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# Prediction of Electricity Usage with Back-propagation Neural Network

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*Abstract*— **The use of electricity has become a need that is increasing day by day. So it is not surprising that the problem of using electricity has attracted the attention of many researchers to research it. Electricity users make various efforts and ways to save on the use of electrical energy. One of them is saving electricity usage by electricity users using electrical energy-efficient equipment. That is why the previous research confirms the need for interventions to reduce the use of electrical energy. Therefore, this study aims to predict electricity use and measure the performance of the anticipated results of electricity use. This study uses the back-propagation method in predicting the use of electricity. This study concluded that the backpropagation architectural model with better performance is the six hidden layer architecture, 0.4 learning rate, and the Root Means Square Error (RMSE) value of 0.203424. Meanwhile, the training data test results get the best architectural model on hidden layer 8 with a learning rate of 0.3 with an RMSE performance value of 0.035811. The prediction results show that the prediction of electricity consumption is close to the actual data of actual electricity consumption.**

*Keywords* : **Back-propagation Neural Network, Electricity Usage, MSE and RMSE.**

## I. INTRODUCTION

Currently, the use of electricity and economic development has become the attention of many people for research [1]. Electricity has become a vital component in daily work and other needs [2][3]. The higher the country's economy, the greater the use of electricity that occurs, meaning that there is a robust relationship between economic progress and electricity use [1]. In other words, the human need for electricity has affected electricity consumption, increasing day by day, especially for users who have a better economic level.

The use of electricity occupies a major position in all households [4]. The use of electricity in the home occurs from the use of electrical equipment for lighting purposes as well as for electrical equipment to work according to its function [4]. Various efforts and ways to save the use of electrical energy have been carried out, even reaching electricity consumption which is also a concern [5]. Generally, consumers in achieving the efficiency of electricity use reduce the use of electrical energy [6]. Consumers' efficient use of electrical power also uses energyefficient equipment [7]. Previous research confirms a need for intervention to reduce the use of electrical energy [8]. Therefore, this research aims to predict the use of electricity using the backpropagation neural network method; as an intervention model, people can predict electricity use and at least inspire people to save electricity consumption by knowing the prediction of electricity consumption.

The artificial neural network consists of several nodes, which is a model that imitates the work of the human brain [9][10]. Back-propagation or multilayer perceptron is one of the artificial neural networks, besides perceptron, radial basis network, and others. Back-propagation artificial neural network is a supervised learning algorithm [3]. Backpropagation is a large family of artificial neural networks that have various architectural variations between layers and the number of nodes in the layer [11]. In back-propagation, it starts randomly initializing the initial weight. Then, there was a change in weights according to the training data. The training is finished until a specific iteration limit or the weight change process is stopped and produces the desired predictive output. At this point, the predictive model is defined. Review results from several related works:

1. Lai Mei Yan and Hong Choon Ong (2000) modeled the prediction of electricity usage using back-propagation [12]. However, this previous study only made a predictive model of electricity use, in contrast to the analysis in this article which was appointed not only to model the prediction of electricity use but also to predict electricity use.
2. Nnamdi I. Nwulu and O. Phillips Agboola (2012) models patterns of electricity use. This previous research and the research in this article both use the back-propagation method [13]. The difference is that previous studies designed an efficient electricity consumption model, while this study designed an electricity consumption model and created an intelligent application to determine electricity consumption.

3. Nidhi Tewathia (2014) explored the average monthly electricity use of the household and changes in electricity consumption with changing seasons [4]. This previous research is survey research. In contrast to the research in this article, it does not examine monthly household electricity consumption and changes in electricity consumption in different seasons. Instead, it builds an artificial neural network system model and intelligent application of big annual data. Besides that, another difference is that the research in this article does not use the survey method but uses the back-propagation neural network method.
4. Yu-Rong Zeng, Yi Zeng, Beomjin Choi, Lin Wang (2017) examined the combination of adaptive differential evolution and back-propagation neural network methods to create a more efficient prediction model [3]. On the other hand, the article in this study makes models and applications with three input layers and four neurons that are useful for predicting electricity consumption according to the number of input layers.
5. Anthony Anggrawan, Satuang, and Mokhammad Nurkholis Abdillah (2020) built an expert system for diagnosing diseases in chickens [14]. Previous research with the research in this article is both intelligent building applications. The difference is that the previous research builds innovative applications using forward chaining and certainty factor methods, while this article makes innovative applications using back-propagation neural networks.
6. Yunqin Lu, Weijun Gao, Soichiro Kuroki, and Jian Ge (2021) revealed the factors that influence the consumption of household electricity using the survey method [15]. However, in contrast to the study in this article, it is not a survey method but a study predicting the use of electricity by using a back-propagation artificial neural network.
7. Anthony Anggrawan, Christofer Satria, Che Ku Nuraini, Lusiana, Ni Gusti Ayu Dasriani, and Mayadi (2021) built an intelligent application system to predict the use of drugs and the types of drugs used [16]. On the other hand, the article in this study builds an intelligent application system to predict electricity usage. Another difference between the previous research and the research in this article is the method and programming language used in realizing the developed application system. For example, previous studies used the PHP programming language to build applications the Forward Chaining method and the Certainty Factor method to predict users and types of drugs. In contrast, the research in this article uses the Python programming language in building applications and uses the backpropagation method to predict electricity usage.

