Demand of Electricity Consumption in Central Java For A Better Future Living Life; An Forecasting

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Abstrak

The population of Central Java Province keeps increasing each year and so does the electricity consumption. The increase of electricity consumption in Central Java was obtained, as well as an interconnected system to electricity production. However, some power plants are no longer operational. To cover population growth which is directly proportional to electricity demand, an estimate is needed. This research discusses the forecasting of electricity consumption in the next few years to determine the actual load using an artificial neural network (backpropagation) and then compared it with the linear regression method. Based on the research results, it can be concluded that the application of artificial neural network system with Backpropagation algorithm had a better level of accuracy, as evidenced by training results with MSE value of 8.2765e-15 on the Best Training Performance graph, which is very far from the target error. As for manual calculation of MSE between neural networks and linear regression, it was shown that linear regression had a larger MSE. The results of forecasting using artificial neural networks architectural design for predicting the total electrical energy consumption had a fixed value in the next 3 years of 29,814,872.55 MWh.

***Keywords**: Electrical Energy Consumption, Forecasting, Artificial Neural Networks, Linear Regression*

1. Introduction

The population of Central Java Province keeps increasing each year and so does the electricity consumption. The reason is the existence of an interconnected system of electricity production. Based on data taken from The National Electricity Company (PT PLN) Persero UP2B JTD, several power plants in Central Java, namely Electric Steam Power Plant High Speed Diesel and Electric Steam Power Plant Marine Fuel Oil are no longer operating due to overhaul [1]. Therefore, based on data from PLN, the demand for electricity is greater, namely ± 26,708,039 MWh per year, compared to the availability of electricity, namely 11,462,888 MWh per year [2].

The solution provided by this research is to predict electricity consumption for the next few years in order to know the actual load that will be needed. Along with the development of computer technology, artificial intelligence is added to a computer system that can adapt a computer machine to work like humans. Several fields that make use of artificial intelligence include fuzzy logic, expert systems, robotics, games, and artificial neural networks. Artificial neural networks act as indispensable predictor because they can perform computations in a pre-determined way and produce accurate predictions of classification, optimization and pattern recognition. Based on the abilities possessed, results of Artificial Neural Network learning can be used to find solutions from a problem in everyday life. From time to time this ANN continues to develop and getting ahead and better than previous [3]. Backpropagation is a learning algorithm for predicting supervised neural networks which has a strong and objective mathematical basis. This algorithm obtains the form of equations and coefficient values in the formula by minimizing the number of squared error errors through a developed model [4]. Regression analysis is a statistical technique for modeling and investigating the relationship between two or more variables. In regression, there are one or more independent/predictor variables which are usually represented by variable X and one dependent/response variable which is usually represented by variable Y [5].

Several research have discussed artificial neural networks for forecasting include research forecast the demand for household electricity consumption in 2016 based on validation data from 2011-2015 using application of neural networks backpropagation method [6]. The study discusses the application of neural networks to forecast building energy use and demand, with a particular focus on application reviews, data, forecasting models, and performance metrics used in model evaluation [7]. Study about A novel feed forward two layer ANN neural network based function approxiinator model is irtilized to forecase electric system hourly load [8]. Research on the comparison of the accuracy of the results of the methods used in the method used in this study is the Artificial Neural Network algorithm with the PLN RUPTL (Electricity Supply Business Plan) to estimate electricity consumption [9]. Research discusses the presentation of the peak load forecasting system for transformer 1 and transformer 2 at the substation using backpropagation artificial neural network [10]. Other research discusses the application of ANNs to predict the long range energy consumption for a country and the long-term energy consumption for the years ahead is predicted [11]. Artificial neural network approach for short-term electricity prices forecasting with the new deregulated framework, producers and consumers require short-term price forecasting to derive their bidding strategies to the electricity market [12]. Research on different forecasting methods autoregressive integrated moving average (ARIMA), artificial neural network (ANN) and multiple linear regression (MLR) were utilized to formulate prediction models of the electricity demand which aims to compare the performance of the three approaches and the empirical data used in this study [13]. Artificial neural network using the feed-forward model to predict the daily energy consumption of a building. The administration building of the University was used as a case study [14]. Research about considers the combination of exponential smoothing for double seasonal patterns and neural network model with the proposed hybrid model is started by implementing exponential smoothing state space model to obtain the levels, trend, seasonal and irregular components and then use them as inputs of neural network [15].

