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ESTIMATED USE OF ELECTRICAL LOAD USING REGRESSION ANALYSIS AND ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

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Abstract

The rapid growth of Indonesia's population increases electricity consumption. Unfortunately, this growth is not followed by the development of new electrical energy sources. Therefore, there needs to be a comprehensive study to ensure that the electrical power supply meets the people's electricity needs. The estimated electrical load is one of the important factors in determining the number of the electrical power system. This study deals with the electrical load estimating using an Adaptive Neuro-Fuzzy Inference System (ANFIS) and Linear Regression methods. The data used for this estimation were data on the use of electricity in the provinces of Central Java and the Special Region of Yogyakarta, Indonesia. The electricity usage data were measured every half hour for six months, so there were 48 data loads in one day. This study uses the methods of analysis with regression analysis and ANFIS. The ANFIS consists of two inputs and is measured using two rules. The Fuzzy inference system applies the first order of the Takagi-Sugeno-Kang model. The result of estimation shows the Public Electricity Company Ltd. or Perseroan Terbatas Perusahaan Listrik Negara (PT PLN) has a good accuracy rate, with a Mean Absolute Percent Error (MAPE) error of 4.47%. On the other hand, based on the simulation results, the Regression Analysis method is fairly accurate for estimating electrical loads with a MAPE error of 1.92%, while the ANFIS method shows the most accurate estimation result with MAPE error of less than 0.96% of the actual value.

Keywords: ANFIS, Electrical load, Estimation, Regression analysis.

1. Introduction

The estimated electrical load is used to determine the amount of electrical energy generated and should be adjusted to the demand for electrical power according to consumer needs. Electrical energy cannot be stored in large quantities. If the electricity generated by the power plant is not used entirely by consumers, the electricity will be wasted, causing energy waste. In addition to the magnitude of power and electricity losses, it is necessary to estimate the load used by consumers so that the electricity generated can be prepared as efficiently as possible [1].

To provide sufficient electricity, short-term comprehensive studies are required so that electrical power can be distributed effectively [2]. One of the most determining factors in preparing an electrical power system operation plan is the estimated electrical load that will be borne by the electrical power system [3].

Estimation is essentially an estimate about the occurrence of an event in the future to come [4, 5]. Estimations can be qualitative (non-numeric) or quantitative (numeric). It is not easy to obtain a good result in qualitative estimation because the variables are very relative. Meanwhile, quantitative estimations are divided into two, namely single estimation (point estimation) and interval estimation. A single estimation consists of one value, while an interval estimation consists of several values, in the form of an interval that is limited by the lower and upper limit values [6].

Meanwhile, to make the estimation process, several methods can be done, including regression analysis, naive bayes, decision trees, and artificial intelligence. Regression analysis is a mathematical model, which can be used to evaluate the relationship pattern involving two or more variables [7].

Regression analysis shows more accurate results in conducting correlation analysis. The problematic phenomenon in showing the level of change of a variable against other variables can be determined by something often referred to as a slope. With regression analysis, the estimation of the value of the dependent variable on the value of the independent variable can be done more accurately [8].

The nature of the relationship between variables in the regression equation is a causal relationship. Therefore, before using the regression equation to explain the relationship between two or more variables, it is necessary to believe first that theoretically or in advance, the two or more variables have a causal relationship [9].

Discrete data can be made continuum through a curve-fitting process. Curve-fitting is a process of data-smoothing, which is the process of approaching data trends in the form of mathematical model equations. Curve fitting is the process of forming a curve of mathematical functions that are compatible with several data points and produces a plot representing data with an equation and its limitations (parameters) [7].

Meanwhile, to estimate the value of the electrical load, there is one fitting method that can be employed, namely the Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS is a blend of Fuzzy Inference Systems and Artificial Neural Networks. The ANFIS method was preferred in this study because Neural Networks will effectively learn from past experience/data. Just like Neural Networks, Fuzzy Logic can also provide computational functions without mathematical modeling as output depending on the input [10].

The ANFIS method regulates the parameters of the membership function of input or output parameters of a fuzzy inference system using prepared data. This arrangement uses ANN so that ANFIS has the ability to study past data [11].

