# Prediction of Daily Electricity Use in Residential High-Rise Buildings Using Artificial Neural Networks

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Keywords: JST, Backpropagation Method, MATLAB, MSE, MAPE.

Abstract: The high demand for electrical energy from consumers requires producers to provide a reliable but economic supply of electrical energy. Therefore, strategies and methods are needed to match the power generation and demand. This can be achieved by planning a good and proper operation. One of the important steps in planning the operation of the electric power system is predicting the need for electrical loads. One method of predicting electrical loads is to use ANN (Artificial Neural Networks). ANN is an information processing system with characteristics similar to biological neural networks. This method uses ANN with a backpropagation algorithm, and the prediction results are obtained by adding electrical load data (KW) for the selected similar days. ANN processing using MATLAB software. The artificial neural network architecture uses 15 input layers, 15 output layers, and ten hidden layers, and the activation function used is logsig and purelin. Logsig for hidden layers and purelin for output layers. The results of the electrical load prediction using an artificial neural network with the backpropagation method, the Mean Square Error (MSE) value of network training is 0.1, and the MAPE value of data testing is 6.5%. The results of the prediction of electricity use in high-rise residential buildings in February 2023 are predicted.

## 1 INTRODUCTION

One of the types of energy that propagates through the cable network. electricity, has played an essential role in the progress of human civilization in various fields. The use of electricity will be affected by increased human activities. Electricity providers must provide enough electricity to meet high consumer demand. Second type will cause obesity and lack of physical activity. The electricity sector is considered to be a field that requires long-term forecasts so that the power plant infrastructure is ready to be supplied with electricity. However, long predictions are difficult to achieve. Timeframes and financing factors are often the obstacles faced. Therefore, to anticipate the events mentioned above, it is necessary to make projections to estimate how much electrical energy will be consumed.

Artificial intelligence software is now being developed due to computational advances to create alternative techniques for long-term electrical energy forecasting. In addition to being easier to use, computational innovations result in more accurate findings. Experts are working to develop an artificial intelligence system that can estimate future electrical energy needs.

Artificial neural networks are one the most effective intelligent systems in making predictions. Artificial neural networks are used to predict the use of electricity that will be used in buildings.  in this way we can predict the use of electricity in a building

## 2 LITERATURE REVIEW

Research conducted by Fathur Rohman et al. (2021) with the title "Electrical Load Prediction Using Artificial Neural Network Method Backpropagation". This study used the method of predicting electrical loads using JST (Artificial Neural Network) Backpropagation. The study
has indicated electrical loads using artificial neural networks backpropagation method of the largest MAPE (Mean Absolute Percentage Error) value obtained with a value of 4.32 %. And the smallest MAPE value is obtained with a value of 2.71 %. (Rohman, 2022).

Research conducted by Yuan Octavia et al. (2018) with the title "Study of electrical load forecasting



Rofii, A. and Ibrahim, H.
Prediction of Daily Electricity Use in Residential High-Rise Buildings Using Artificial Neural Networks.
DOI: 10.5220/0011980100003582
In *Proceedings of the 3rd International Seminar and Call for Paper (ISCP) UTA âĂŹ45 Jakarta (ISCP UTA'45 Jakarta 2022)*, pages 293-299
ISBN: 978-989-758-654-5; ISSN: 2828-853X

using artificial neural network method."In a case study of the distribution of electrical energy in the Mojokerto Region, this study using the Artificial Neural Network (JST) approach with the use of backpropagation algorithms to predict long-term electricity needs. In this study, there were eight variables used, with variables bound is the amount of electricity consumption. The free variable is the sum of population, GRDP, number of household sector customers, number of sector customers, industry, number of business sector customers, number of social sector customers, number of business sector customers, and distribution losses. According to this analysis, the electrical load of The Mojokerto region is predicted to grow by 22.641 percent between 2018 and 2030, an average of 1.728% per annum. (Yuan et al., 2018).

