnaharzhia@gmail.com*

[b)]*agustinus@upj.ac.id*

[c)] *rufman.iman@upj.ac.id*

Abstract. This research was conducted to determine the accuracy of the prediction of the artificial neural network on the compressive strength of normal concrete. This study employed the backpropagation algorithm as a form of network architecture to make a predictive model of the compressive strength of concrete. This study used 2 types of data: secondary data which is the composition of the normal concrete mixture as well as the results of the compressive strength of 28 days old concrete and the primary data which is the concrete mix design based on SNI 7656:2012 that had been tested in the laboratory to obtain the concrete compressive strength as validation data from secondary data. The results of this study indicate that the concrete compressive strength prediction model had a percentage of 86.10% for training data; while for data 1 to 3, it had a percentage of 85.77%, 86.77% and 80.76% respectively. Meanwhile, the MSE value generated by the prediction model was 0.0023, 0.0051 and 0.0106 and had a difference between the predicted data and the target data of 0.045, 0.064 and 0.096. In conclusion, the ANN model is quite accurate in predicting the compressive strength of concrete.

INTRODUCTION

The development of construction in Indonesia continues over time. Technological developments have become increasingly sophisticated so that the construction sector requires new breakthroughs. Construction in Indonesia is also developing AI-based technology into concrete mix design planning.

Concrete is a construction material produced from several mixtures such as coarse aggregate, fine aggregate, cement, and water. In addition, there are other additional materials for the purposes of concrete innovation with mixed proportions that have been taken into account in the manufacture of the mixed design. Testing of the compressive strength of concrete is generally conducted in the laboratory using a compression test device. The number of samples in the compressive strength test of concrete can reach tens or even hundreds of samples. This is intended to obtain valid concrete compressive strength data and it varies depending on the percentage of the weight of the concrete mixture specified in the concrete mix design. A large number of samples require a lot of cost, effort, and time. The factor that determines the yield of the concrete compressive strength is the composition of the concrete mixture. Concrete mix design can assist in the manufacture of concrete with the planned quality. However, in the process of work, of course, the results of the concrete compressive strength testing are not necessarily in accordance with the quality of the planned concrete. Thus, we need a method to predict the results of the 28-day concrete compressive strength so that the compressive strength test can be carried out efficiently and economically.

Artificial Neural Networks (ANN) has the ability to analyze multi-variables; it attracts a lot of attention in all fields, one of which is in the field of construction. Artificial neural networks were first introduced by McCulloch and Pitts in 1943 (Jong Jek Siang, 2005). But its development had stopped in the 1970s. Hope came back when the discovery of backpropagation with multiple layers of opening was created. People began to be interested in ANN because backpropagation had been proven to be successful in solving various applications that were difficult to complete before. Backpropagation consists of an input layer, a hidden layer, and an output layer. The hidden layer serves to set a predictive model for the concrete compressive strength of. The resulting model to predict the results of the concrete compressive strength generally requires validation by comparing the predicted results with the results of the plan for the compressive strength of concrete. The objectives of this thesis research are as follows:

- To design an appropriate artificial neural network architecture to predict the concrete compressive strength.

- To know the results of the backpropagation algorithm accuracy to train the designed artificial neural network.
- To know the comparison of the results of the backpropagation algorithm prediction data with the results of the concrete compressive strength planning.

LITERATURE REVIEW

Artificial neural network (ANN) is an information processing system that has similarities with biological neural networks in terms of characteristics. Based on the book written by Jong Jek Siang in 2005, it was explained that ANN was formed as a generalization of the mathematical model of biological neural networks. ANN is able to recognize a pattern from data that has existed before. The data will be studied by ANN by reading the pattern so that ANN has the ability to provide a decision result that has never existed; this is commonly called forecasting. ANN has many methods or algorithms that can be used in forecasting or prediction. The algorithm that is suitable and often used in predicting data is the backpropagation algorithm. Backpropagation algorithms can also be used to solve complex problems. This can happen due to the fatigue given to the network with this algorithm, namely by recognizing the input pattern of data that has a high level of accuracy. The backpropagation network has 3 layers, namely the input layer, the output layer, and the hidden layer. This network is known as an architectural network. In the backpropagation training process, there are 3 phases, namely the forward phase, backward phase, and the weight modification phase. In the forward phase, the input pattern is calculated forward from the input layer to the output layer. In the reverse phase, each output unit receives a pattern corresponding to the input pattern to calculate the error value. The calculated error will be propagated backwards. In the weight modification phase, it aims to reduce the occurrence of errors. All these phases will continue to be repeated until the desired condition is acquired.

The training makes the backpropagation network able to give the correct response to a given pattern; though the pattern is similar, it is not the same pattern. The training is carried out repeatedly so that the accuracy in a forecast is higher. Backpropagation has multiple units present in one or more hidden screens. Figure 2.1 is a backpropagation architecture with n inputs (plus a bias), a hidden layer consisting of p units (plus a bias), and m output units.