ANFIS is a hybrid system of artificial neural networks and fuzzy logic. The artificial neural network method serves to provide learning and adaptation capabilities to the fuzzy rule base parameters of the data set. ANN can be used to eliminate the deficiencies of conventional fuzzy systems, in which the fuzzy system developers must regulate both the input and output of the fuzzy set membership functions [12]. The learning process in ANFIS is achieved by adjusting the input and output parameters of membership functions. A backpropagation algorithm or hybrid algorithm is a learning system that can be used in ANFIS [13, 14]. A hybrid algorithm is a fusion of the Least Squares Estimate method with a backpropagation algorithm. The Least Squares Estimate method is used to evaluate the impact parameters, while the backpropagation algorithm is used to change the weighting of the premises [15, 16].

Several studies in estimating the electrical long-term peak load demand with the methods of ANFIS and Multiple Linear Regression (MLR) [17]. ANFIS method was applied to get an accurate and reliable in short-term electrical load forecasting system [18]. Also, the method of ANFIS was used with the Gbell membership function in forecasting electrical load [19]. Determining the actual variables that affect the load consumption in short-term electric load forecasting through three different models based on data selection criteria were tested using ANFIS [20]. While a similar study also presented the univariate electrical data consumption was taken from January 2009 to December 2018 through the ANFIS method to forecast consumption in 2019 [21]. Several tutorials were presented practically to make forecasting for power electrical load using ANFIS [22].

This study applied the Regression Analysis and ANFIS methods to forecast short-term electrical loads, and to examine the accuracy of the Regression Analysis and ANFIS methods for estimating short-term electrical loads. This study describes the process of estimating the use of electrical loads based on a comparison between actual data, estimations made by the Indonesian public company of electrical power system (PT PLN), estimations using the regression method, and estimations using the ANFIS method. The baseline for the estimation calculation was real data from six months of observation with sampling done every 30 minutes for 24 hours straight. Data on the load usage were taken in two provinces namely Central Java and the Special Region of Yogyakarta, Indonesia.

The contribution of this study is it explained the estimated electrical load using ANFIS with a MAPE of 0.96%, while the previous study [18] obtained a MAPE of 2.23% through the ANFIS method.Also in the previous study [18], the result only explained the performance of ANFIS without being compared to other methods. Another contribution in this study, it was conducted a comparison between the ANFIS method and other methods. This study has presented an estimated electrical load using the ANFIS method with a smaller MAPE. In this study, through the ANFIS method, it can prove that the electrical load is more accurate than the previous study. In contrast, previous studies neither record the data for a longer period nor did they compare the actual data and clarify them in various estimation methods. Therefore, the other contribution in this study, three types of estimation methods were validated by comparing them with the actual results of the load use. Thus, the results of this study with the ANFIS technique are more convincing than those of PT PLN estimation and regression technique because real data were validated and clarified using several methods to compare. This study shows that the ANFIS method produces more accurate estimations compared to the other two methods in this study. This study purposes to test and to obtain a model for a medium stage of electrical load estimation to meet a simplified previous model referring to complexity, time-consuming, and big scale of data.

2. The ANFIS Method for Estimation System of Electrical Loads

The human experience and human estimation-making behavior are modeled efficiently with the use of ANFIS. The linguistic rules or relational expressions are used to express the input-output relationship, which is an important issue in estimating with ANFIS.

Figure 1 shows the ANFIS system used in the electrical load system estimation. ANFIS output was obtained by determining the weight of the input membership value based on the fuzzy rules. The rule served as the theoretical foundation which is determined from a neural network algorithm. One ANFIS was made up of two inputs (*x* and *y*) and measured using two rules. The Fuzzy inference system applied was the first order of the Takagi-Sugeno-Kang model.