Research conducted by Diah Setyowati and Said Sunardiyo (2020) under the title "Forecast of Electrical Energy Needs with Artificial Neural Networks (Artificial Neural Network) Backpropagation Method 2020-2025". With using the Artificial Neural Network Backpropagation technique using MATLAB software, this research predicts the electrical energy needs of PT PLN 7 (Persero) UP3 Semarang in 2020–2025. The study resulted in a growth annual of a total percent (GOT%) of 2.7% and the average percentage of errors absolute (MAPE) of 0.4%. (Setyowati & Sunardiyo, 2020).

## 2.1 Theoretical Basis

### 2.1.1 Predictions

Forecasting is the practice of predicting events or items in the future (Jay, 2009). Three prediction categories depending on the time frame that can be made: short-term, medium-term, and long-term (Aryan Hamidie, 2009). Hourly, daily, and three-month periods are included in the short-term forecasts. Predictions for the medium term or medium period often range from three months to two years.

Long-term predictions are generally for two-year planning or more (Sugiarto & Harijono, 2000). To foresee events that are not desirable and get ready to take the necessary actions and predictions required (Arifah et al., n.d.). Although it is difficult to foresee the future, Forecasts can be used as a guide to reduce errors. Achievement of long-term goals in the installation of production control systems (production) and allocation of power lines require accurate projections, in particular for energy producers.

### 2.1.2 Electrical Energy

Energy from natural resources is converted into electrical power by generating electricity. According to the resources used, Power plants are classified as PLTU, PLTA, PLTN, PLTS, and others. Generators in power plants convert mechanical energy into electricity using the concept of conductors and electric fields. The energy produced will be stored in accumulators or energy storage devices. Transmission lines will channel the electrical energy that has been kept to the customer. Based on the voltage value, shape, the type of conductor used, line arrangement, and circuit array, transmission and distribution lines Classified. However, the alternating current voltage transmission line of the 3-phase and 1-phase is usually used to distribute electricity from power plants. However, some transmission lines also use direct current voltage.

### 2.1.3 Electric System Power

Electrical power components, such as electric power production, transmission systems, and distribution systems, form the electric power system. Third, these components comprise most of the power grid that transports electricity from the production station to the load station. Transmission lines connect production stations to distribution systems and, through interconnections, to other power systems. All individual loads are connected to the transmission line through a distribution system at substations that handle voltage conversion and switching operations. Figure 2.1 below shows the power system circuit electricity (Eirene & Sau, 2019).

The electrical installation system in high-rise buildings is divided into utility lines, lighting lighting, air conditioning channels and stop contact channels. How to find out the use of electrical power in each room of the building is to place a measuring instrument on the main panel as well as in every room that is considered a tenant or occupant. To identify the use of electrical power in each room, a set of measuring instruments is installed starting from measuring power, current, voltage, and cos phi. Recording is carried out in accordance with operational standards determined by the building management. the relationship between current, voltage, power based on the following formula sebagai berikut

$$P=\sqrt{3}\, V_p\, I_p \cos\emptyset$$

Where Vp is the phase voltage, Ip is the phase current and cos∅ is the power factor.

In the electrical system of residential buildings, the parameters measured are single-phase parameters, so to determine and predict the use of electrical power in residential buildings, it is necessary to carry out the results of phase measurements into 3 phase calculations.

### 2.1.4 Artificial Neural Network

The functioning system of neural networks can be compared with the human brain. Many neurons are found in the neural network, which is connected. The information obtained through the outgoing connection will be altered by these neurons and sent to different contacts. Report (called input). It will have a certain arrival weight when it is delivered to neurons. By summing all the weight values in this input, a particular propagation function will process them. What will then compare the results with a specific threshold value using the activation function of each neuron? The neuron is not triggered if the input drops below the threshold value, but if it is, it is involved and transmits the output to all neurons connected to it with its output weight (Kusumadewi, 2004)

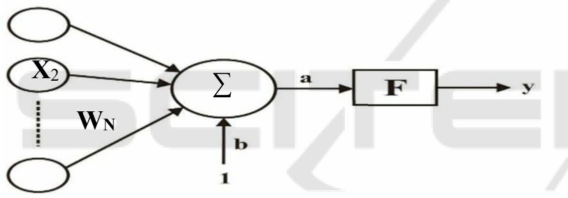


Figure 1: Activation Function on Simple Neural Networks

In the figure, a neuron will process N inputs ($x_1$, $x2$, ..., $x_N$) which each have weights $w_1$, $w_2$, ..., wN, and bias weight b, with the formula :

$$a = \sum_{i=1}^{N} x_i w_i$$

Then the activation function F will activate into the output of the network y.