Then, The learning of forecasting electricity consumption in India, to forecast future projection of demand for a period of 19 years from 2012 to 2030 using artificial neural network with linear regression [16]. A research to predict the future energy consumption with Regression analysis is conducted to select the most relevant independent variables as well as building the multiple linear regression (MLR) models In addition, an artificial neural networks model is developed as a comparison [17]. Research about forecasting electricity consumption with neural networks and support vector regression [18]. Study about regression analysis was performed to accurately identify the impact of each element on energy consumption,then from the regression analysis, the input variables for the training of the artificial neural network model (ANN) are selected for each period, and the housing energy consumption prediction model is implemented based on the actual consumption [19]. Energy the least squares support vector machines (LS-SVM) is implemented for the prediction of electricity energy consumption. In addition to the traditional regression analysis and artificial neural network (ANN) are considered [20]. Research on new techniques to predict electric loads using the multiple linear regression (MLR) model, which adopts a statistical approach that assumes the past load and weather data have information for forecasting the target load [21]. Study about uses linear regression analysis technique to forecast the energy load demand in Ogun State and the population for a 10-year period [22].

2. Demand Of Electrical Energy Consumption Model

This chapter describes the model demand of electrical energy consumption are shown in Fig. 1. The first input historical data and target on electricity consumption and population central java, then the data obtained were analyzed using the backpropagation artificial neural network method to determine the relationship between input and output. If the prediction of the bacpropagation neural network has met the target, calculate by getting the best MSE (mean square error) value. Next the forecasting data is obtained for the next 3 years (2020 to 2022).

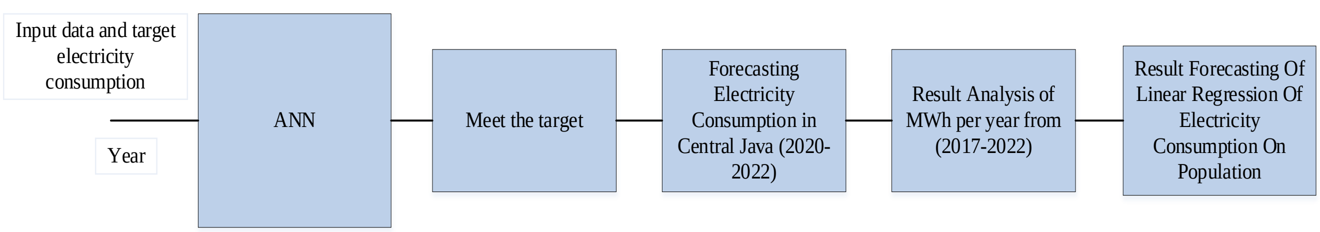

Figure 1. Modelling Steps

The results of forecasting energy consumption are tests carried out using different testing data from learning data. The testing data used is electrical energy consumption data of Central Java from 2017 to 2019 whose output was obtained using artificial neural networks with backpropagation. Linear regression forecasting of electricity consumption in the population are compared with the backpropagation neural network forecasting which is obtained from the mean square error value.

2.1. Backpropagation Artificial Neural Network Architecture on Demand for Electrical Energy Consumption

The artificial neural network architecture used was the back propagation algorithm. It had multiple units that are on another hidden screen. The population prediction inputs of electricity consumption and neural network targets with variables Year-1, Year-2, and Year-3 represented the value of electricity consumption before the year to be predicted. For example if we are predicting 2017, then data input of Year-1, Year -2, and Year-3 are 2014, 2015, and 2016, and 2017 as the target. Therefore, in order to get the forecast results for 2020 to 2022, the output values of ANN from 3 years before required the results of the 2017, 2018, and 2019.