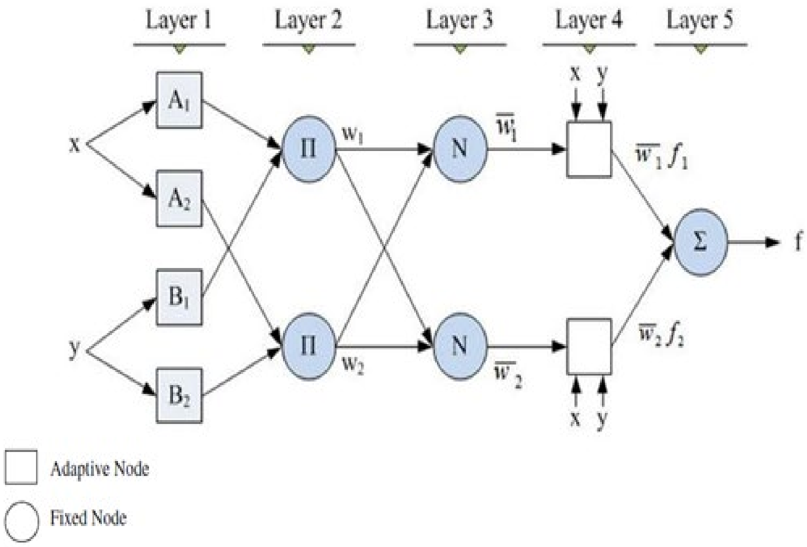

Fig. 1. The ANFIS system used in the electrical load estimation on system with two inputs and an output.

where A_1, A_2, B_1 and B_2 are fuzzy sets of input *x* and *y*, f_i (i = 1, 2) are the outputs within the fuzzy region specified by the fuzzy rule, for input *x* and *y*, [23] p_{ij}, q_{ij}, and r_{ij}, (i, j = 1,2) are the design parameters that are determined during the training process. Figure 1 shows ANFIS Structure with two inputs, one output and two rules.

Rule 1: if (x is A_1) and (y is B_1) then ($f_1 = p_1 x + q_1 y + r_1$)

Rule 2: if (x is A_2) and (y is B_2) then ($f_2 = p_2 x + q_2 y + r_2$)

The ANFIS structure consisted of five layers. Each layer was symbolized by a square indicating that the layer was adaptive. There were four layers represented by circles indicating that the layers were fixed. The functions of each layer are as follows [23]:

- **Layer 1**

Layer 1 is a fuzzification layer that generates a degree of membership. In this layer, there is an adaptive node (parameters can be changed), in which the node functions according to Eq. (1).

$$O_{1,i} = \mu_{Ai}\ (x),\ \ i = 1{,}2\ \ or\ \ O_{1,i} = \mu_{Ai} - 2(y),\ \ i = 3{,}4 \tag{1}$$

The node of O_1 shows the degree of membership of each input to the fuzzy set A and B. The values of x and y, the input at node i, μ_{Ai} and $\mu_{Ai} - 2$ are the membership functions of each node. The membership function $\mu_{Ai}(x)$ is based on the membership function of the generalized bell (gbell) curve with a minimum value of 0 and a maximum value of 1 according to Eq. (2).

$$\mu_{Ai}(x) = \frac{1}{1+\left|\frac{x=c}{a}\right|^{2b}} \tag{2}$$

In the gbell membership function, parameters a, b, and c are labeled adaptive premise parameters. If this type of membership function is changed, the shape of the curve produced after the training process and the formula will also change.

- **Layer 2**

In this layer, all vertices are non-adaptive, indicating that they are fixed parameters. The knot multiplies each input signal that comes. The function of the node in this layer is presented in Eq. (3).

$$O_{2,i} = w_i = \mu_{Ai}\Delta\mu_{Bi}\ (y), i = 1 \tag{3}$$

So *that*,

$$w_1 = \mu_{A1}\Delta\mu_{B1}\ (y)$$

$$w_2 = \mu_{A2}\Delta\mu_{B2}\ (y)$$

In this layer the output node reflects the degree of activation for each Fuzzy rule (firing strength). This feature can be expanded if the part of the premise has more than a fuzzy set. This function, in other words, is directly proportional to the amount of the Fuzzy set. The number of vertices in this layer indicates how many rules will be created.

- **Layer 3**

The node in this layer is the non-adaptive one which displays the normalized firing strength function and the ratio of the *I* output on the previous layer to the previous layer's overall output. The node functions in layer 3 are specified in Eq. (4).

$$O_{3,1} = \overline{w}_i = \frac{w_i}{w_1+w_2},\ i = 1{,}2 \tag{4}$$

The function can be extended by dividing the value of w_i by total w for all rules if more than two rules are formed.

