Long-term electrical consumption forecasting using Artificial Neural Network (ANN)

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Abstract. Long-term forecasting of electricity energy consumption has become one of the main fields in the electricity sector in each country. This study aims to compare the accuracy of the results of the method used in this study with research conducted by the government to estimate electricity consumption in Indonesia. Many methods can be used to estimate electrical energy consumption such as statistic methods (Exponential Smoothing, ARIMA, Regression), fuzzy logic and artificial neural network algorithms. The method used in RUPTL is Simple E (Simple Econometric) and method used in this study is the Artificial Neural Network algorithm. The results of this research are data on estimates of electricity consumption in Indonesia for 2019-2025. This research is expected to prove the accuracy of the Artificial Neural Network (ANN) method to estimate electricity consumption in Indonesia.

1. Introduction
Load forecasting is the main step in optimizing the operation of the electric power system [1]. Load forecasting plays an important role in the operation and management of electric power systems [2]. Load forecasting presents a reliability basis for network system planning, for the construction of new power plants and electric power distribution systems [3]. For long-term load forecasting plays an important role in power system planning, construction and maintenance [4]. In long-term electricity demand forecasting, it is evaluated by using past load demand [5]. The factors in long-term loads forecasting include GDP (Gross Domestic Product), electrification ratio and population [6].

Differences in forecasting models in practice usually get different results [7]. Methods for estimating long-term loads can be divided into two categories: parametric methods and artificial intelligence methods [8]. Traditional load forecasting methods (parametric), including time series, regressive analysis, etc., cannot meet the demand for demand accuracy predicted in practical communities [9]. The forecasting method with fuzzy theory, such as fuzzy exponential smoothing method, fuzzy linear regression method and fuzzy clustering method [4]. At present, many non-linear intelligent algorithms about load forecasting are widely used, such as artificial neural network algorithms or artificial neural networks [10].

Electric companies require load forecasting models to accurately predict the amount of power that must be sent to their customers and to adjust the balance of supply or demand at all times in the best cost and security conditions [11]. But like weather forecasting, electricity load forecasting is not entirely accurate [12]. Over the past two decades many techniques have been developed to improve the accuracy of long-term forecasting [13]. However, both the accurate amount of power needed and preparation for...
such amount of power is not as easy as it seems, because: (1) the estimated long-term load is always inaccurate (2) peak demand is very dependent on temperature, (in peak periods, an increase in temperature of 1 degree Celsius causes around 4500 MW to increase electricity demand), (3) some data needed for long-term estimates including weather conditions and economic data not available, (4) it is very difficult to save electricity with technology now (5) it takes several years and large amounts of investment to build new power plants and transmission facilities [14].

Artificial Neural Network is a distributed computing inspired form of biologically [15]. Artificial neural networks provide an accurate approach to problems and have the advantage of not requiring users to have a clear understanding of the underlying mathematical relationships between input and output [16]. Artificial Neural Networks (ANN) are a powerful way for time-series forecasting because in many studies, methods of forecasting artificial neural networks (ANN) have proven to be more accurate than traditional statistical methods [17,18]. The most popular artificial neural network architecture for electricity load forecasting is back-propagation neural networks [19]. Estimates of electrical energy consumption are an important problem for a country in optimizing its electric power system, so the authors try to use ANN methods (Artificial Neural Networks). The expected results are the estimated electricity energy consumption data that is not much different from the data in the RUPTL (Electricity Supply Business Plan) issued by the Ministry of Energy and Mineral Resources of the Republic of Indonesia.

The acquisition of long-term electrical energy consumption is an estimate made in a period of more than one year [20]. Every year the demand for electricity in each country tends to increase significantly, along with industrial and economic developments [21]. Therefore, estimates of long-term electrical energy consumption are important in the production and operation, planning and construction of electric power systems [22]. Estimates of long-term electrical energy consumption are suitable for long maintenance planning, construction scheduling for the development of new generating facilities, construction of generating units, development of electric power distribution and transmission systems [13]. Thus, the electric power system will be able to have an idea of the amount of power needed to prepare for future electricity demand [23]. The variables used in estimating electricity consumption in a country include GDP (Gross Domestic Product), population, peak load data, and data on electricity consumption in previous years [24].