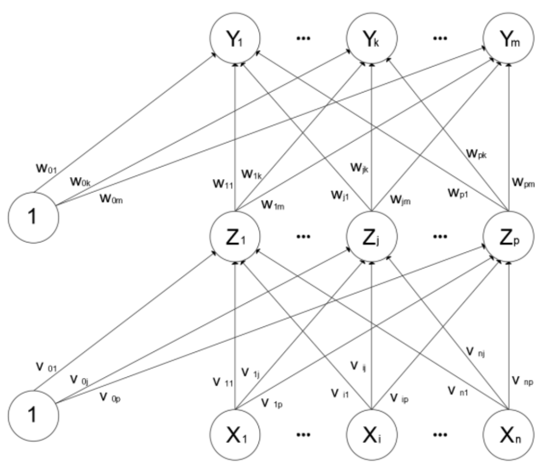


FIGURE 1. Network Architecture with One Hidden Layer

The activation function is one of the most important points in training an artificial neural network. The activation function is used to assist a system in recognizing a data pattern. The condition for the activation function for the backpropagation algorithm is that it is continuous, easily differentiated, and is not a non-deriving function. There are 3 functions that meet these requirements, namely the logsig, tansig, and purelin functions. The functions that are often used by most researchers are the logsig function and the tansig function.

- Logsig Function (0,1)

  The binary logsig or sigmoid function is a function that can read a data pattern in the form of numbers and has a number range from 0 to 1. This means that the data that can be read by this sigmoid function is data that has a value of 0 > x < 1. The following is a function binary sigmoid:

$$f(x) = \frac{1}{1+e^{-x}} \qquad (1)$$

with derivative

$$f'(x) = f(x)(1 - f(x)) \quad (2)$$

- Tansig function (-1,1)

  The tansig or bipolar sigmoid function is a function that works the same way as the binary sigmoid function, but the data pattern that it can read is different. The data pattern that can be read by the bipolar sigmoid function is -1 > x < 1. The following is a bipolar sigmoid function:

  $$f(x) = \frac{2}{1+e^{-x}} - 1 \quad (3)$$

  with derivative

  $$f'(x) = \frac{(1+f(x))(1-f(x))}{2} \quad (4)$$

The sigmoid function above has a data limit, so if there is data that has more numbers than the limit of the activation function, it is necessary to normalize the data. According to the book written by Jong Jek Siang, which discusses the steps for using an artificial neural network using the MATLAB application, a formula is needed to help the process of normalizing data into the range of a function used. To do this, a linear transformation is used so that the data is in the interval [0.1,0.9] for binary sigmoid. The linear transformation used is:

$$x' = \frac{0.8(x-b)}{a-b} + 0.1 \quad (5)$$

There are several problems encountered when making the backpropagation architecture such as the length of time iterations carried out and the unknown number of epochs used to achieve the goals. Therefore, there are several things that need to be considered in optimizing the backpropagation architecture.

- Selection of Weights and Initial Bias

  The initial weight will affect a network such as its convergence speed and determination of whether the network reaches a local minimum point or a global minimum point. The value on the weights should not be too small and should not be too large because it will cause the result of the derivative value of the function to be very small. There is a way of determining the weights proposed by Nguyen and Widrow in 1990 which is by initializing the weights and biases to hidden units.
- Number of Hidden Units

  The theoretical results show that the hidden layer of backpropagation is good enough to recognize data and its relationship from the input data to the target data. However, increasing the number of hidden layers can also facilitate the training of the backpropagation network. If a network has two or more hidden layers, there are things that must be revised. For example, in forward propagation, the output data needs to be calculated for each layer starting from the hidden layer from the bottom.
- Number of Training Patterns

  The number of patterns has no certainty in making a network perfect. The number of patterns required is influenced by the number of weights in a network and the expected level of accuracy. This can be formulated as follows:

  Number of patterns = number of weights / level of accuracy
- Iteration Time

  The use of the backpropagation algorithm has the main goal of getting a balance between correct training pattern recognition and a good response to similar but different patterns. A network can be trained continuously until all patterns can be recognized, but such a thing does not guarantee the ability to recognize the test pattern correctly. If in training all errors have decreased in every 10 epochs, the training can continue. On the other hand, if the error increases, the training does not need to be continued.

RESEARCH METHODOLOGY

The research object in this thesis is data on the composition of normal concrete mixtures and the results of the compressive strength of 28 days old concrete. The data used by the researcher was obtained from studies that had been done by other researchers. After the data had been obtained, the data was recapitulated through the Ms. Excel software. Then, the data was analyzed using SPSS 24 software and used as training data to be entered into the MATLAB R2017a software.

The variables used to conduct this research were the compressive strength of 28 days old concrete and the composition of the concrete mixture, such as the composition of coarse aggregate, fine aggregate, water, and cement. These variables were divided into 2 types: the dependent variable (Y) which includes the results of the compressive strength of 28 days old concrete and the independent variable (X) which includes cement (x_1), water (x_2), coarse aggregate (x_3), fine aggregate (x_4) and water cement ratio (x_5). There were 2 ways of collecting data, namely primary data collection and secondary data collection.