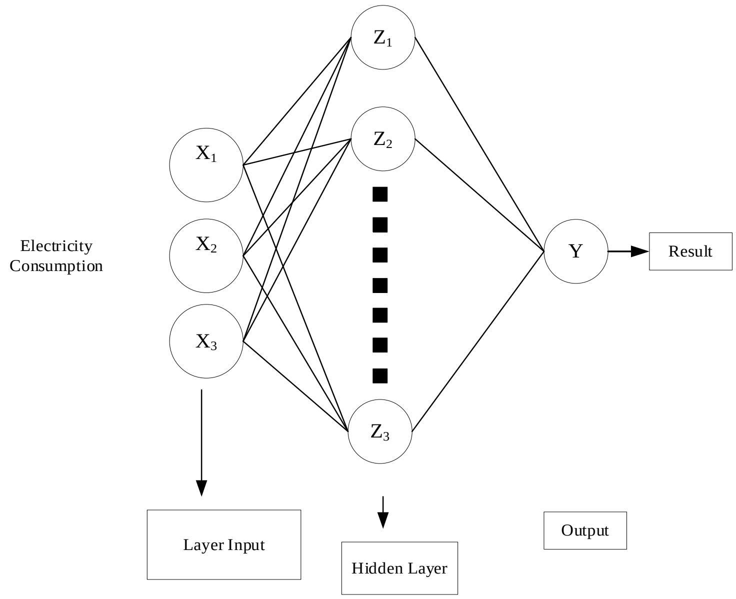

Figure 2. Research Architecture of Electrical Energy Consumption

Fig. 2 shows a backpropagation network architecture with X inputs, Z is hidden layer and Y is Y is the output.

- The input layer had two population parameters of waste with 3 input neurons per parameter (X1, X2, and X3), the input data contained normalized data with each neuron representing 1 data.
- The hidden layer had a function to train data which then produces output (Y). The transfer function used was sigmoid because the data used after being normalized has a range of [0 1], while to produce the output function, a tansig transfer was used.
- One neuron output layer which represented the 1st data referred to the forecast data for each parameter in the next 3 years.

2.2 Flow Diagram Demand Of Electrical Energy Consumption

The flow chart for forecasting Central Java electrical energy consumption using a neural network system is shown in Fig. 3. Preceded by a study of various theories relating to artificial neural networks for forecasting electrical loads, then data collection is carried out from related agencies, in the form of data on electricity consumption and population data of Central Java for the last six years (2014-2019). Then data normalization process with transforming the data first, because the output range of the activation transformation was between 0 and 1. The data obtained were analyzed using the backpropagation neural network method to determine the relationship between input and output. For forecasting electrical energy consumption using banckpropagation, the data used for forecasting electric loads as input is the previous year's data. The input and target of neural networks with variables of Year-1, Year-2, and Year-3 are the value of electricity consumption before the year to be predicted. For instance, to predict 2017, then data input Year-1, Year -2, and Year-3 are 2014, 2015, and 2016. So, to get the forecasting results for 2020 to 2022, the output value should be ANN of 2017, 2018, and 2019. The input that produces the best output is used as input to be used in forecasting electrical loads. Next, an analysis of artificial neural networks for electrical energy Consumption from testing was done using different data from training data. The testing data used were data on the electricity consumption of Central Java from 2017 to 2019 whose output was obtained using artificial neural networks with backpropagation. Then, it was shown that the results of forecasting electricity consumption in Central Java from 2020 to 2022 using the artificial neural networks with backpropagation algorithm had a better level of accuracy. Regression analysis is a statistical technique for modeling and experimenting the relationship of two or more variables. In the regression forecasting analysis, there are one or more independent / predictor variables which are usually represented by the variable X and one response variable which is usually represented by Y.