• **Layer 4**

This layer is a layer with a defuzzification function in an adaptive node type. The function of the node in this layer is shown in Eq. (5).

$$O_4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i x + r_1) \tag{5}$$

The $\overline{w}_i$ and w_i parameters are the output of layer 3 and a normalized weight from layer 3. The p, q, and r parameters represent the consequent adaptive parameters (fuzzy inference systems). The parameters in this layer are called the consequent parameters.

• **Layer 5**

There is only one fixed node on this layer that functions to add up all the inputs. In this layer, the node functionality is shown in Eq. (6). If an estimate is made using ANFIS, the mean score of the output at the fifth layer can later be calculated.

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{6}$$

In the ANFIS learning algorithm, several parameters determine the results during training and testing of data; hence, selecting the appropriate parameters is needed to get the expected output.

Simulated data are the data of electricity usage in the Central Java and Special Region of Yogyakarta. Because the data on electricity usage are taken every half hour, there will be 48 data loads in one day. Those data are classified on the same day. In this simulation, the electrical load data were taken between December 31, 2018, and June 3, 2019. Historical data of the previous load were used to estimate the data of electrical load usage on June 3, 2019.

After estimations were made on June 3, 2019, the results were then compared to the actual value of the load on the same day. The estimated accuracy was calculated using the Mean Absolute Percent Error (MAPE) in Eq. (7) below:

$$MAPE = \frac{1}{n} \frac{\sum_{i=1}^{n} |X_t - F_t|}{X_t} \ x \ 100\% \tag{7}$$

X_t, F_t, and n are actual value at time t, estimated value at time t, and number of observations respectively. MAPE is an indicator value that is commonly used to show performance or accuracy in the estimation process results.

2.1. Estimating using regression analysis

In the simulation, load data obtained from December 31, 2018, to June 3, 2019, were arranged based on the same time span, before being used to forecast data for the same time range. In this study, the linear regression method was employed to carry out classification techniques on the technical data. Therefore, at the same time, the data of electrical load usage had the same or linear tendencies. Load data taken at 00.30 were used to estimate the load usage at 00.30. Likewise, load data obtained at 01.00 was used to estimate the load usage at 01.00, and so on. Fig. 2 shows the characteristics of using the electrical load at the same time range.

Based on Fig. 2, it can be indicated that the use of electrical loads from time to time always increases. This is impacted by the population growth, which in contrast is not followed by the development of more electrical power sources to generate energy. In addition, the increase in electricity consumption is influenced by the length of time in which the load is used. For residential customers, electricity is more widely used during working hours i.e., in the morning, evening to night, and leisure time. Meanwhile, the use of electrical power for the industry is more stable as there is no time limit, meaning that it is continuously used for 24 hours straight.

A linear regression equation [24] was used to estimate the results. The first step was to find the value of b using Eq. (8).

$$b = \frac{\sum xy - n\bar{x}\bar{y}}{\sum x^2 - n\bar{x}^2} \tag{8}$$

where y, x, and b are dependent variable, independent variable, and slope coefficient respectively. Then, the value of a was calculated using Eq. (9).

$$a = \frac{\sum y}{n} - b\frac{\sum x}{n} \tag{9}$$

where a is the interception coefficient. Next, the value of Y was determined using Eq. (10):

$$Y = a - bx \tag{10}$$

In this study, to carry out simulations, MATLAB-assisted software was used to make further estimations. In this study, the electrical load estimation will be conducted through a comparison of several approaches namely regression analysis, ANFIS, and estimation technique by PT PLN. The reference value is an actual value that appears. From the results of the actual value that appears and the estimated value, it will be obtained MAPE. A MAPE will be a criterion to choose a better approach for estimation.

2.2. Estimation by ANFIS

The data used to forecast electrical loads were taken from previous load data from December 31, 2018, to June 3, 2019. Between this period, load data obtained on national holidays had been removed to further improve the accuracy of estimates. Time-series data were made by sorting load data on each day. The load data were then divided into 900 training data and 100 test data. In this simulation, the *trapmf* membership function was used. This study was conducted within the Matlab environment on Intel Pentium 2.70 GHz and 4.00 GB RAM. The data were simulated to estimate load usage in the coming day. The flowchart of the ANFIS method can be seen in Fig. 2.