### 2.1.5 Backpropagation Algorithm

According to (Kusumadewi, 2004), Perceptrons with multiple layers often use backpropagation-guided learning techniques to modify the weights that connect neurons in the hidden layer. The backpropagation method adjusts the backward weight value by using the error output. What must complete the forward propagation stage first to get this error. Neurons are triggered using the differential activation function as propagation progress.

### 2.1.6 Backpropagation Architecture

Artificial neural network-based backpropagation or propagation feedback consists of many units in one or more hidden layers. The artificial neural network base in the feedback propagation architecture drawing contains n inputs (plus bias), hidden layers with p units (plus bias), and m output units (Prasetyo & Sahala, 2014).

## 3 RESEARCH METHODOLOGY

The research methods used in the preparation of this final project report are:

a. Literature studies examine the necessary theories from handbooks that support and relate to the themes taken to be used as theoretical foundations.
b. Discussion, namely conducting a question and answer with supervisors and technology in the field and friends (University of August 17, 1945 Jakarta).
c. Observation Method, plunge directly into the field to study the selected object.
d. Perform calculations and analyzes.

### 3.1 Flowchart Research

This project research method explains the estimated consumption of electrical energy. The preparation of this final project can be seen in the flowchart.

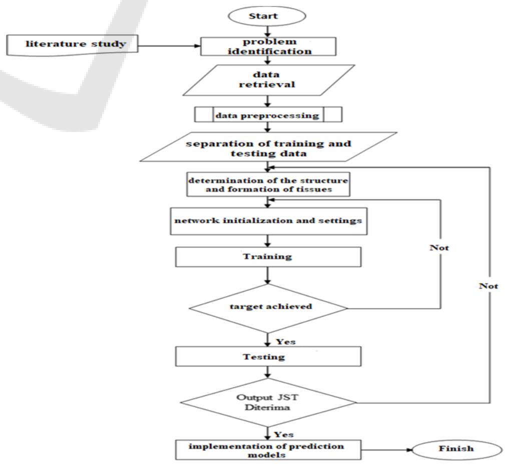


Figure 2: Research Flowchart

# 4 RESULTS AND DISCUSSION

What can analyze the estimated electrical energy consumption for the next month based on connected power (VA) and the amount of energy (kW). What will discuss this regarding the results of estimating electrical energy consumption using the artificial neural network method of backpropagation.

If any, should be placed before the references section without numbering.