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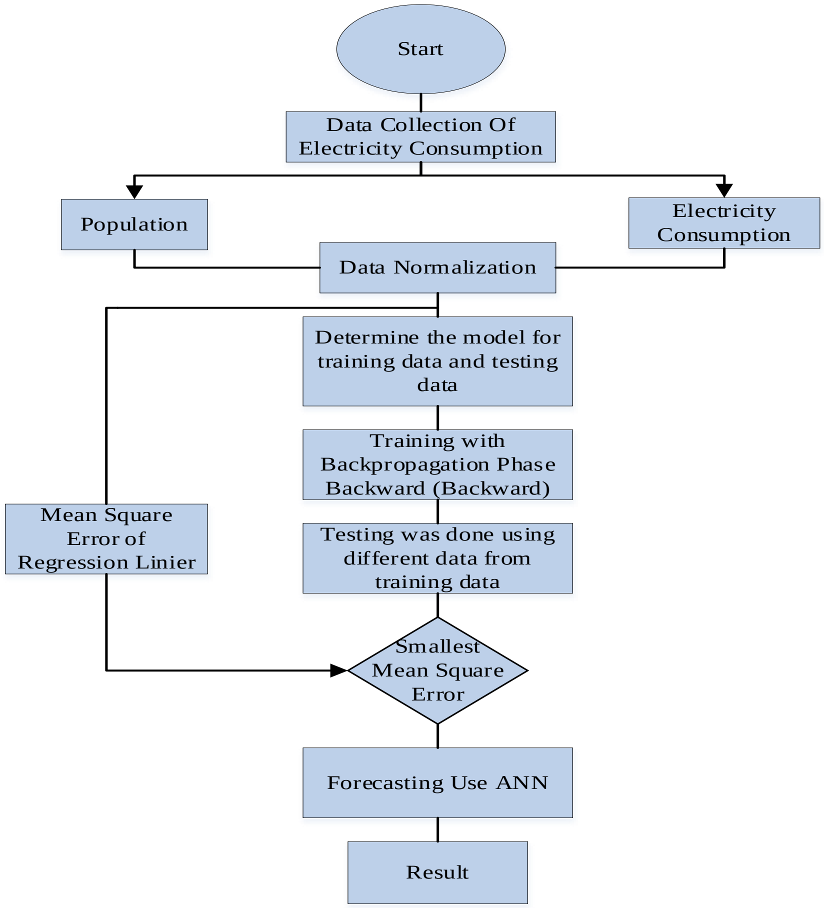

Figure 3. Demand Of Electrical Energy Consumption

In this study, Linear Regression is proposed to compare the performance of backpropagation in electrical energy consumption with the results of the mean square error of artificial neural networks with linear regression. Se that it can be found that the mean squared error (MSE) meets the predetermined value.

2.3 Demand Of Electricity Energy Consumption Data

In order to predict electrical energy consumption, it is necessary to have the historical data beforehand. The data for 2014 to 2019 were historical data on the electricity consumption of community in Central Java. The following was used as forecasting input.

Table 1. Electrical Energy Consumption (Mwh) Data In Central Java [2]

Electrical Energy Consumption (Mwh) Data In Central Java	
Year	Energy Consumption (*Y*)
2014	23,992,872.51
2015	24,820,932.20
2016	26,286,628.30
2017	26,862,572.49
2018	28,470,357.89
2019	29,814,872.55

Table 1 that shows data for 2014 to 2019 is historical data on people's electricity consumption in Central Java, which shows that this data has increased by up to 24 percent. for that we need a forecast to find out the actual load in the future and for a better life in the future.