![Figure 1. Projection of Indonesia's electricity needs (TWh).](Source: RUPTL Ministry of ESDM Republic of Indonesia 2018-2027)

Artificial Neural Networks (ANN) have been used to estimate electrical energy requirements since around 1990 [25]. ANN has been shown to have broad uses in the field of engineering optimization because it has excellent capabilities in non-linear mapping, generalization and self-learning [26]. Because the demand for electrical energy is very nonlinear, ANN can be said to be a good method
because it does not require an explicit model [27]. Therefore, ANN has replaced traditional methods in many applications due to better performance [28].

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Artificial neural network feed-forward, back propagation is the most frequently used artificial neural network architecture [29]. Back-propagation network is a multi-layer neural network whose function is to spread learning algorithms, back-propagation networks usually consist of layers of input layer, hidden layer and output layer [30]. Choices in the number of hidden layers (hidden layer) and the number of processing elements in each layer are related to the problem under study [31]. In general conditions, non-linear continuous functions can be conveyed through the three layers [32]. Back-propagation neural networks are used to estimate electricity consumption in an area for the following year where load data and economic data for the entire community can be obtained [33]. The idea of estimating electrical energy consumption using back-propagation networks uses variables as input for neural networks, then
testing estimates of electrical energy consumption as network output can be equipped with self-learning networks, adaptive capabilities and automatic estimates [6].

There are two programs in the learning process on back-propagation neural network algorithms, the first is input information transmitted in the forward direction where the input information will go to the hidden layer and then to the output layer. Second, errors are transmitted in "backward direction" where when the output layer is different from the desired output, the output error will be calculated, the error will be transmitted to "backward-direction" which will create weights in each layer of neurons to be modified to reduce the percentage error. Furthermore, artificial neural networks are trained to process data. The difference between the actual response and the target will produce an error signal. In the end, the error signal generated is sent from "backward" to the input layer through a hidden layer. During forward pass, the synaptic weight of the network will be corrected. During backward pass, synaptic weights are adjusted to adjust the network to produce the output produced [34].

2. Methods
The first thing to do is to determine the research objective, namely to estimate electricity consumption in Indonesia using the Artificial Neural Network (ANN) and compare it with the RUPTL (Electricity Supply Business Plan) issued by the Ministry of Energy and Mineral Resources. Then do a literature survey that deals with the estimation of electricity consumption. The literature used is sourced from international journals and text books which are then processed using Mendeley software. International journals used are sourced from IEEE, Elsevier, ScienceDirect and so on. After the literature was collected, the survey instrument was compiled which included electricity consumption in Indonesia in 2009-2018, GDP (Gross Domestic Product), population and number of PLN customers. Then data was collected at the West Java Provincial Statistics Agency and the Department of Energy and Mineral Resources of West Java Province. After the data is collected, data is processed using the software Zaitun Time-Series with the Artificial Neural Network algorithm. The results of data processing are then compared with the data in the Electricity Supply Business Plan (RUPTL) issued by the Directorate General of Electricity at the Ministry of Energy and Mineral Resources of the Republic of Indonesia. From the results of the analysis it can be concluded how accurate the Artificial Neural Network (ANN) method is in estimating electrical energy consumption in Indonesia.

The data used in research on electricity consumption in Indonesia can be obtained through:

2.1. Documentation/ Literature
This data collection technique is sourced from data contained in the West Java Central Bureau of Statistics and the Department of Energy and Mineral Resources of West Java Province. The data collected includes: electricity consumption, number of customers, GDP and population.