Table 1: Three-phase data

| Date | Electricity consumption of residential high-rise buildings | | | | | |
|---|---|---|---|---|---|---|
| | 6:00 | 8:00 | 14:00 | 18:00 | 22:00 | 23:00 |
| 1/1/2021 | 188.7139 | 173.6666 | 167.7429 | 205.2738 | 232.5847 | 316.2564 |
| 1/2/2021 | 134.4561 | 145.485 | 162.036 | 165.1591 | 203.5554 | 135.6753 |
| 1/3/2021 | 151.5442 | 138.7565 | 147.7581 | 156.6775 | 187.1722 | 182.1096 |
| 1/4/2021 | 132.616 | 157.952 | 178.1023 | 152.5722 | 220.8541 | 224.4732 |
| 1/5/2021 | 158.642 | 156.609 | 145.0169 | 154.2733 | 210.9078 | 224.1336 |
| 1/6/2021 | 147.6728 | 150.4463 | 173.4356 | 177.0195 | 187.7345 | 195.3308 |
| 1/7/2021 | 147.7581 | 125.843 | 136.9365 | 148.0636 | 214.8411 | 205.8894 |
| 1/8/2021 | 153.7923 | 170.3523 | 152.0285 | 163.1113 | 204.9519 | 204.9049 |
| 1/9/2021 | 146.2542 | 150.3373 | 152.581 | 147.9637 | 258.4366 | 203.3236 |
| 1/10/2021 | 142.5553 | 152.9381 | 154.0529 | 143.5379 | 198.6938 | 193.7646 |
| 1/11/2021 | 116.5893 | 161.8682 | 156.6467 | 151.2287 | 209.5729 | 204.5045 |
| 1/12/2021 | 137.1422 | 161.9562 | 148.1965 | 155.6701 | 203.4926 | 215.75 |
| 1/13/2021 | 143.5158 | 170.5487 | 143.797 | 148.8077 | 197.2976 | 202.4907 |
| 1/14/2021 | 164.4192 | 159.3128 | 153.2844 | 173.1816 | 202.5528 | 211.5633 |
| 1/15/2021 | 146.1189 | 168.5987 | 154.8349 | 164.1554 | 238.4071 | 655.7143 |
| 1/16/2021 | 154.894 | 152.0135 | 177.3734 | 161.2747 | 233.573 | 209.6939 |
| 1/17/2021 | 431.944 | 143.1755 | 203.9932 | 167.259 | 213.14 | 223.4589 |
| 1/18/2021 | 166.0804 | 149.9547 | 145.225 | 153.4902 | 181.47 | 193.994 |
| 1/19/2021 | 164.4192 | 159.3128 | 153.2844 | 173.1816 | 202.5528 | 211.5633 |
| 1/20/2021 | 153.9008 | 223.5154 | 121.6555 | 139.9384 | 184.4222 | 182.7862 |
| 1/21/2021 | 146.2666 | 160.7262 | 280.2185 | 153.2273 | 209.6506 | 215.468 |
| 1/22/2021 | 155.9956 | 158.7527 | 135.7604 | 135.6358 | 238.9169 | 209.8548 |
| 1/23/2021 | 155.1068 | 141.0434 | 174.931 | 145.4767 | 215.9491 | 214.2138 |
| 1/24/2021 | 153.516 | 219.5157 | 119.1472 | 138.8429 | 182.5404 | 183.2228 |
| 1/25/2021 | 131.9207 | 145.1633 | 153.2136 | 634.2832 | 193.357 | 211.5748 |
| 1/26/2021 | 144.3949 | 149.3037 | 136.9548 | 144.4022 | 184.4931 | 181.8976 |
| 1/27/2021 | 119.478 | 149.2926 | 142.4313 | 151.2435 | 182.344 | 180.7739 |
| 1/28/2021 | 139.3777 | 153.5554 | 138.0063 | 143.8691 | 195.0083 | 195.9126 |
| 1/29/2021 | 141.1813 | 130.7564 | 138.6807 | 126.4422 | 183.8728 | 175.6534 |
| 1/30/2021 | 127.7109 | 120.522 | 139.9113 | 132.4211 | 197.7921 | 174.9376 |

The neural network training process for artificial backpropagation requires several parameters, including the number of hidden layers, epoch, error goals, and learning rate. Parameter changes made during training are the number of hidden layers 10, starting from the number of epochs 4000, 6000, and 8000, the number of learning rates starting from 0.001, 0.01,0.1, and for error goals 0.001. This is done to obtain good training results. The training data used for the training are connected power data (VA) and amount of energy (kW) from January 1, 2021 to January 30, 2021 and training target data, namely connected power data (VA) and energy amount (kWh) from January 16 to January 31. Before the data is entered into the artificial neural network, the data must be normalized in the range [0 to 1] because the input data of the artificial neural network uses the logsig activation function (binary sigmoid). To convert the original data into normalization data using a formula.