2.4 Backpropagation For Electricity Energy Consumption

Learning algorithm in the forecasting of artificial neural network method was performed by studying existing historical data and generalizing the behavioral characteristics of objects, learning from large by building networks, initializing weights for initial learning, determining network parameters. For each epoch forward propagation was carried out. If the error is greater than the minimum error, then back propagation is carried out. Modifying of weight is done by change in weight which was determined by the learning rate if the number of epoch targets are met, which include the final criterion of weight and, thus, termination has been achieved [23].

2.5 Activation Function For Electricity Energy Consumption

In the forecasting using artificial neural network with backpropagation algorithm, we have to use a mathematical function to reveal the output and input values. This research used the sigmoid activation function (tansig) which has a value range of [-1 to 1].

2.6 Parameters Of Electricity Energy Consumption

To conduct training on artificial neural networks, the following parameters were determined:

- Epoch : 500
- Show : 25
- MSE : 0.0001
- Activation function: Sigmoid bipolar [-1 1]

2.7 Normalization Of Electricity Energy Consumption

This research used the sigmoid activation function, which was done by transforming the data first, because the output range of the activation transformation was between 0 and 1. According to a research [24], to calculate the normalization formula, the equation used is as the following:

$$X' = \frac{(X0 - Xmin)}{(Xmax - Xmin)} \quad (1)$$

With,
X' : transformation result
X_0 : actual data
$Xmax$: maximum value of actual data
$Xmin$: minimum value of actual data

2.8 De-Normalization Of Electricity Energy Consumption

De-normalization is the process of returning the predicted results of the network to its original data form (before normalization). According to a research [24], the formula used to de-normalize data is shown in equation 2.

$$X' = y(Xmax - Xmin) + Xmin \quad (2)$$

With,
X' : value of X to de-normalize
y : value of prediction result
$Xmax$: maximum value of actual data
$Xmin$: minimum value of actual data

2.9 Linier Regression

To compare backpropagation result, it is need often method validation. Linear Regression is proposed to compare the performance of backpropagation a in electrical energy consumption. Linear regression is a statistical technique for experimenting with two or more variables. It is used for predicting one or more variables that are usually represented by variables X and Y [23]. The independent variable is X and the dependent variable is Y [22]. The calculations for calculating linear regression are shown in the equation 3.

$$Y = a.X + b \tag{3}$$

With,
X : Population Data
Y : Electricity Consumption Data
n : Total Data

To find the values of *a* and *b*, the following formulas are used:

$$a = \frac{n\ \Sigma XY - (\Sigma X).(\Sigma Y)}{n\ \Sigma X^2 - (\Sigma X)^2} \tag{4}$$

$$b = \frac{(\Sigma Y).(X^2) - (\Sigma X).(\Sigma XY)}{n\ \Sigma\ X^2 - (X)^2} \tag{5}$$

2.10 Mean Square Error

In a forecasting, MSE (mean square error) testing is required to determine the error value. The MSE value in one training cycle is represented by the error value = output value - input value, then squared and divided by the number of data. MSE generates small errors and sometimes generates large error [25]. The equation used to calculate MSE according to researcher [20], can be explained by the following equation.

$$MSE = \frac{\Sigma e^2}{n} \tag{6}$$

Σe^2 : the difference between the target value and the predicted output value and squa
n : the amount of learning data

3. Result And Analysis

3.1 Data Normalization

The input and target of neural networks with variables of Year-1, Year-2, and Year-3 are the value of electricity consumption before the year to be predicted. For instance, to predict 2017, then data input Year-1, Year -2, and Year-3 are 2014, 2015, and 2016. So, to get the forecasting results for 2020 to 2022, the output value should be ANN of 2017, 2018, and 2019.

Table 2. Data Normalization And Electricity Consumption Target Of Central Java In 2014-2019

Normalization Data and Electricity Consumption Targets				
Year	X1	X2	X3	Target
2017	0	0,1422	0,3939	0,4929
2018	0,1422	0,3939	0,4929	0,7690
2019	0,3939	0,4929	0,7690	1

Referring to Table 2, the time series normalization data, X1, X2, and X3 are the electricity consumption for the previous 3 years, meanwhile Y is the target. The results of normalization presented above are the results of parameter data which show the maximum and minimum values used as representatives of the original data without changing their characteristics.