A review of several previous related works shows that this research is not the same as the previous research. So, in other words, this research has the novelty of the research results obtained. The structure of this manuscript is as follows: the second subsection discusses the background of this study, including the differences between this study and previous studies. The third subsection discusses the methodology of this research. The fourth subsection describes the artificial neural network model and includes everything related to the prediction of electricity consumption. Meanwhile, the fifth subsection describes the conclusion of the study's results, including suggestions for future research.

## II. MATERIALS AND METHODS

This study is a case study of electricity consumption data in the Mataram, Sumbawa, and Bima areas of West Nusa Tenggara. Furthermore, the data is processed using a back-propagation neural network which consists of several input layers, hidden layers, and output layers. This study used programming language in building back-propagation data processing of electricity consumption. There are many kinds of computer programming languages [17]. The programming language used in this research is Python.

### A. Data Collection

The electricity consumption data collected in this study is from 2008 to 2018 obtained from the Central Statistics Agency of West Nusa Tenggara Province. The electricity usage data collected is 132 data from the three areas of Mataram, Sumbawa, and Bima (as shown in Table 1).

Table 1. Electricity Consumption Data

| | Date | Mataram | Sumbawa | Bima |
|---|---|---|---|---|
| 1. | 2008-01 | 34.470.807 | 8.018.871 | 7.791.608 |
| 2. | 2008-02 | 35.267.524 | 7.718.016 | 7.687.715 |
| 3. | 2008-03 | 33.460.716 | 7.642.508 | 7.649.522 |
| 4. | 2008-04 | 34.670.014 | 7.357.594 | 7.310.157 |
| 5. | 2008-05 | 35.002.854 | 7.992.551 | 7.716.816 |
| 6. | 2008-06 | 36.170.553 | 8.004.306 | 7.755.221 |
| 7. | 2008-07 | 35.732.219 | 8.343.908 | 7.851.373 |

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| | | | | |
|---|---|---|---|---|
| 8. | 2008-08 | 35.332.363 | 8.125.042 | 7.574.326 |
| 9. | 2008-09 | 36.691.297 | 8.565.646 | 7.914.139 |
| 10. | 2008-10 | 38.906.903 | 8.724.551 | 8.468.444 |
| 11. | 2008-11 | 35.672.846 | 9.072.941 | 8.370.307 |
| 12. | 2008-12 | 37.395.469 | 8.810.725 | 8.536.249 |
| ….. | ………. | …………. | ………… | ………… |
| 108 | 2017-01 | 97.211.767 | 17.969.839 | 18.850.181 |
| 109 | 2017-01 | 184.178.540 | 33.666.263 | 37.255.104 |
| …. | ……… | …………… | …………. | …………. |
| 132. | 2018-12 | 114.335.265 | 24.629.310 | 22.772.095 |

## B. Model Development

Things that are done in realizing the back-propagation neural network model in this research are the determination of training data, test data, number of layers, number of input layers, number of hidden layers, and number of output layers.

### 1) Training Data

Training data is a reference in knowing patterns in predicting by training a predetermined back-propagation neural network model. The training data used in this study was 80% of the total research data. The training data used in this study are as shown in Table 2.