Min – max normalization:

$$X'' = \frac{X - min\,(X)}{range(X)} = \frac{X - min\,(X)}{(X)\ - min\,(X)}$$

$$X'' = \frac{X - mean\,(X)}{SD(X)}$$

Table 2: normalization data.

| Date | Electricity consumption of residential high-rise buildings | | | | | |
|---|---|---|---|---|---|---|
| | 06:00 | 08:00 | 14:00 | 18:00 | 22:00 | 23:00 |
| 01/01/2021 | 0,133780915 | 0,105870195 | 0,094883 | 0,164497 | 0,215155 | 0,370354 |
| 02/01/2021 | 0,033140337 | 0,053597353 | 0,084297 | 0,09009 | 0,16131 | 0,035402 |
| 03/01/2021 | 0,064836312 | 0,041116986 | 0,057814 | 0,074358 | 0,130921 | 0,121531 |
| 04/01/2021 | 0,029727219 | 0,076721994 | 0,114098 | 0,066743 | 0,193396 | 0,200109 |
| 05/01/2021 | 0,078001726 | 0,074230858 | 0,052729 | 0,069898 | 0,174947 | 0,199479 |
| 06/01/2021 | 0,05765546 | 0,062799974 | 0,105442 | 0,112089 | 0,131964 | 0,146054 |
| 07/01/2021 | 0,057813595 | 0,017164213 | 0,037741 | 0,05838 | 0,182243 | 0,165639 |
| 08/01/2021 | 0,06900625 | 0,099722739 | 0,065735 | 0,086292 | 0,1639 | 0,163813 |
| 09/01/2021 | 0,055024245 | 0,062597685 | 0,06676 | 0,058195 | 0,263107 | 0,16088 |
| 10/01/2021 | 0,048163268 | 0,067421787 | 0,06949 | 0,049986 | 0,152292 | 0,143149 |
| 11/01/2021 | 0,18548568 | 0,083985924 | 0,074301 | 0,064251 | 0,172471 | 0,16307 |
| 12/01/2021 | 0,038122738 | 0,084149182 | 0,058627 | 0,072489 | 0,161193 | 0,183929 |
| 13/01/2021 | 0,049944851 | 0,100086917 | 0,050466 | 0,059761 | 0,149702 | 0,159335 |
| 14/01/2021 | 0,088717644 | 0,079245989 | 0,068064 | 0,104971 | 0,15945 | 0,176163 |
| 15/01/2021 | 0,054773159 | 0,096470034 | 0,07094 | 0,088228 | 0,225955 | 1 |
| 16/01/2021 | 0,071049679 | 0,065706813 | 0,112746 | 0,082885 | 0,216988 | 0,172696 |
| 17/01/2021 | 0,584937964 | 0,049313595 | 0,162122 | 0,093985 | 0,179088 | 0,198228 |
| 18/01/2021 | 0,091799004 | 0,061888132 | 0,053115 | 0,068446 | 0,120344 | 0,143575 |
| 19/01/2021 | 0,088717644 | 0,079245989 | 0,068064 | 0,104971 | 0,15945 | 0,176163 |
| 20/01/2021 | 0,069207512 | 0,198332755 | 0,009397 | 0,043309 | 0,12582 | 0,122786 |
| 21/01/2021 | 0,055047071 | 0,081867619 | 0,303509 | 0,067958 | 0,172615 | 0,183406 |
| 22/01/2021 | 0,073093109 | 0,07820716 | 0,03556 | 0,035329 | 0,2269 | 0,172994 |
| 23/01/2021 | 0,071444439 | 0,045358943 | 0,108215 | 0,053582 | 0,184298 | 0,18108 |
| 24/01/2021 | 0,068493852 | 0,190913834 | 0,004744 | 0,041277 | 0,12233 | 0,123596 |
| 25/01/2021 | 0,028437593 | 0,053000722 | 0,067933 | 0,960248 | 0,142393 | 0,176185 |
| 26/01/2021 | 0,051575487 | 0,060680558 | 0,037775 | 0,051589 | 0,125952 | 0,121138 |
| 27/01/2021 | 0,005358038 | 0,060660021 | 0,047933 | 0,064279 | 0,121966 | 0,119053 |
| 28/01/2021 | 0,042269153 | 0,068566758 | 0,039726 | 0,0506 | 0,145456 | 0,147133 |
| 29/01/2021 | 0,045614628 | 0,026278033 | 0,040976 | 0,018276 | 0,124801 | 0,109556 |
| 30/01/2021 | 0,020628995 | 0,007294675 | 0,043259 | 0,029366 | 0,15062 | 0,108228 |

Backpropagation Artificial Neural Network Program for electric power load forecasting using 15 input and 15 target data. It consists of 15 input units and ten layers on the hidden layer and 15 units on the output layer. The activation function of the input unit to the hidden layer is a binary sigmoid (logsig) and purelin.