- Secondary Data

  Secondary data collection was done by looking for data from studies that had been done by other researchers and had been published on the internet which can be accessed in general. The data was collected in the form of data on the concrete compressive strength and the composition of the concrete mixture; each of which consists of 50 data.
- Primary Data

  Primary data collection was conducted by taking data from the concrete mix design and conducting a 28-day test of cylindrical specimens made in the laboratory of Pembangunan Jaya University. The data was used for validation of the predictive model of concrete compressive strength using secondary data as the processing data.

Data Processing

Data processing was carried out using SPSS Version 25 software to test variations on the data, Ms. Excel software to perform normalization tests on data, and MATLAB R2017a software to build architectural networks with backpropagation algorithms.

- Data Normalization

  Data normalization was used to convert the data into data that has a range of 0.1 - 0.9. This data processing was needed so that the data could be read by the binary sigmoid function when testing the data with the backpropagation algorithm. Data normalization was done through Ms. Excel. The following are the steps in normalizing the data:

  1. Ms. Excel was opened and the data was prepared to be normalized.
  2. The maximum and minimum data in each of the existing data variables were set.
  3. A new table was created and formula 2.3 was entered into the newly created table, where x was the data from the table to be processed, symbol a was the maximum data, and symbol b was the minimum data.
  4. The procedure was repeated throughout the data with the same formula.
  5. After completion, all data were turned into data with a range of 0.1 - 0.9 and ready for network training.
- Network Architecture Creation

  This stage was the stage of forming a network architecture using the normalized training data. The network architecture creation process coincided with the AI training process. The following are the stages in establishing a backpropagation network architecture using the MATLAB application version R2017a:

  1. In MATLAB application, a new file was created by right-clicking in the workspace window and training data was inputted by clicking new. The file naming format was: Data_Latih, Target_Latih, and Data_Uji. It was saved as dot mat (.mat) format. In naming files, using spaces was avoided so that the file was not read as a programming language.

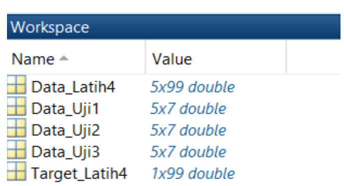
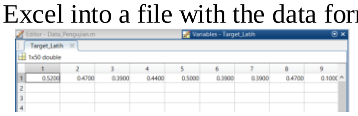


FIGURE 2. Workspace Window Display

  2. The training data was entered into the file that had been created by double-clicking on the file. After that, the data was pasted from Ms. Excel into a file with the data format already transposed.



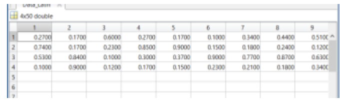


FIGURE 3. Data Entry into Workspace Files

3. In the command window, the command nntool was typed then entered.
4. After that, the Neural Network/Data Manager (nntool) window would appear. In the nntool window, there were many columns used to create the backpropagation network architecture.
5. The training data was entered, namely Data_Latih and Data_Uji into the Input Data column by clicking Import.
6. Same as the third method, Target_Latih, which was the result of the 28-day concrete compressive strength test, was inputted into the Target Data column.
7. After that, a network architecture in the Networks column was created by clicking new.
8. The network name was changed, then the type of feed-forward backpropagation algorithm was selected.
9. In the Training Function option, TRAINGD was selected. In the Adaptation Learning Function option, LEARNGD was selected. In the Performance Function option, MSE was selected.
10. In Number of Layers, the layers were selected according to the needs of the researcher. This option served to determine the number of the desired layers to use on the network architecture.
11. In Properties, Layer 1 was selected. The number of neurons was entered according to the required variable or layer.
12. After that, on Transfer Function, LOGSIG was selected. For this option, the following functions would be used. The researcher used the binary sigmoid function and therefore used LOGSIG. Then Create was selected to form the network architecture.

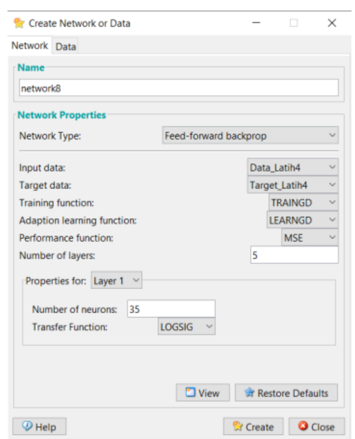


FIGURE 4. Making Backpropagation Network Architecture

13. The results of the network architecture that had been created were viewed by double left-clicking on the network, then train was selected to start training.
14. After that, a new window would appear containing the results of the training that had been carried out by ANN. In addition, there were also reports in the form of regressions that occurred as well as the results of compressive strength prediction data.