Table 2. Training Data

| | Date | Mataram | Sumbawa | Bima |
|---|---|---|---|---|
| 1 | 2008-01 | 34.470.807 | 8.018.871 | 7.791.608 |
| 2 | 2008-02 | 35.267.524 | 7.718.016 | 7.687.715 |
| 3 | 2008-03 | 33.460.716 | 7.642.508 | 7.649.522 |
| 4 | 2008-04 | 34.670.014 | 7.357.594 | 7.310.157 |
| 5 | 2008-05 | 35.002.854 | 7.992.551 | 7.716.816 |
| 6 | 2008-06 | 36.170.553 | 8.004.306 | 7.755.221 |
| 7 | 2008-07 | 35.732.219 | 8.343.908 | 7.851.373 |
| 8 | 2008-08 | 35.332.363 | 8.125.042 | 7.574.326 |
| 9 | 2008-09 | 36.691.297 | 8.565.646 | 7.914.139 |
| 10 | 2008-10 | 38.906.903 | 8.724.551 | 8.468.444 |
| 11 | 2008-11 | 35.672.846 | 9.072.941 | 8.370.307 |
| 12 | 2008-12 | 37.395.469 | 8.810.725 | 8.536.249 |
| … | … | … | … | … |
| 96 | 2015-12 | 82.714.772 | 17.243.973 | 18.708.383 |

### 2) Testing Data

Test data is data used to test the developed back-propagation neural network model.. In this study, the test data used was 20%. of the overall data from the study (see Table 3).

Table 3. Testing Data

| | Date | Mataram | Sumbawa | Bima |
|---|---|---|---|---|
| 1 | 2016-01 | 93.106.502 | 17.210.110 | 19.159.477 |
| 2 | 2016-02 | 86.094.377 | 15.367.956 | 17.782.326 |
| 3 | 2016-03 | 95.258.907 | 17.199.037 | 19.570.340 |
| 4 | 2016-04 | 94.585.597 | 16.990.270 | 18.611.301 |
| 5 | 2016-05 | 99.126.920 | 17.863.411 | 19.453.782 |
| 6 | 2016-06 | 92.831.847 | 17.493.322 | 19.080.803 |
| 7 | 2016-07 | 95.493.898 | 17.539.492 | 19.761.794 |
| 8 | 2016-08 | 97.051.736 | 17.359.140 | 19.533.780 |
| 9 | 2016-09 | 98.146.470 | 17.490.719 | 19.703.350 |
| 10 | 2016-10 | 101.147.042 | 17.975.404 | 19.224.669 |
| 11 | 2016-11 | 99.512.352 | 17.920.385 | 19.413.767 |
| 12 | 2016-12 | 99.901.124 | 17.712.205 | 19.657.749 |
| … | …. | …. | …. | …. |
| 35 | 2018-11 | 113.643.664 | 23.664.804 | 23.211.730 |
| 36 | 2018-12 | 114.335.265 | 24.629.310 | 22.772.095 |

### 3) Backpropagation Architecture

The input value in the back-propagation neural network input layer in this study is expressed by X1, X2, and X3, as shown in Table 4.

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Table 4. Variables in the Input Layer

| **Variable in the Input Layer** | **Data on electricity consumption in** |
|---|---|
| X1 | Mataram |
| X2 | Sumbawa |
| X3 | Bima |

While the output value in the back-propagation neural network output layer in this study is expressed by Y1, Y2, and Y3, Y1, Y2, and Y3 represent the predicted electricity usage data Mataram, Sumbawa, and Bima areas as shown in Table 5.

Table 5. Variables Target

| **Variables in the Output Layer** | **The target for the region** |
|---|---|
| Y1 | Mataram |
| Y2 | Sumbawa |
| Y3 | Bima |

Figure 1 shows the back-propagation neural network architecture to predict electricity consumption.