3.2 Forecasting Using Training Artificial Neural Networks

In training data to forecast electricity consumption in Central Java using input models and neural network, the input and target of neural networks with variables of Year-1, Year-2, and Year-3 are the value of electricity consumption before the year to be predicted. For instance, to predict 2017, then data input Year-1, Year -2, and Year-3 are 2014, 2015, and 2016. So, to get the forecasting results for 2020 to 2022, the output value should be ANN of 2017, 2018, and 2019. Then, the followings will be obtained; output plot in the form of Regression, Best Training Performance, with each plot has different functions to display results for certain epoch. The following is the plot of the electricity consumption forecast:

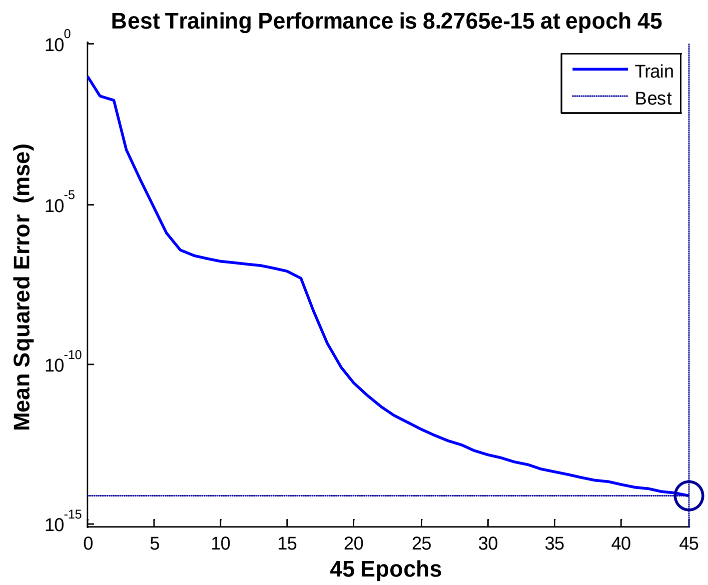

Figure 4. Graph Of Graph of MSE in Training of Electricity Consumption Parameter

Figure 4 illustrates a graph MSE value in training of electricity consumption data in Central Java, which is a learning in each epoch. In the testing process, the iteration stopped at the 45th epoch, because the limit of the desired epoch had been reached and results in an MSE of 8.2765e-15 less than 0.001, which indicated that the MSE is included in the target MSE