Research Flowchart

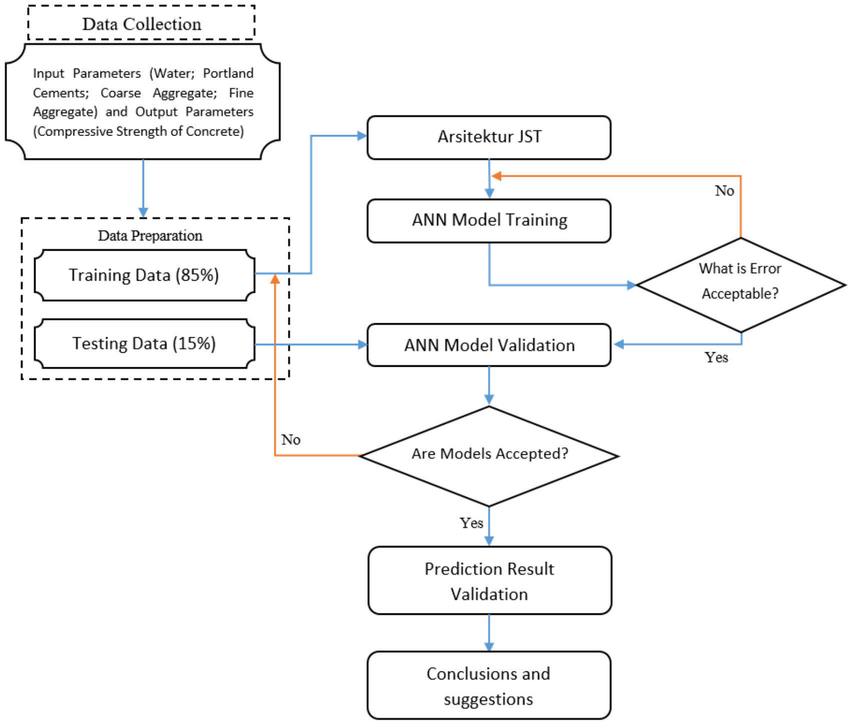


FIGURE 5. Research Flowchart

RESULT AND ANALYSIS

This sub-chapter contains the presentation of data used by researchers to conduct research on making predictive models of concrete compressive strength. The data is the composition of normal concrete mix or normal concrete mix design and data on the compressive strength of 28 days old concrete. The data in this study was divided into 2: primary data which was obtained from the manufacture of mix designs as well as the results of the 28-day concrete compressive strength test in the Laboratory of Pembangunan Jaya University and secondary data which was obtained from several journals on the internet as well as preliminary thesis reports.

TABLE 1. Primary Data - Proportion of normal concrete mix

No	Concrete Mix Proportion 1 m^3				
	Water (L)	Cement (kg)	Coarse (Kg)	Fine (Kg)	Rasio W/C
1	199	1,027.620	509.187	574.190	0.194
2	190	311.475	1142.985	700.539	0.610
3	199	326.229	1017.319	767.451	0.610
4	199	326.229	945.928	838.842	0.610
5	216.75	355.328	921.099	816.823	0.610
6	216.75	355.328	921.099	816.823	0.610
7	216.75	355.328	921.099	816.823	0.610