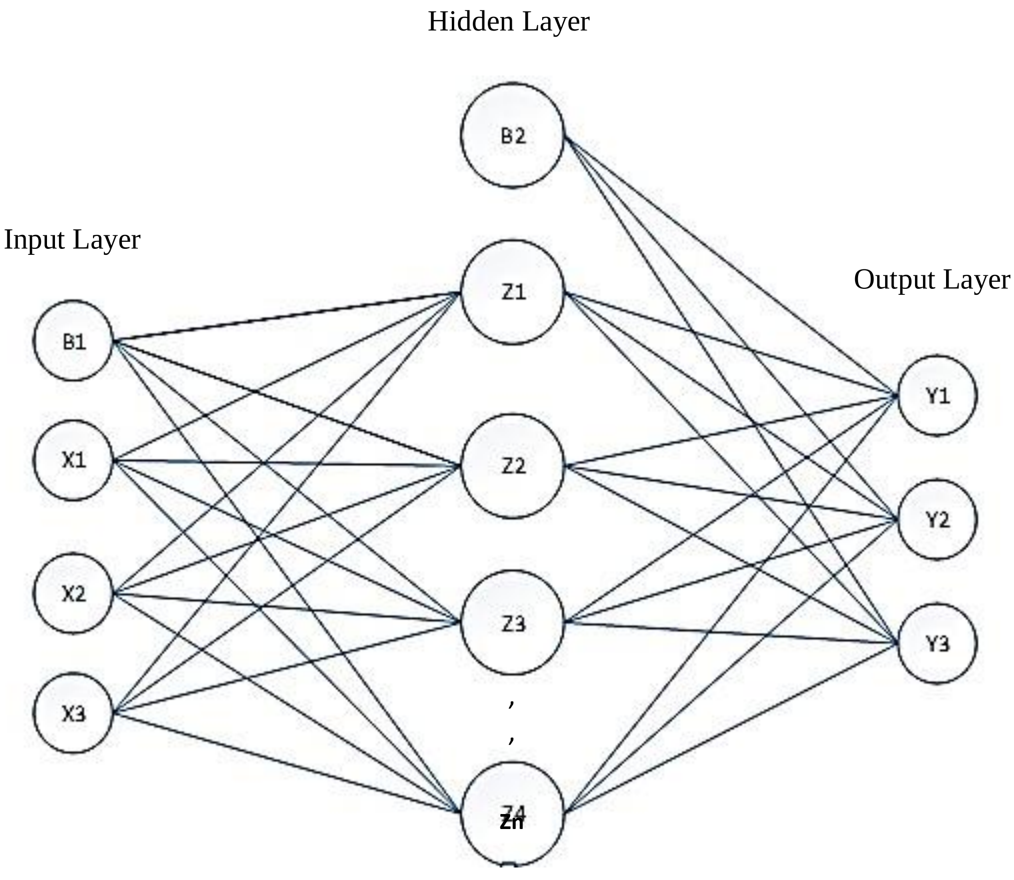


Figure 1. Back-Propagation Neural Network Architecture

The input data comes from electricity consumption data for Mataram, Sumbawa, and Bima, which are symbolized by the variables x1, x2, and x3. The hidden layer consists of 4 neurons symbolized by Z. Each neuron in the input and output layers will be connected to the hidden layer through the weight value and activation function. The output weight of the hidden layer will be forwarded to the output layer, which consists of 3 outputs. Y1, Y2, and Y3. Symbolize the neurons in the output layer. Neurons B1 and B2 are the bias values of the backpropagation neural network in the hidden layer and output layer. There are five models of backpropagation architecture that were tested in this study, namely 3-4-3, 3-4-3, 3-6-3, 3-7-3, and 38-3 architecture (number of input layer nodes-number of nodes -number of output layer nodes).

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### 4) Block Diagram of Back-propagation Training and Testing Process

Figure 2 shows a block diagram of the training process of a back-propagation neural network. While Figure 3 shows a block diagram of the test process of a backpropagation neural network.