2.2. Discussion
In carrying out this research, the researcher held a discussion with the supervisor from the Department of Electrical Engineering Education and other related parties.

2.3. Data processing techniques
The supporting aspects for data processing are hardware and software. The hardware used is a PC Laptop with specifications for the Windows 10 Home Single-Language Operating System, Intel® Core™ i3-4005U Processor (1.7 GHz, 3MB L3 cache). The software used in this research is Zaitun Time-Series, Microsoft Office 2016, Mendeley version 1.19.3 and Microsoft Edge. Then the collected data is processed using the Zaitun Time-Series software with the Artificial Neural Network algorithm.

2.4. Data analysis technique
To estimate electrical energy consumption in this study carried out by Artificial Neural Network Feed-forward Back-Propagation algorithm found in the Zaitun Time-Series software.
Figure 4. Illustration of electrical consumption forecasting using neural networks.

3. Results and discussion

3.1. Electric energy consumption in Indonesia
As the population increases and the number of PLN customer’s increases, the demand for electricity will be even higher. According to data contained in the PLN RUPTL (Electricity Supply Business Plan) and Electricity Statistics, electricity consumption in Indonesia has increased significantly in the past 19 years in both the various consumer sectors and as a whole.

Figure 5. Profile of electricity consumption in 2000-2018.
3.2. Number of PLN customers
As the human population increases and the economy grows in Indonesia, the number of PLN customers increases. According to data contained in the PLN RUPTL and Electricity Statistics, in the last 19 years the number of PLN customers has increased in various sectors. The description of the growth rate of electricity consumption in each sector is as follows:

3.3. Number of population
According to the data contained in the Population Projection Book, the population or population in Indonesia in the last 19 years continues to increase every year. With the increasing population, it will affect the increase in electricity consumption in all sectors.
3.4. Gross Domestic Product
Gross Domestic Product (GDP) at constant prices according to the business field shows that the value added of goods and services that are calculated using current prices every year and in this study uses 2000 base years. Over the past 19 years Indonesia's GDP has continued to increase.

3.5. Electrical consumption forecasting using Artificial Neural Network feed forward backpropagation algorithm
The research begins with collecting data from 2000 to 2018 which includes electricity consumption for each sector, gross domestic product, population and number of PLN customers. The first step is to find the number of neurons in the hidden layer with learning parameters as follows: Epoch maximum 500 iterations; Learning speed 0.5; Constant momentum 0.9; binary sigmoid activation function.
Table 1. The error value from the optimization of the number of hidden neuron layers.

| Neuron Hidden Layer | Trial (%) | Average (%) |
|----------------------|-----------|-------------|
|                      | 1 | 2 | 3 | 4 | 5 |       |
| 9                    | 1.2 | 1.3 | 1.3 | 1.4 | 1.6 | 1.36 |
| 18                   | 1.5 | 1.1 | 1.2 | 1.2 | 1 | 1.2 |
| 27                   | 1.1 | 1 | 0.9 | 0.9 | 0.9 | 0.96 |
| 36                   | 1.2 | 1.2 | 1 | 1.2 | 1.2 | 1.16 |
| 45                   | 1.7 | 1 | 1.6 | 1.1 | 1.2 | 1.32 |
| 48                   | 1.7 | 1.3 | 0.9 | 1 | 1 | 1.18 |

In the first experiment, the number of neurons in the hidden layer that has the best accuracy is the hidden layer with 27 neurons that have an accuracy of 98.9% and the average of the five trials is 99.04%. Observation of the average number of neurons in the hidden layer is illustrated by the graph as follows.

Figure 10. The level of accuracy is based on the number of neurons in the hidden layer.

In the graph illustrates that the use of neurons in the hidden layer as many as 27 has a better level of accuracy than the others. Then from that hidden layer with 27 neurons will be used in the next optimization process.

After searching for the most optimal hidden neuron layer, the next step is to find the best number of iterations. The number of iterations to be used is 500, 1000, 2500, 5000 and 10000.