TABLE 2. Primary Data - Proportion of normal concrete mix

No	Concrete Mix Proportion 1 m³					Strength	No	Concrete Mix Proportion 1 m³					Strength
	Water (L)	Cement (kg)	Coarse (Kg)	Fine (Kg)	Rasio W/C	Day 28 (Mpa)		Water (L)	Cement (kg)	Coarse (Kg)	Fine (Kg)	Rasio W/C	Day 28 (Mpa)
1	181.00	934.67	893.09	401.24	0.19	29.40	51	198.75	375.00	1,143.75	592.50	0.53	36.84
2	166.00	307.00	1,222.00	1,947.60	0.54	26.97	52	200.00	400.00	1,128.00	572.00	0.50	43.13
3	228.00	373.77	437.31	437.31	0.61	22.45	53	212.00	400.00	1,196.00	616.00	0.53	38.58
4	181.00	1,055.83	645.24	527.93	0.17	25.10	54	199.75	425.00	1,096.50	544.00	0.47	47.16
5	166.00	1,111.95	729.33	504.92	0.15	28.60	55	208.25	425.00	1,177.25	590.75	0.49	45.05
6	155.62	283.00	1,288.00	653.60	0.55	22.50	56	198.00	450.00	1,057.50	513.00	0.44	49.63
7	190.00	316.67	1,152.68	620.67	0.60	22.55	57	211.50	450.00	1,143.00	562.50	0.47	47.42
8	205.00	383.18	1,257.06	564.76	0.53	26.68	58	199.50	475.00	1,040.25	498.75	0.42	54.01
9	215.00	247.00	999.00	869.00	0.87	7.40	59	209.00	475.00	1,168.50	565.25	0.44	50.05
10	215.00	276.00	1,012.00	828.00	0.78	9.80	60	198.75	375.00	1,143.75	592.50	0.53	37.81
11	215.00	299.00	1,017.00	799.00	0.72	12.20	61	200.00	400.00	1,128.00	572.00	0.50	44.11
12	215.00	326.00	1,029.00	760.00	0.66	14.50	62	212.00	400.00	1,196.00	616.00	0.53	40.90
13	215.00	352.00	1,031.00	731.00	0.61	16.90	63	199.75	425.00	1,096.50	544.00	0.47	47.51
14	215.00	371.00	1,047.00	698.00	0.58	19.30	64	208.25	425.00	1,177.25	590.75	0.49	45.30
15	215.00	384.00	1,039.00	692.00	0.56	21.70	65	216.75	425.00	1,253.75	641.75	0.51	42.54
16	215.00	406.00	1,026.00	684.00	0.53	24.00	66	198.00	450.00	1,057.50	513.00	0.44	52.03
17	215.00	413.00	1,021.00	681.00	0.52	26.40	67	211.50	450.00	1,143.00	562.50	0.47	48.74
18	215.00	439.00	1,006.00	670.00	0.49	28.80	68	220.50	450.00	1,228.50	616.50	0.49	46.59
19	215.00	448.00	1,000.00	667.00	0.48	31.20	69	199.50	475.00	1,040.25	498.75	0.42	54.49
20	255.71	390.00	1,031.95	629.72	0.66	26.06	70	209.00	475.00	1,168.50	565.25	0.44	53.06
21	210.00	390.00	1,039.50	696.00	0.54	26.24	71	218.50	475.00	1,192.25	584.25	0.46	49.18
22	192.62	428.04	1,084.07	676.24	0.45	33.34	72	221.00	425.00	858.50	607.75	0.52	40.02
23	192.62	385.23	1,084.07	719.04	0.50	30.73	73	220.50	450.00	837.55	580.50	0.49	45.25
24	192.62	350.21	1,084.07	754.07	0.55	23.75	74	229.50	450.00	855.00	175.95	0.51	42.68
25	156.25	438.00	1,237.00	519.18	0.36	31.09	75	218.50	475.00	817.00	555.75	0.46	48.67
26	214.90	358.17	1,014.23	792.88	0.60	18.12	76	228.00	475.00	869.25	598.50	0.48	45.52
27	214.90	390.73	1,020.26	754.11	0.55	23.78	77	178.50	350.00	1,141.00	486.50	0.51	39.52
28	214.90	429.80	1,006.47	728.83	0.50	27.84	78	189.00	350.00	1,197.00	521.50	0.54	31.66
29	194.90	324.83	1,150.21	720.05	0.60	17.17	79	180.00	375.00	1,121.25	468.75	0.48	42.73
30	194.90	354.36	1,141.26	699.48	0.55	22.46	80	191.25	375.00	1,196.25	506.25	0.51	40.69
31	194.90	389.80	1,146.37	658.94	0.50	27.08	81	180.00	400.00	1,080.00	440.00	0.45	47.99
32	205.00	259.49	1,010.00	870.51	0.79	16.70	82	192.00	400.00	1,168.00	484.00	0.48	44.89
33	205.00	297.10	1,010.00	832.90	0.69	21.42	83	178.50	425.00	1,049.75	416.50	0.42	51.25
34	205.00	336.07	1,010.00	793.93	0.61	26.14	84	191.25	425.00	1,139.00	463.25	0.45	49.05
35	181.00	229.11	1,204.94	794.95	0.79	15.15	85	189.00	450.00	1,102.50	441.00	0.42	53.69
36	181.00	262.32	1,204.94	761.74	0.69	20.95	86	189.00	350.00	1,197.00	521.50	0.54	36.64
37	181.00	296.72	1,204.94	727.34	0.61	25.76	87	191.25	375.00	1,196.25	506.25	0.51	41.57
38	203.00	388.00	848.00	735.00	0.52	26.23	88	192.00	400.00	1,168.00	484.00	0.48	46.22
39	205.00	861.35	870.23	488.17	0.24	49.34	89	191.25	425.00	1,139.00	463.25	0.45	50.35
40	186.76	358.26	1,017.82	832.76	0.52	20.95	90	189.00	450.00	1,102.50	441.00	0.42	54.11
41	272.14	429.79	1,285.60	758.22	0.63	39.20	91	198.75	375.00	903.75	551.25	0.53	37.30
42	225.00	459.18	993.50	662.32	0.49	30.02	92	200.00	400.00	884.00	528.00	0.50	44.04
43	202.91	408.16	1,124.33	664.59	0.50	26.09	93	212.00	400.00	944.00	576.00	0.53	39.61
44	225.00	460.00	987.00	658.00	0.49	25.00	94	199.75	425.00	862.75	505.75	0.47	47.37
45	225.00	500.00	906.54	656.46	0.45	38.00	95	208.25	425.00	926.50	548.25	0.49	44.69
46	260.44	528.43	1,132.34	749.23	0.49	22.25	96	198.00	450.00	837.00	481.50	0.44	50.93
47	210.00	500.00	1,259.50	1,030.50	0.42	15.45	97	211.50	450.00	900.00	526.50	0.47	48.08
48	160.04	455.20	1,111.02	619.96	0.35	30.01	98	199.50	475.00	798.00	451.25	0.42	54.14
49	194.23	379.63	1,161.37	614.78	0.51	15.22	99	209.00	475.00	874.00	503.50	0.44	51.31
50	167.44	372.10	1,116.28	744.18	0.45	16.52							

Data Analysis

This sub-chapter contains data analysis with the help of MATLAB R2017a to predict the concrete compressive strength with the backpropagation algorithm.

1. Training Process

   Epochs was used to determine the number of training steps in a backpropagation neural network, where min_grad or gradient descent was the maximum gradient performance, max_fail was the maximum value of failure validation, and lr was the learning rate which functions to control the algorithm parameters used to train the network. The training parameters used were epochs of 1000, min_grad of 1e-05, max_fail of 6, and lr of 0.5, as shown in Figure 2 above. After the parameters were formed, the training process could be run.