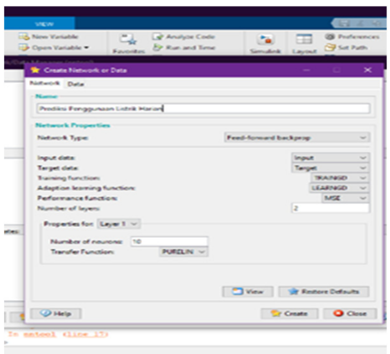

Figure 3: Network creation toolbox

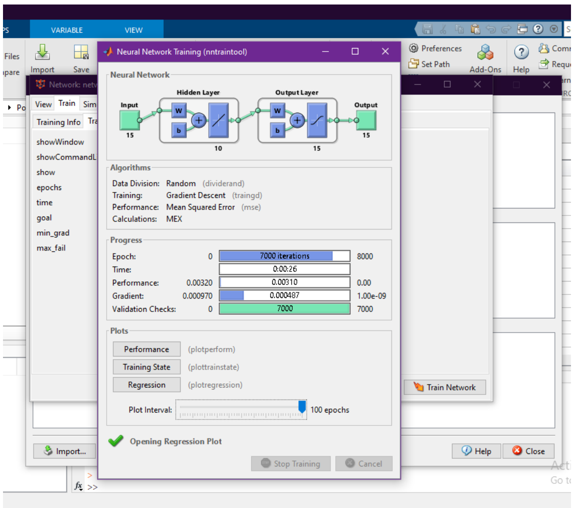


Figure 4: Best training and gradient with learning rate 0.1 and purelin activation function

Figures 3 and 4 show the best training and gradients using ten hidden layers, learning rate 0.1 and binary sigmoid activation functions (logsig) and purelin. In training with the best iteration with conditions without isolation using the activation function of binary sigmoids (logsig) and purelins, binary sigmoids with a range of 0 to 1 while purelin is a function of linearizing each input into its linear value. The linear process will produce an input value equal to the output value (y = x). These two activation functions are commonly used for artificial neural networks trained using the backpropagation method. The identity activation function returns an MSE value close to reaching the target. This is affected because the input of the activation function is the same as the output.

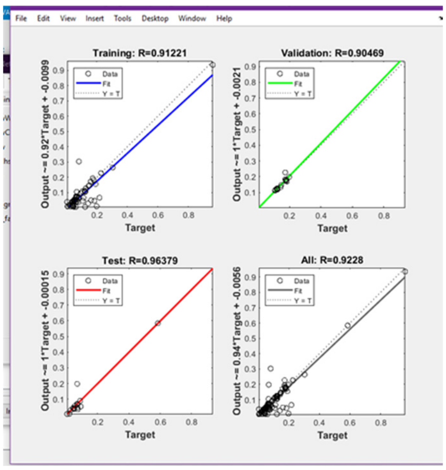


Figure 5: Regression of daily electricity use of high-rise residential buildings

Figure 5 is a Regression of training results using Hidden Layer 10, epoch 8000, and Learning Rate 0.1. With a regression value of 0.91, the degree of proximity between the training target and the training result is very close.