Table 2. Error value in number of iterations.

| Epoch | Trial (%) | Average (%) |
|-------|-----------|-------------|
|       | 1 | 2 | 3 | 4 | 5 |       |
| 500   | 1 | 0.9 | 1.2 | 1.3 | 1 | 5.4 |
| 1000  | 0.94 | 1.04 | 1.11 | 1.05 | 1.18 | 5.32 |
| 5000  | 0.38 | 0.32 | 0.46 | 0.35 | 0.53 | 2.04 |
| 10000 | 0.20 | 0.19 | 0.22 | 0.15 | 0.13 | 0.89 |
From these experiments it can be concluded that the greater the number of iterations, the smaller the number of errors produced. So from that chosen the number of iterations of 10000 as a setting for the optimal learning rate search.

Learning rate is an important factor in processing data using artificial neural networks. So the search for optimal learning rate will be tested from a range of 0.1 - 0.9 with the aim of finding a learning rate that produces the smallest error.

Table 3. Error value at learning rate value.

| Learning Rate | Trial 1 | Trial 2 | Trial 3 | Trial 4 | Trial 5 | Average (%) |
|---------------|--------|--------|--------|--------|--------|-------------|
| 0.1           | 0.69   | 0.68   | 0.96   | 0.71   | 0.66   | 0.74        |
| 0.2           | 0.32   | 0.34   | 0.44   | 0.33   | 0.32   | 0.35        |
| 0.3           | 0.37   | 0.43   | 0.34   | 0.40   | 0.22   | 0.35        |
| 0.4           | 0.33   | 0.29   | 0.31   | 0.23   | 0.19   | 0.27        |
| 0.5           | 0.17   | 0.10   | 0.09   | 0.08   | 0.12   | 0.11        |
| 0.6           | 0.29   | 0.20   | 0.30   | 0.09   | 0.09   | 0.19        |
| 0.7           | 0.23   | 0.28   | 0.22   | 0.30   | 0.29   | 0.26        |
| 0.8           | 0.23   | 0.19   | 0.26   | 0.24   | 0.20   | 0.22        |
| 0.9           | 0.23   | 0.33   | 0.10   | 0.21   | 0.24   | 0.22        |

In the first experiment, the learning rate that had the least error value was a learning rate of 0.5 with an error value of 0.17% and the average error value of the five trials was 0.1%. Observation of the amount of learning rate to the level of accuracy is illustrated by the graph as follows.

Figure 11. Level of accuracy based on learning rate.

In the graph illustrates that the use of a learning rate of 0.5 has an accuracy rate of 99.89% which means better than the number of other learning rates. So from that the learning rate of 0.5 will be used in the next optimization process.

The next optimization process is to do a research again on the learning rate of 0.5 because it has the most accurate results compared to other learning rate values. The optimization process is improved by testing the learning rate between 0.47 to 0.56. The aim is to find out whether there is a learning rate whose accuracy is better than the learning rate with a value of 0.5.
Table 4. Error value in the number of learning rates.

| Learning Rate | Trial | Average (%) |
|---------------|-------|-------------|
|               | 1     | 2           | 3           | 4           | 5           |             |
| 0.47          | 0.22  | 0.14        | 0.21        | 0.15        | 0.13        | 0.17        |
| 0.48          | 0.11  | 0.11        | 0.10        | 0.08        | 0.22        | 0.12        |
| 0.49          | 0.10  | 0.11        | 0.10        | 0.13        | 0.35        | 0.16        |
| 0.50          | 0.17  | 0.10        | 0.09        | 0.08        | 0.12        | 0.11        |
| 0.51          | 0.15  | 0.12        | 0.13        | 0.13        | 0.10        | 0.13        |
| 0.52          | 0.17  | 0.33        | 0.30        | 0.19        | 0.27        | 0.25        |
| 0.53          | 0.12  | 0.17        | 0.15        | 0.16        | 0.11        | 0.14        |
| 0.54          | 0.30  | 0.18        | 0.18        | 0.30        | 0.11        | 0.22        |
| 0.55          | 0.26  | 0.13        | 0.13        | 0.09        | 0.08        | 0.14        |
| 0.56          | 0.09  | 0.10        | 0.05        | 0.06        | 0.07        | 0.07        |