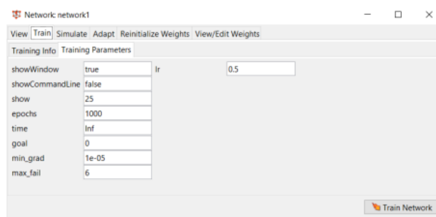


FIGURE 6. Network Training Parameters

The neural network training would stop when the validation check or max_fail reached a value of 6 and the epochs reached a value of 1000, as shown in Figure 7. In the plot window, there were performance, training state, and regression.

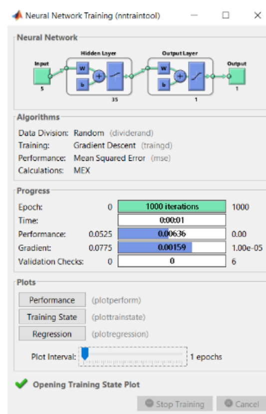
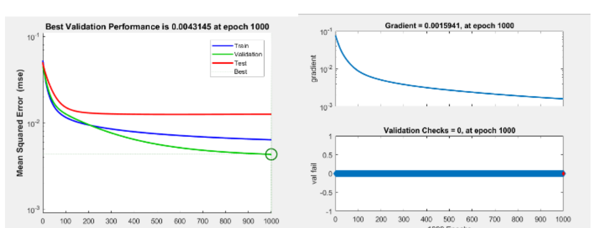


FIGURE 7. Network Training Process

Based on Figure 8, it can be concluded that the performance value in training reached 0.0097125 out of 1000 epochs. Mean Squared Error (MSE) in training was close to zero, training was assumed to have good predictive accuracy. Figure 8 shows that the largest training state gradient was 0.0022534 at 1000 epochs. Figure 8 shows that the data or fit line being trained was quite good because it is close to the dotted line Y=T.



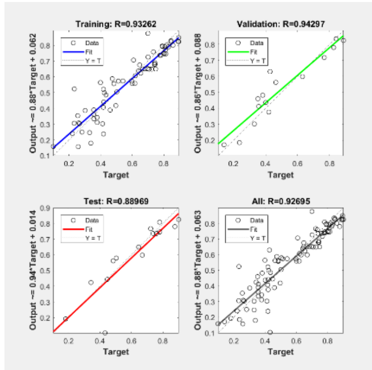


FIGURE 8. Network Training Result

2. Results of Backpropagation Network Architecture Design. The equation and equation number were manually inserted.

TABLE 3. Comparison of Network Architecture Types

Types	Layers	Learning Rate	Gradient	Epochs	Max Fail	Performance	Percentage (%)
1	1	0.5	0.001767	1000	0	0.0072556	78.26
2	5	0.5	0.002253	1000	0	0.0097125	84.08
3	10	0.5	0.003348	1000	0	0.0141520	80.68
4	15	0.5	0.001084	1000	0	0.0199990	82.00
5	20	0.5	0.001827	1000	0	0.0061015	83.91
6	25	0.5	0.002187	1000	0	0.0165870	81.55
7	30	0.5	0.004816	6	6	0.0042418	82.29
8	35	0.5	0.001594	1000	0	0.0043145	86.10
9	40	0.5	0.100940	130	6	0.0248890	78.02
10	45	0.5	0.002524	1000	0	0.0274670	81.08

Based on Table 3 above, it can be seen that the type of network architecture with the best percentage of accuracy was the 8th network architecture type with network specifications of having 35 hidden layers, 0.5 learning rate, 0.001594 gradient, reaching 1000 epochs, 0 max fail, and having a performance of 0.0043145 with the largest percentage of 86.10%.

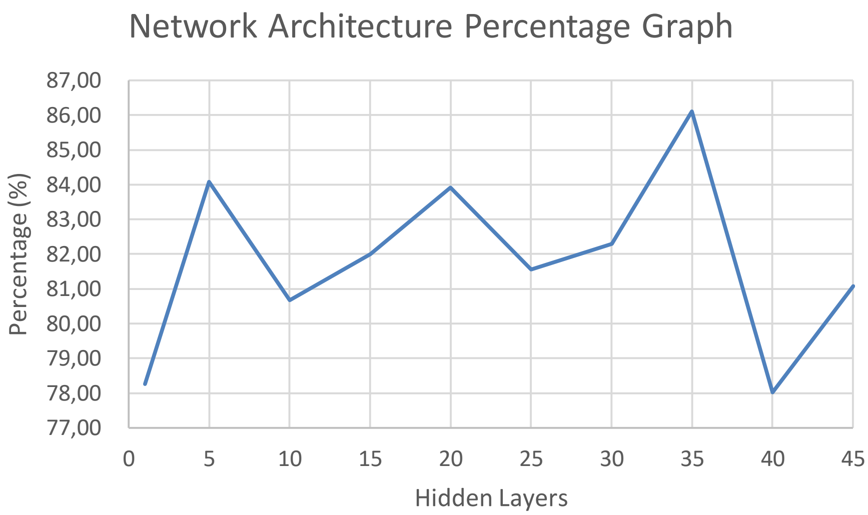


FIGURE 9. Network Architecture Percentage Graph

Based on Figure 9, the comparison graph of network architecture types experiences an unstable percentage change from each type of network architecture designed. It can be seen that the best network architecture design performance had 35 hidden layers with a percentage of 86.10%. From the results of the study, it can be said that the design of an artificial neural network architecture that is suitable for predicting the concrete compressive strength with high predictive accuracy has the following network architecture design parameters:

- Using the feed-forward backprop network type.
- Using 5 normal layers with 35 hidden layers.
- Using the LOGSIG activation function.
- Using the TRAINGD training function.
- Using the LEARNGD adaptation learning function.
- Using MSE performance.