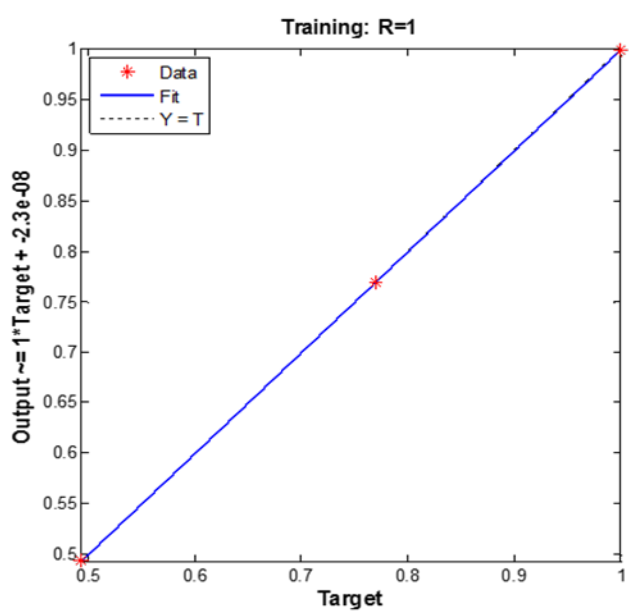

Figure 5. Regression Value In Training Of Electricity Consumption Parameter

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In figure 5, the data spread between lines are the input of parameter, gradient of x is the target, and gradient of y shows the output of the forecasting. The regression value of population data parameter training with 10 neurons in the hidden layer when the training data for a match between the network output and the target is obtained if the training is perfect, the network output and the target will be exactly the same, it can be proven that the correlation coefficient (R) is 1 and to get the best result is if the correlation coefficient (R) is 1. It can also be described that the ordinate x that meets at the point 0.49 also has the same value in the ordinate y, the ordinate x at the value point 0.76 also meets at the same value in the ordinate y and the value point 1 is also in the ordinate x and y.

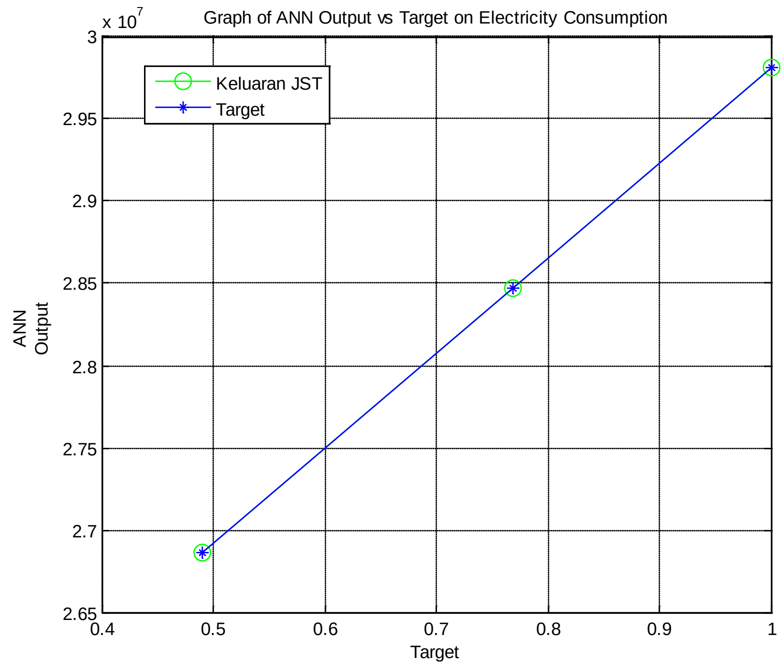

Figure 6. Graph Of ANN Output Vs Forecasting Target Of Electricity Consumption

Figure 6 shows the comparison between ANN output and the target in training of population forecasting. In the figure, there is a graph with a close value comparison between ANN output and the target. Therefore, the best results are obtained if they are in a close position. This can be proven by the fact that the two scores are almost the same, between the output and target at 0.76 which is at the same point as the number 28,470,339.86, at 1 which is at the same point as the number 29,814,872.55 due to the significant amount of MSE during the training process. The best results are obtained if ANN versus target are in coincide position or exactly the same.

3.3 An Analysis Of Artificial Neural Networks For Electrical Energy Consumption

The testing data used were data on the electricity consumption of Central Java from 2017 to 2019 whose output was obtained using artificial neural networks with backpropagation. Then, it was shown that the results of forecasting electricity consumption in Central Java from 2020 to 2022 using the artificial neural networks with backpropagation algorithm had a better level of accuracy.

3.4 De-Normalization Of Electrical Energy Consumption

The process of de-normalization is done to revert the data to its original data (before normalization). Denormalization is carried out on a normalized database, by saving the table structure and ignoring the (controlled) duplication of data to improve database performance. which aims to prevent the network from failing when experiencing learning, training, or testing.