From the table above it is found that the learning rate with a value of 0.56 has an average error value of 0.07% or accuracy of 99.93% which means better than the learning rate with a value of 0.5 which has an average error value amounting to 0.11% or accuracy of 99.89%. So from that the learning rate of 0.56 will be used in the next optimization process.

Momentum is one of the important parameters in the process of learning artificial neural networks. The momentum value has a range from 0 to 1, so the optimal momentum value search will be tested from a range of 0.1 to 0.9 with the aim of finding the smallest error value.

Table 5. Error value for momentum optimization results.

| Momentum | Trial | Average (%) |
|----------|-------|-------------|
|          | 1     | 2           | 3           | 4           | 5           |             |
| 0.1      | 1.07  | 0.87        | 0.90        | 1.05        | 1.05        | 0.99        |
| 0.2      | 0.87  | 0.90        | 0.79        | 1.02        | 0.70        | 0.86        |
| 0.3      | 0.75  | 0.68        | 0.76        | 0.84        | 0.74        | 0.76        |
| 0.4      | 0.87  | 0.72        | 0.59        | 0.80        | 0.61        | 0.72        |
| 0.5      | 0.67  | 0.80        | 0.42        | 0.51        | 0.54        | 0.59        |
| 0.6      | 0.61  | 0.51        | 0.83        | 0.44        | 0.57        | 0.59        |
| 0.7      | 0.41  | 0.39        | 0.33        | 0.47        | 0.34        | 0.39        |
| 0.8      | 0.20  | 0.29        | 0.29        | 0.34        | 0.31        | 0.29        |
| 0.9      | 0.09  | 0.10        | 0.05        | 0.06        | 0.07        | 0.07        |

In the first experiment the momentum value has the smallest error value, namely momentum with a value of 0.9 and in the next experiment the 0.9 momentum value continues to produce the smallest error value with an average error value of 0.07%. Observation of momentum values for accuracy in the learning process of artificial neural networks can be illustrated with the following graph.
Figure 12. Accuracy level based on momentum value.

From the graph shows that the momentum value of 0.9% has the best accuracy value compared to other momentum values. So from that momentum with a value of 0.9 will be used in the next optimization process.

The last optimization process is to find the number of neurons in the input layer. The number of neurons in the input layer represents the frequency (years) of data that will be used as input to the process of estimating electrical energy consumption. The results of the process of optimizing the number of neurons in the input layer are as follows:

Table 6. Value of error results for optimizing the value of neurons in the input layer.

| Input Layer Neuron | Trial 1 | Trial 2 | Trial 3 | Trial 4 | Trial 5 | Average (%) |
|-------------------|--------|--------|--------|--------|--------|-------------|
| 3                 | 0.90   | 1.70   | 1.58   | 1.70   | 1.42   | 1.46        |
| 4                 | 1.25   | 1.27   | 1.00   | 1.41   | 0.89   | 1.16        |
| 5                 | 1.13   | 1.33   | 1.15   | 1.24   | 1.31   | 1.23        |
| 6                 | 0.29   | 0.33   | 0.33   | 0.34   | 0.57   | 0.37        |
| 7                 | 0.51   | 0.44   | 0.44   | 0.30   | 0.45   | 0.43        |
| 8                 | 0.15   | 0.26   | 0.22   | 0.16   | 0.13   | 0.18        |
| 9                 | 0.09   | 0.10   | 0.11   | 0.06   | 0.07   | 0.09        |

From the table above it is found that the input layer with nine neurons has the smallest error value compared to the number of other neurons, which is equal to 0.09% or accuracy of 99.91%. So from that input layer with nine neurons will be used in this study.