The network architecture training parameters are as follows:

- Epochs in this study were arranged for 1000 times of training.
- The minimum gradient used was 1e-05.
- Maximum fail set was 6 times.
- The learning rate used was 0.5.
- Other settings were default.

3. Data on Artificial Neural Network Training Results

The training results on the training data got an average presentation of 86.10% out of 99 training data. After the network reached a pretty good percentage, it could proceed to the test data validation stage.

4. Simulation Results of Test Data on the Backpropagation Model

The simulation results for test data 1 had a predicted average compressive strength of 17.37 Mpa. Test data 1 was 100% data from data outside of training. The results of the simulation of test data 2 had an average predicted concrete compressive strength of 29,586 MPa. Test data 2 was mixed data: 50% training data and 50% data outside of training. The results of the simulation of test data 3 had an average predicted compressive strength of 38,414 MPa of concrete. Test data 3 was 100% from training data.

Backpropagation Model Validation

Validation of the backpropagation model was done by comparing the simulation results of the predicted compressive strength with the planned compressive strength which was the result of the MATLAB calculations. The calculation of the percentage can be expressed by the following formula:

$$Presentase = \frac{f'c\ Prediksi}{f'c\ Rencana} x\ 100\% \quad (6)$$

To transfer Logsig data into normal data, the following formula is needed:

$$X = \frac{(X' - 0.1)\ x\ (Data\ Max - Data\ Min)}{0.8} + Data\ Min \quad (7)$$

TABLE 4. Prediction Comparison with f'c Data Plan 1

No	f'c Predict (Logsig)	f'c Design (Logsig)	Error Data	Percentage (%)
1	0.236	0.314	0.078	75.104
2	0.290	0.314	0.024	92.301
3	0.279	0.314	0.035	88.764
4	0.252	0.314	0.062	80.300
5	0.276	0.314	0.038	87.965
6	0.276	0.314	0.038	87.965
7	0.276	0.314	0.038	87.965
Average			0.045	85.766

Based on Table 4, it is known that the artificial neural network could predict the concrete compressive strength with an average percentage of 85.766% and had an average data error of 0.045.

TABLE 5. Prediction Comparison with f'c Data Plan 2

No	f'c Predict (Logsig)	f'c Target (Logsig)	Error Data	Percentage (%)
1	0.236	0.314	0.078	75.104
2	0.290	0.314	0.024	92.301
3	0.279	0.314	0.035	88.764
4	0.252	0.314	0.062	80.300
5	0.742	0.791	0.049	93.854
6	0.766	0.894	0.128	85.732
7	0.773	0.846	0.073	91.339
Average			0.064	86.771

Based on Table 5, it is known that the artificial neural network could predict the concrete compressive strength with an average percentage of 86.771% and had an average data error of 0.064.

TABLE 6. Prediction Comparison with f'c Data Plan 3

No	f'c Predict (Logisg)	f'c Target (Logsig)	Error	Percentage (%)
1	0.424	0.255	0.169	33.771
2	0.530	0.600	0.070	88.353
3	0.621	0.707	0.086	87.770
4	0.532	0.630	0.098	84.488
5	0.742	0.791	0.049	93.854
6	0.766	0.894	0.128	85.732
7	0.773	0.846	0.073	91.339
Average			0.096	80.758

Based on Table 6, it is known that the artificial neural network could predict the concrete compressive strength with an average percentage of 80.758% and had an average data error of 0.096.

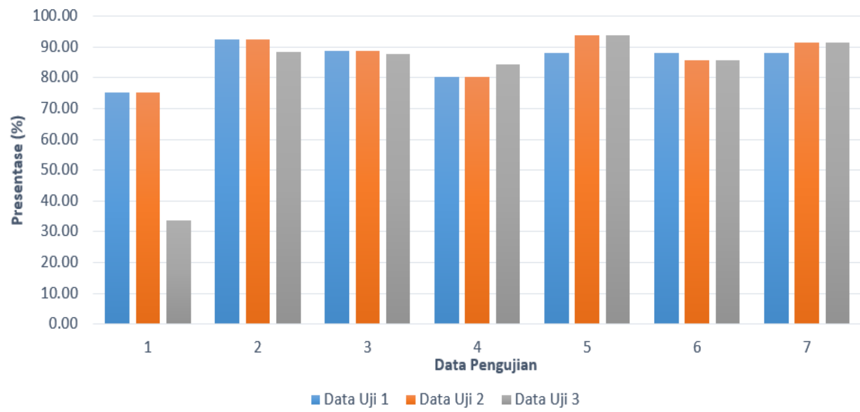


FIGURE 10. Diagram of the Results othehe Predictiothef the Compressive Strength of Concrete