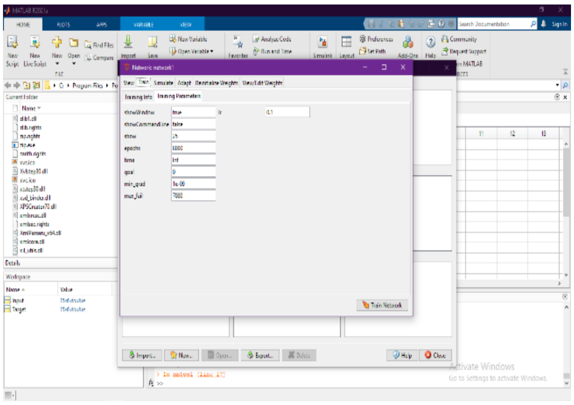

Figure 6: Training Parameters

Figure 6 is the parameter used to perform JST testing with the backpropagation method. The parameters used are epochs 8000, learning rate 0.1, min_grad 10-9, and max_fail 7000. Comparison table and errors that what can obtain in the prediction of daily electricity use in high-rise buildings: Based on table 3, we can see that the results of predicting the use of electricity in high-rise buildings calculate the accuracy of the forecasting/prediction that has been carried out, namely using calculations and analysis of the Mean Absolute Percentage error (MAPE). Mean Absolute Percentage error (MAPE) is the percentage of the average error absolutely (absolute). The definition of Mean Absolute Percentage Error is a statistical measurement of the accuracy of forecasts (predictions) on forecasting methods. The wider community can use measurement using Mean Absolute Percentage Error (MAPE) because MAPE is easy to understand and apply in predicting forecasting accuracy. The Mean Absolute Percentage Error (MAPE) method provides information on how much the forecasting error is compared to the actual value of the series. The smaller the percentage error value on MAPE, the more accurate the forecasting results will be.

The Mean Absolute Percentage Error (MAPE) value is analyzed:

Table 3: Comparison of electric power load forecasting in high-rise residential buildings

| Data | Actual | Predictions | *standard deviation* |
|---|---|---|---|
| 1. | 0.071049679 | 0.065732 | 0.005318 |
| 2. | 0.584937964 | 0.58424 | 0.000694 |
| 3. | 0.091799004 | 0.053198 | 0.038601 |
| 4. | 0.088717644 | 0.089721 | 0.001 |
| 5. | 0.069207512 | 0.19797 | 0.12876 |
| 6. | 0.055047071 | 0.057802 | 0.00276 |
| 7. | 0.073093109 | 0.035361 | 0.037732 |
| 8. | 0.071444439 | 0.046307 | 0.025137 |
| 9. | 0.068493852 | 0.069559 | 0.00107 |
| 10. | 0.028437593 | 0.029833 | 0.0014 |
| 11. | 0.051575487 | 0.037783 | 0.013793 |
| 12. | 0.005358038 | 0.005358 | 2.82E-07 |
| 13. | 0.042269153 | 0.043607 | 0.00134 |
| 14. | 0.045614628 | 0.039553 | 0.006061 |
| 15. | 0.020628995 | 0.007302 | 0.013327 |

Table 4: Range Mean Absolute Percentage Error (MAPE)

| Range MAPE | the meaning of value |
|---|---|
| < 10% | excellent forecasting model capability |
| 10 - 20% | good forecasting model capability |
| 20 - 50 % | decent forecasting model capability |
| >50% | poor forecasting model capability |

From the table above, we can understand the range of values that show the meaning of the error percentage value on MAPE, where the MAPE value can still be used if it does not exceed 50%. If the MAPE value is above 50%, then the forecasting model cannot be used.

The calculation of the MAPE method is as follows:

$$MAPE = \frac{\sum_t^n = 1 \left| (\frac{A_t - F_t}{A_t})100 \right|}{n}$$

Information

$A_t$ = Actual request to t

$F_t$ = forecasting result to t

N = magnitude of forecasting data

Where there is an absolute symbol in the MAPE formula indicating that the negative value of the calculation result will remain positive.

Table 4: Range Mean Absolute Percentage Error (MAPE)