Table 3. Result Of De-Normalization Of Electricity Consumption

Forecasting ANN (Denormalization) of Electricity Consumption		
Year	ANN	Denormalization
2017	0.49	26,862,594.55
2018	0.76906	28,470,339.86
2019	1	29,814,872.55
2020	1	29,814,872.55
2021	1	29,814,872.55
2022	1	29,814,872.55

Table 3 shows the result of data de-normalization in forecasting the result of total electricity consumption. From the results of Table 3, the number of forecasting had also experienced an increase, but had a constant value in the next 3 years. The years of 2020 to 2022 showed the same forecasting results as they are close to the original input data. The de-normalization value was exactly the same as the input and target data.

3.4 An Analysis Of Linear Regression Forecasting Of Electrical Consumption For Central Java

In forecasting the regression of electricity consumption on population, it was calculated using Matlab calculations with the program that had been made. Where Y is the dependent variable (Electricity consumption) and X are the independent variable. The calculations produced an equation, namely:

$$Y = (52.56019254 \,.\, X) + (-59{,}402{,}550.52)$$

Table 4. Forecasting Of Linear Regression Of Electricity On Population

Results of Forecasting Linear Regression for Electricity Consumption		
Year	Population (X)	Electricity Consumption (Y)
2014	1,584,906	23,900,414
2015	1,595,267	24,444,990
2016	1,648,279	27,231,311
2017	1,658,552	27,771,262
2018	1,668,578	28,298,230
2019	1,674,358	28,602,028

Table 4 shows the result of linear regression of electricity consumption In Central Java . From the results of the table above, the linear regression calculation had also increased in 6 years, in 2014 to 2017 had an increase of 19%. From Table 4 we can also see that the most influential predictor for energy consumption is X population

3.5 Analysis Of Mean Square Error Result

Presented in Table 5 are the error results, namely the calculation of difference between the target and the artificial neural network (ANN) output, compared with the ANN output with linear regression, resulting forecasting of each mean square error. The mean square error used for comparison is the MSE of the results testing data used were data on the electricity consumption of Central Java from 2017 to 2019 whose output was obtained using artificial neural networks with backpropagation.

Table 5. MSE Of Artificial Neural Networks Of Electricity Consumption

MSE Results Of Electricity Consumption From The Artificial Neural Network Method			
Year	Target	ANN	Error2
2014	0	0	0
2015	0.142229419	0.142229419	0
2016	0.393980724	0.393980724	0
2017	0.492906211	0.492906211	0
2018	0.76906	0.76906	0
2019	1	1	0
MSE			**0**

Table 5 shows the MSE result of 0, meaning that this was very perfect because the target and ANN output had no difference. This means that the results of forecasting electricity consumption using the backpropagation algorithm artificial neural network method had a better level of accuracy.

Table 6. Mse Of Liner Regression Of Waste

MSE Results Electricity Consumption From The Linear Regression Method			
Year	ANN	Regression	Error2
2014	0.90854	1	0.008364932
2015	1	0.884172517	0.013416006
2016	0.15056	0.291541832	0.019875877
2017	2.2815E-14	0.176698117	0.031222225
2018	0.00018793	0.06461566	0.004150932
2019	0.85332	0	0.728155022
MSE			**0.134197499**

From Table 6, it is shown that MSE linear regression result was 0.134197499. Tables 5 and 6 are a comparison of the two different forecasting methods. The forecasting of artificial neural networks waste produced a fairly perfect output, because it had smaller MSE than the one produced from linear regression. Both methods were still in range [0 1], meaning that they were quite accurate, regardless

4. Conclusion

Based on the research results, it can be concluded that the application of artificial neural network system with backpropagation algorithm had a better level of accuracy, because it was evident from the training results that had MSE value of 8.2765e-15 on the Best Trainig Performance graph which was very far from the target error. Meanwhile, for manual calculation of MSE between neural networks and linear regression, linear regression had a larger MSE.
The forecasting of ANN architectural design to forecast the results of the total electrical energy consumption had a fixed value in the next 3 years of 29,814,872.55 MWh.

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