The accuracy of the assessment can also be measured by the Mean Square Error (MSE) method. MSE can be calculated using formula 4.3 as follows:

$$\text{MSE} = \frac{\sum_{t=1}^{n}(At-Ft)^2}{n} \qquad (8)$$

Note:
At = Request Factual'Value (f'c Plan)
Ft = Forecasting Result'Value (f'c Prediction)
n = Lots of Data

TABLE 7. MSE Calculation Data 1

No	f'$_c$ Design (Logsig)	f'$_c$ Predict (Logsig)	Error Data	Error Square
t	–t	Ft	At – Ft	(At - Ft)2
1	0.314	0.236	0.078	0.0061
2	0.314	0.290	0.024	0.0006
3	0.314	0.279	0.035	0.0012
4	0.314	0.252	0.062	0.0038
5	0.314	0.276	0.038	0.0014
6	0.314	0.276	0.038	0.0014
7	0.314	0.276	0.038	0.0014
Total				0.016
MSE				0.0023

TABLE 8. MSE Calculation Data 2

No	f'$_c$ Design (Logsig)	f'$_c$ Predict (Logsig)	Error Data	Error Square
t	–t	Ft	At – Ft	(At - Ft)2
1	0.314	0.236	0.078	0.0061
2	0.314	0.290	0.024	0.0006
3	0.314	0.279	0.035	0.0012
4	0.314	0.252	0.062	0.0038
5	0.791	0.742	0.049	0.0024
6	0.894	0.766	0.128	0.0163
7	0.846	0.773	0.073	0.0054
Total				0.036
MSE				0.0051

TABLE 8. MSE Calculation Data 3

No	f'c Design (Logsig)	f'c Predict (Logsig)	Error Data	Error Square
t	–t	Ft	At – Ft	(At - Ft)2
1	0.255	0.424	0.169	0.0285
2	0.600	0.530	0.070	0.0049
3	0.707	0.621	0.086	0.0075
4	0.630	0.532	0.098	0.0095
5	0.791	0.742	0.049	0.0024
6	0.894	0.766	0.128	0.0163
7	0.846	0.773	0.073	0.0054
Total				0.074
MSE				0.0106

Based on Table 6, Table 7, and Table 8, the MSE values in the three tables sequentially were 0.0023, 0.0051, and 0.0106. The MSE values ranged from 0. The closer the MSE value is to 0, the more accurate the prediction results are. It can be said that the three data have good accuracy in predicting the concrete compressive strength. In Figure 11, the MSE values in the three data were 0.0023, 0.0051, and 0.0106.

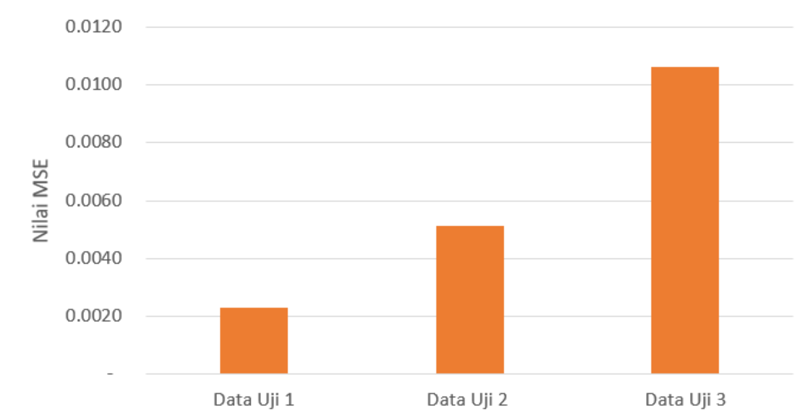


FIGURE 11. Diagram of MSE Calculation Result

CONCLUSION

Based on the results of the research and discussion, it can be concluded that:

a. There are several parameters that need to be considered in the design of the artificial neural network architecture: using the feed-forward backpropagation network type, using the TRAINGD training function, using the LEARNGD adaptation learning function, using the MSE performance function, using 5 normal layers with 35 hidden layers, and using the LOGSIG activation function. The training parameters that must be considered are epochs number of 1000, a minimum gradient of 1e-05, a maximum file of 6, and a learning rate of 0.5.

b. The accuracy of the concrete compressive strength prediction model with the backpropagation algorithm can be seen from the obtained MSE value. The MSE values in test data 1 to test data 3 had the values of 0.0023, 0.0051, and 0.0106. It can be said that the prediction model designed already has a fairly good accuracy because the MSE value of the three data is close to 0.

c. The comparison of the results of the prediction of the concrete compressive strength with the design data of the concrete compressive strength based on SNI 7656:2012 can be seen from the results of the average data error and the average percentage. The results of data errors from data 1 to data 3 were 0.045, 0.064, and 0.096. The percentages of the three data obtained were 85.77%, 86.77% and 80.76%.

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