| Actual ($A_t$) | Predictions ($F_t$) | Error ($A_t$ - $F_t$) | absolute errors value | Absolute Value divided by actual value |
|---|---|---|---|---|
| 154.8939583 | 152.0271 | 2.8668938 | 2.8668938 | 0.018508752 |
| 431.94398 | 431.5677 | 0.37629 | 0.37629 | 0.000871155 |
| 166.080438 | 145.2697 | 20.8107663 | 20.81076625 | 0.125305343 |
| 164.4192 | 164.9601 | -0.54093413 | 0.540934125 | 0.003289969 |
| 153.9008 | 223.3199 | -69.4190763 | 69.41907625 | 0.451063778 |
| 146.266552 | 147.7518 | -1.48525125 | 1.48525125 | 0.010154415 |
| 155.9956223 | 135.6533 | 20.3423232 | 20.34232318 | 0.130403167 |
| 155.106783 | 141.5546 | 13.5522216 | 13.55222163 | 0.087373494 |
| 153.516048 | 154.0903 | -0.57424787 | 0.574247875 | 0.003740637 |
| 131.9207173 | 132.673 | -0.75229882 | 0.752298825 | 0.005702659 |
| 144.3949343 | 136.9591 | 7.43587443 | 7.435874425 | 0.051496782 |
| 119.4779521 | 119.4781 | -0.00014139 | 0.000141387 | 1.18338E-06 |
| 139.3776573 | 140.0989 | -0.72126657 | 0.721266575 | 0.005174908 |
| 141.1812863 | 137.9133 | 3.26797518 | 3.267975175 | 0.023147368 |
| Total | | | | 0.972491563 |

$$MAPE = \frac{0.972491563}{15} \times 100 = 6.483\ \%$$

Based on the calculation results, it can be seen that the MAPE value is 6.5%. This shows that the prediction of electricity use in residential buildings using the JST Backpropagation method has excellent forecasting capabilities.

Table 5: Results of Predicted Electricity Consumption of Residential High-Rise Building

| Electricity consumption of residential high-rise buildings (Kw) | | | | | | |
|---|---|---|---|---|---|---|
| Tanggal | 6:00 | 8:00 | 14:00 | 18:00 | 22:00 | 23:00 |
| 1/1/2021 | 152.0271 | 152.0136 | 152.0136 | 152.0136 | 152.2907 | 215.1737 |
| 1/2/2021 | 431.5677 | 143.765 | 143.2102 | 168.5566 | 214.4674 | 223.3792 |
| 1/3/2021 | 145.2697 | 145.2255 | 145.2249 | 145.2255 | 176.3944 | 188.7458 |
| 1/4/2021 | 164.9601 | 153.425 | 154.3189 | 174.2703 | 208.8983 | 209.2918 |
| 1/5/2021 | 223.3199 | 121.6824 | 122.2016 | 131.3586 | 184.1956 | 180.5403 |
| 1/6/2021 | 147.7518 | 280.0412 | 258.9021 | 172.971 | 220.8237 | 208.2783 |
| 1/7/2021 | 135.6533 | 135.7234 | 137.4761 | 135.7584 | 238.9168 | 238.9168 |
| 1/8/2021 | 141.5546 | 141.0451 | 141.0629 | 146.3463 | 141.0796 | 214.7316 |
| 1/9/2021 | 154.0903 | 200.3693 | 136.9806 | 123.1715 | 119.6894 | 183.6511 |
| 1/10/2021 | 132.673 | 144.0054 | 157.5105 | 621.2265 | 131.9328 | 211.9066 |
| 1/11/2021 | 136.9591 | 136.9628 | 137.0033 | 141.0144 | 184.4867 | 184.4759 |
| 1/12/2021 | 119.4781 | 119.4848 | 119.9693 | 157.634 | 172.3995 | 181.7264 |
| 1/13/2021 | 140.0989 | 138.0066 | 138.0141 | 138.1441 | 193.4308 | 195.5172 |
| 1/14/2021 | 137.9133 | 126.7529 | 126.444 | 126.5814 | 173.7042 | 178.9822 |
| 1/15/2021 | 120.5262 | 121.331 | 120.5883 | 120.6652 | 196.0617 | 177.0144 |

From the results of the predicted data, it can be concluded that the network can study the dispersion of data based on 30 data used and 560 data patterns used. The network can also find the optimal solution to minimize cost functioning. The result of prediction or forecasting for 15 days in the coming month is a solution in this case, which is useful for understanding the peak load in the upcoming month so that you can determine how much energy will be used.

## 5 CONCLUSIONS

Based on the training results using several parameters, the best results for the testing and prediction process were obtained, namely using Hidden Layer 10, epoch 8000 and Learning Rate 0.1. The results of calculating the MAPE value of 6.5% show that the prediction of electricity use in residential buildings using the JST Backpropagation method has excellent forecasting accuracy capabilities.

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