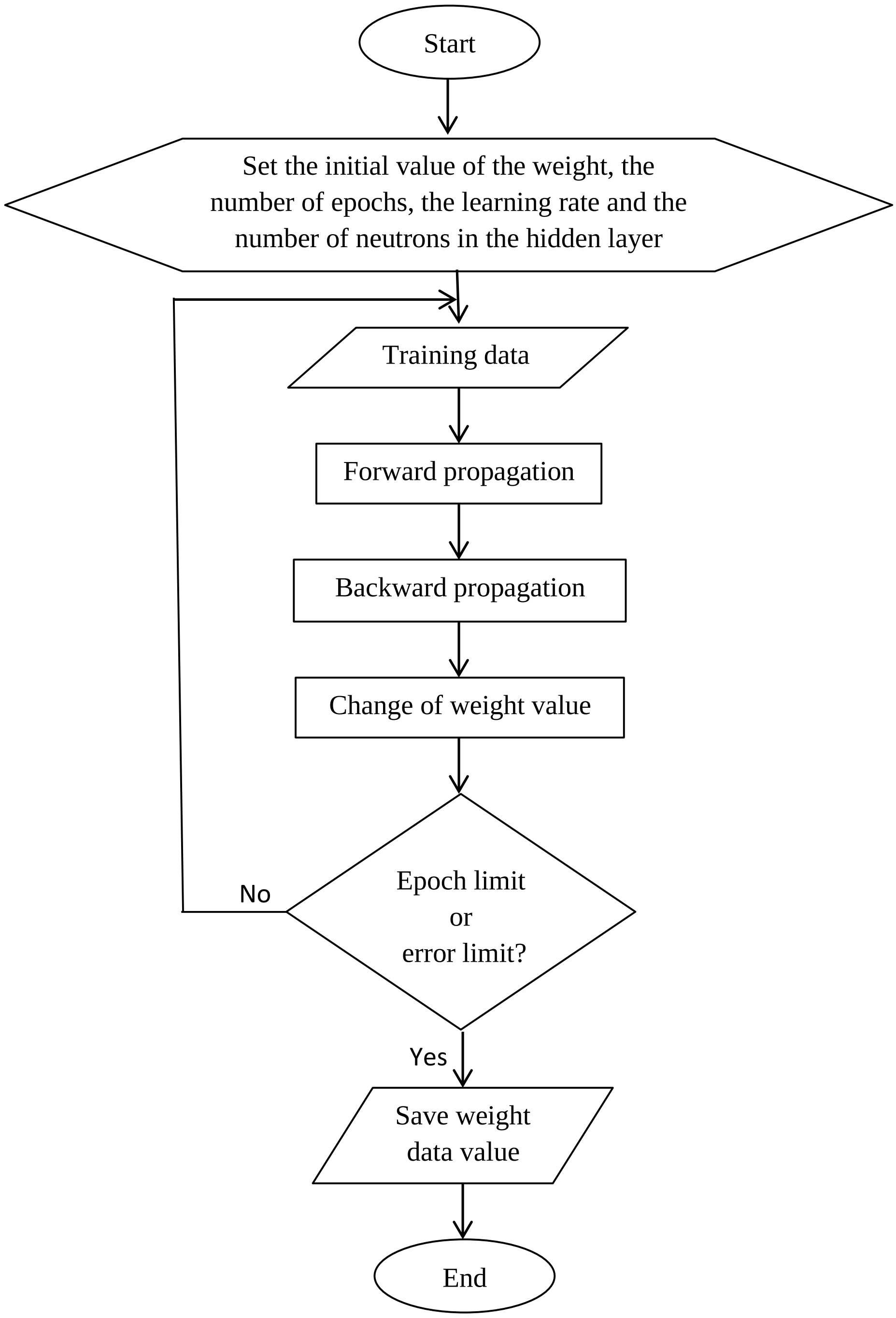


Figure 2. Block Diagram of the training process of back-propagation

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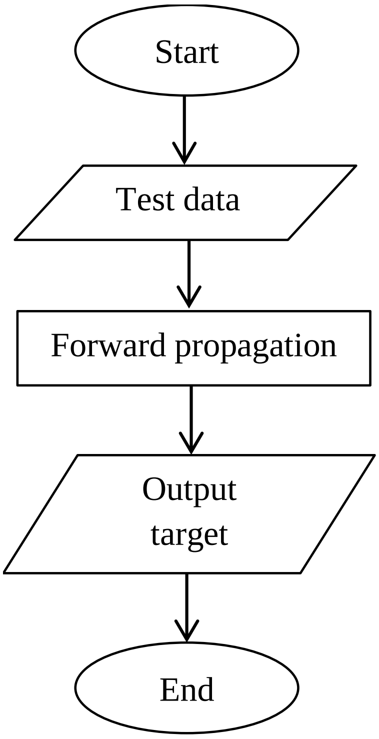


Figure 3. Block Diagram of the test process of back-propagation

## III. RESULTS AND DISCUSSION

In this study, the combination of the back-propagation neural network architecture model that was tested for training data and test data is as follows: 3 nodes in the input layer and three nodes in the output layer, while the number of nodes in the hidden layer varies from 4 nodes to 8 nodes.

### A. Training Data Result and Discussion

Testing training data on the back-propagation architecture with a combination of 3 input layers, 4 to 8 hidden layers, and three output layers, with 1,000 total epochs and a learning rate range from 0.1 to 0.9, obtained the results as shown in Table 6. The results of the training data test show that the best model is an architecture with eight nodes in the hidden layer, and the learning rate is 0.3 because it has the lowest RMSE value of 0.035811.