The next step is estimating the electricity consumption in Indonesia for the next seven years using artificial neural networks with the best parameters obtained from the optimization process. The parameters to be used in estimating electrical energy consumption are as follows: maximum iteration of 10000; learning rate 0.5; momentum 0.9; hidden layer neuron 27; binary sigmoid activation function.
Table 7. Learning process results.

| Year | Electrical Energy Consumption | Actual | Predicted | Residual |
|------|--------------------------------|--------|-----------|----------|
| 2000 | 79,164                         | NaN    | NaN       | NaN      |
| 2001 | 84,52                          | NaN    | NaN       | NaN      |
| 2002 | 87,089                         | NaN    | NaN       | NaN      |
| 2003 | 90,441                         | NaN    | NaN       | NaN      |
| 2004 | 100,097                        | NaN    | NaN       | NaN      |
| 2005 | 107,032                        | NaN    | NaN       | NaN      |
| 2006 | 112,609                        | NaN    | NaN       | NaN      |
| 2007 | 121,246                        | NaN    | NaN       | NaN      |
| 2008 | 129,018                        | NaN    | NaN       | NaN      |
| 2009 | 133,826                        | 133,816| 0,010     |
| 2010 | 147,297                        | 147,368| -0,071    |
| 2011 | 157,992                        | 157,747| 0,245     |
| 2012 | 171,985                        | 172,185| -0,200    |
| 2013 | 184,665                        | 184,756| -0,091    |
| 2014 | 196,617                        | 196,540| 0,077     |
| 2015 | 200,807                        | 200,752| 0,055     |
| 2016 | 213,671                        | 213,587| 0,084     |
| 2017 | 221,067                        | 221,295| -0,228    |
| 2018 | 232,296                        | 232,177| 0,119     |

The learning process found very good results due to the very small difference between predictions and actual data sourced from the PLN RUPTL. The prediction is the result in the form of NaN (Not a Number) because the neurons in the input layer are nine.

Figure 13. Comparison between actual (red dots) and predictions (blue lines) in the learning process.

On the actual and prediction comparison chart, the results of the accuracy of the prediction are very good for the actual data sourced from the PLN RUPTL. Although the learning process is very good predictions, the estimation is not optimal in the process. The results of the estimation of electricity consumption using artificial neural networks (ANN) are as follows:
Table 8. Forecasting results.

| Year | JST (TWh) | RUPTL PLN (TWh) | Residual (TWh) |
|------|-----------|-----------------|----------------|
| 2019 | 237.92    | 245.38          | 7.46           |
| 2020 | 242.70    | 261.45          | 18.75          |
| 2021 | 244.26    | 279.35          | 35.10          |
| 2022 | 246.56    | 299.51          | 52.95          |
| 2023 | 247.62    | 320.00          | 72.38          |
| 2024 | 248.68    | 339.92          | 91.24          |
| 2025 | 249.29    | 360.94          | 111.65         |

Figure 14. Actual data from 2000-2018 (blue line) and forecast results 2019-2025 (red line).

Figure 15. Comparison of the growth rate of forecasting electricity energy consumption.

The results of the estimation of electrical energy consumption using artificial neural networks are found to be large differences compared to the estimated electricity energy consumption contained in the PLN RUPTL 2019-2028. This can be caused by different methods of estimating electrical energy consumption wherein this study uses an artificial neural network algorithm and the PLN RUPTL uses the "Simple E" method.

In the estimation using artificial neural networks requires quite a lot of input data in order to get optimal results and in this study due to the limitations of input data causing results that are not optimal.
The other factors that cause different results of the estimation of electrical energy consumption in this study compared to the PLN RUPTL are due to differences in input data where the PLN RUPTL uses more factors such as inflation, electrofication ratio and electricity price rates. Furthermore, in the input data in the form of population numbers sourced from the Indonesian Population Projection Book for 2000-2025, the population growth rate data tends to be slower or the population is less than the data contained in the PLN RUPTL.