Tabel 6. Training Data Result

| No | Epoch | Hidden Layer | Learning Rate | MSE Training | RMSE Training | Accuracy |
|---|---|---|---|---|---|---|
| 1 | 1,000 | 4 | 0.1 | 0.001457 | 0.038165 | 97.19 |
| 2 | 1,000 | 4 | 0.2 | 0.001368 | 0.036981 | 97.34 |
| 3 | 1,000 | 4 | 0.3 | 0.002186 | 0.046760 | 96.27 |
| 4 | 1,000 | 4 | 0.4 | 0.001312 | 0.036226 | 97.34 |
| 5 | 1,000 | 4 | 0.5 | 0.001595 | 0.039935 | 97.00 |
| 6 | 1,000 | 4 | 0.6 | 0.001372 | 0.037044 | 97.23 |
| 7 | 1,000 | 4 | 0.7 | 0.001416 | 0.037631 | 97.20 |
| 8 | 1,000 | 4 | 0.8 | 0.001435 | 0.037887 | 97.17 |
| 9 | 1,000 | 4 | 0.9 | 0.002487 | 0.049867 | 96.13 |
| 10 | 1,000 | 5 | 0.1 | 0.001374 | 0.037073 | 97.28 |
| 11 | 1,000 | 5 | 0.2 | 0.001371 | 0.037025 | 97.26 |
| 12 | 1,000 | 5 | 0.3 | 0.001533 | 0.039148 | 97.05 |
| 13 | 1,000 | 5 | 0.4 | 0.001895 | 0.043533 | 96.73 |
| 14 | 1,000 | 5 | 0.5 | 0.001400 | 0.037422 | 97.23 |
| 15 | 1,000 | 5 | 0.6 | 0.001710 | 0.041351 | 96.89 |

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| | | | | | | |
|---|---|---|---|---|---|---|
| .. | … | … | … | … | .. | … |
| 39 | 1,000 | 8 | 0.3 | 0.001282 | 0.035811 | 97.41 |
| 40 | 1,000 | 8 | 0.4 | 0.001473 | 0.038384 | 97.11 |
| 41 | 1,000 | 8 | 0.5 | 0.001351 | 0.036760 | 97.27 |
| .. | … | … | … | … | .. | … |
| 45 | 1,000 | 8 | 0.9 | 0.001319 | 0.036320 | 97.34 |

## B. Test Data Result and Discussion

Testing the test data on the back-propagation neural network architecture is using the training data weights from the architectural model that has been trained. The test results of the test data are as shown in Table 7. The experimental results on the test data show that the backpropagation neural network architecture model with the best performance is a combination of learning rate 0.4 and hidden layer 6, because it has the lowest RMSE value of 0.203424.

**Tabel 7. Test Data Result**

| No | Epoch | Hidden Layer | Learning Rate | MSE Test Data | RMSE Test Data | Accuracy |
|---|---|---|---|---|---|---|
| 1 | 1,000 | 4 | 0.1 | 0.042259 | 0.205570 | 83.64 |
| 2 | 1,000 | 4 | 0.2 | 0.042947 | 0.207237 | 83.27 |
| 3 | 1,000 | 4 | 0.3 | 0.042356 | 0.205807 | 83.56 |
| 4 | 1,000 | 4 | 0.4 | 0.044886 | 0.211864 | 83.23 |
| 5 | 1,000 | 4 | 0.5 | 0.045256 | 0.212734 | 82.44 |
| 6 | 1,000 | 4 | 0.6 | 0.045435 | 0.213155 | 83.37 |
| 7 | 1,000 | 4 | 0.7 | 0.047375 | 0.217658 | 82.82 |
| 8 | 1,000 | 4 | 0.8 | 0.050151 | 0.223944 | 81.76 |
| 9 | 1,000 | 4 | 0.9 | 0.051068 | 0.225982 | 81.63 |
| 10 | 1,000 | 5 | 0.1 | 0.046842 | 0.216430 | 82.38 |
| 11 | 1,000 | 5 | 0.2 | 0.043489 | 0.208541 | 83.40 |
| 12 | 1,000 | 5 | 0.3 | 0.048211 | 0.219571 | 82.13 |
| 13 | 1,000 | 5 | 0.4 | 0.047440 | 0.217806 | 82.95 |
| 14 | 1,000 | 5 | 0.5 | 0.047473 | 0.217883 | 82.99 |
| 15 | 1,000 | 5 | 0.6 | 0.048159 | 0.219453 | 82.84 |
| … | … | … | … | … | … | … |
| 22 | 1,000 | 6 | 0.4 | 0.041381 | 0.203424 | 84.08 |
| … | … | … | … | … | … | … |
| 45 | 1,000 | 8 | 0.9 | 0.049580 | 0.222665 | 82.28 |