Figure 16. The rate of growth of electricity consumption in the PLN RUPTL and estimates using Artificial Neural Networks (ANN).

3.6. Comparative research
In the estimation of electrical energy consumption using artificial neural networks is quite good because it produces a very small error and the level of accuracy in the learning process is very high. But the results of the estimation of electrical energy consumption are not satisfactory due to several factors, one of which is the limited data to be used as input (input). A review of the accuracy of the estimates of electricity consumption is done by comparing the methods of artificial neural networks and statistical methods. The statistical method that will be used for comparison is Double Exponential Smoothing (Brown) using the Zaitun Time-Series software. The following is a comparison of the errors generated in the estimation of electrical energy consumption using artificial neural networks and double exponential smoothing (Brown).

| Method           | MSE       |
|------------------|-----------|
| JST              | 0.019560  |
| Double ES        | 24.04682  |

In the estimation of electrical energy consumption using artificial neural networks produces MSE (Mean Squared Error) which is much smaller than the estimated electrical energy consumption using double exponential smoothing, which indicates that the learning process estimates electrical energy consumption using artificial neural networks has an accuracy level very good compared to the double exponential smoothing method. However, at the estimated stage of electrical energy consumption, the results between the method of artificial neural networks and double exponential smoothing are fairly far. The following is a comparison of the results of estimates of electrical energy consumption:
Table 10. Comparison of estimated electricity consumption results.

| Year | JST  | Double ES | RUPTL | PLN |
|------|------|-----------|-------|-----|
| 2019 | 238,17 | 242,43    | 245,38|
| 2020 | 242,73 | 252,67    | 261,45|
| 2021 | 244,19 | 262,91    | 279,35|
| 2022 | 246,47 | 273,14    | 299,51|
| 2023 | 247,65 | 283,38    | 320,00|
| 2024 | 248,66 | 293,61    | 339,92|
| 2025 | 249,34 | 303,85    | 360,93|

Figure 17. Comparison of estimates of electric energy consumption.

The results of the estimation process of electrical energy consumption using double exponential smoothing is better than the artificial neural network method, although the results are still fairly far compared to the PLN RUPTL. This indicates that when carrying out the estimation process with limited input data using double exponential smoothing is better than artificial neural networks because artificial neural networks require sufficient input data to produce optimal estimates.

4. Conclusion

Based on research that has been done by researchers, researchers can draw conclusions as follows: First, the input data used in the estimation of electrical energy consumption using artificial neural networks include electricity energy consumption per sector in 2000-2018, the number of PLN customers per sector from 2000-2018, Gross Domestic Product (GDP) in 2000-2018 and population in Indonesia from 2000-2018. Second, forecasting electricity consumption using artificial neural networks proved to be quite good. The accuracy of the artificial neural network is proven by the resulting error is very small in the learning process. Determination of parameters such as the hidden layer and the number of iterations greatly affects the learning process. Therefore it is necessary to try several times in determining these parameters. The results of the forecasting process are not satisfactory because the input data is still inadequate to estimate the consumption of electrical energy with artificial neural networks. This can be seen from the results that are very far compared to the estimated electricity energy consumption contained in the PLN RUPTL 2019-2028. As for other factors that cause the process of estimating electrical energy consumption using the artificial neural network method is different from the PLN RUPTL from 2019 to 2028 due to the different types of input data. Third, the estimation of electrical energy consumption with artificial neural networks produces MSE (Mean Squared Error) which is much smaller than the statistic double exponential smoothing method. This indicates that artificial neural
networks have very good accuracy compared to double exponential smoothing. However, unlike the artificial neural network method, double exponential smoothing can produce approximate data that is close to the target (PLN RUPTL) even though there are quite a few data and the artificial neural network method requires quite a lot of input data to achieve optimal results.

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