## C. Prediction Results

The process of predicting electricity consumption is carried out using the best architectural model from the results of test data tested previously. The back-propagation neural network architecture model used to predict electricity consumption has three input layer nodes, 6 hidden layer nodes, and three output layer nodes with a 0.4 learning rate. Furthermore, prediction results are differentiated according to data attributes for the areas of Mataram, Sumbawa, and Bima (see Table 8 to Table 10). Prediction of electricity consumption based on actual data in 2018, the prediction results show that the prediction of electricity consumption is close to the actual data of actual electricity consumption.

Table 8. Mataram Data Prediction Results

| Date | Actual Data | Prediction Data |
|---|---|---|
| January 1, 2018 | 101,081,276 | 105,149,936 |
| February 1, 2018 | 96,982,859 | 104,223,152 |
| March 1, 2018 | 108,295,282 | 99,444,023 |
| April 1, 2018 | 108,940,930 | 108,384,081 |
| May 1, 2018 | 110,654,653 | 109,301,735 |
| June 1, 2018 | 103,766,041 | 110,290,487 |

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| | | |
|---|---|---|
| July 1, 2018 | 105,554,858 | 106,349,303 |
| August 1, 2018 | 88,845,116 | 107,430,911 |
| September 1, 2018 | 92,806,890 | 101,580,208 |
| October 1, 2018 | 107,592,233 | 102,395,472 |
| November 1, 2018 | 113,643,664 | 111,210,824 |
| December 1. 2018 | 114,335,265 | 113,339,144 |

Table 9. Sumbawa Data Prediction Results

| Date | Actual Data | Prediction Data |
|---|---|---|
| January 1, 2018 | 20,823,891 | 20,506,962 |
| February 1, 2018 | 19,374,669 | 20,440,546 |
| March 1, 2018 | 21,567,826 | 19,272,835 |
| April 1, 2018 | 22,410,070 | 21,271,665 |
| May 1, 2018 | 22,532,901 | 21,697,831 |
| June 1, 2018 | 21,077,636 | 21,836,475 |
| July 1, 2018 | 21,731,158 | 20,778,881 |
| August 1, 2018 | 21,877,087 | 21,197,287 |
| September 1, 2018 | 21,133,693 | 20,125,813 |
| October 1, 2018 | 23,577,419 | 20,055,070 |
| November 1, 2018 | 23,664,804 | 22,158,864 |
| December 1, 2018 | 24,629,310 | 22,420,898 |

Table 10. Bima Data Prediction Results

| Date | Actual Data | Prediction Data |
|---|---|---|
| January 1, 2018 | 20,705,051 | 20,574,231 |
| February 1, 2018 | 19,178,313 | 20,521,821 |
| March 1, 2018 | 21,570,668 | 19,197,241 |
| April 1, 2018 | 21,526,337 | 21,493,281 |
| May 1, 2018 | 21,865,595 | 21,742,611 |
| June 1, 2018 | 21,561,187 | 21,977,965 |
| July 1, 2018 | 21,402,195 | 21,078,805 |
| August 1,2018 | 21,541,475 | 21,321.551 |
| September 1, 2018 | 21,618,415 | 20,287,693 |
| October 1, 2018 | 22,959,786 | 20,367,461 |
| November 1, 2018 | 23,211,731 | 22,437,031 |
| December 1, 2018 | 22,772,094 | 22,818,217 |

## IV. CONCLUSION

The findings of this study indicate that: the architectural model with the best performance is an architecture with six hidden layers and a learning rate of 0.4 with an RMSE value of 0.203424. Meanwhile, testing the training data with the best architectural model is at hidden layer eight, and the learning rate is 0.3 with an RMSE performance value of 0.035811. The prediction results show that the prediction of electricity consumption is close to the real data of actual electricity consumption.

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