The design of the system in this study was based on the following parameter: Parameter 1 where the input composition consisted of load data of the same days from the previous week with four data (D = 4). In addition, the amount of time delay was one (Δ = 48). As a result, the estimated time (P) equalled 48. Based on the data, the vector is formulated as follows: $[\, x_{t-144}\ , x_{t-96}\ , x_{t-48}\ , x_t\ , x_{t+48}\,]$; Parameter 2 is the membership function consisted of two functions (MF = 2), namely the small membership function and the big membership function; Parameter 3 is the membership function type used the membership function with the smallest training error value at the 500 Epoch; and Parameter 4 is the fuzzy rules in this study were determined according to the following explanation. In this study, there were four inputs and each input had two membership functions, so the number of fuzzy rules formed was 24 = 16 rules.

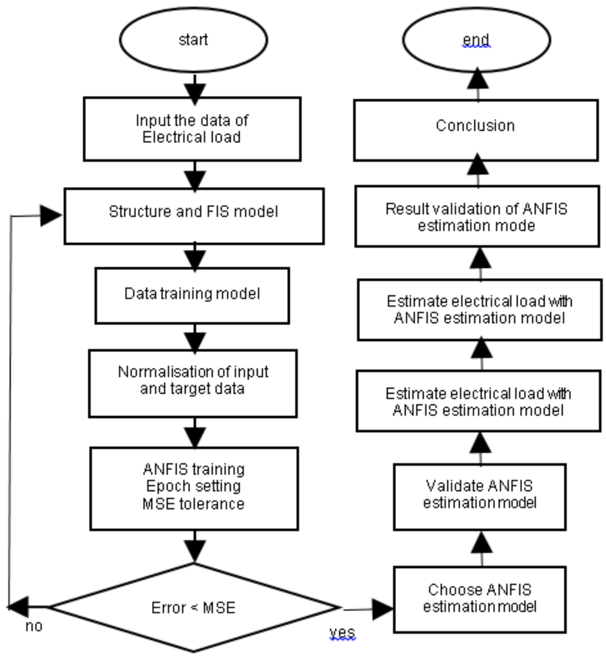

Fig. 2. The algorithm for the ANFIS estimation method.

The fuzzy arrangement to build the rules were elaborated as follows:

- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *small*$_4$ then $x_{t+48} = \vec{c}_1 \cdot \vec{x}$
- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *big*$_4$ then $x_{t+48} = \vec{c}_2 \cdot \vec{x}$
- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *small*$_4$ then $x_{t+48} = \vec{c}_3 \cdot \vec{x}$
- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *big*$_4$ then $x_{t+48} = \vec{c}_4 \cdot \vec{x}$
- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *small*$_4$ then $x_{t+48} = \vec{c}_5 \cdot \vec{x}$
- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *big*$_4$ then $x_{t+48} = \vec{c}_6 \cdot \vec{x}$
- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *big*$_4$ then $x_{t+48} = \vec{c}_7 \cdot \vec{x}$
- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *big*$_4$ then $x_{t+48} = \vec{c}_8 \cdot \vec{x}$
- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *small*$_4$ then $x_{t+48} = \vec{c}_9 \cdot \vec{x}$

- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *big*$_4$ then $x_{t+48} = \vec{c}_{10} \cdot \vec{x}$
- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *small*$_4$ then $x_{t+48} = \vec{c}_{11} \cdot \vec{x}$
- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *big*$_4$ then $x_{t+48} = \vec{c}_{12} \cdot \vec{x}$
- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *small*$_4$ then $x_{t+48} = \vec{c}_{13} \cdot \vec{x}$
- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *big*$_4$ then $x_{t+48} = \vec{c}_{14} \cdot \vec{x}$
- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *small*$_4$ then $x_{t+48} = \vec{c}_{15} \cdot \vec{x}$
- If x_{t-144} is *small*$_1$ and x_{t-96} is *small*$_2$ and x_{t-48} is *small*$_3$ and x_t is *big*$_4$ then $x_{t+48} = \vec{c}_{16} \cdot \vec{x}$

3. Findings and Discussion

Figure 3 presents the use of electrical loads which always increases a lot of times. This was followed also by the continued growth of the human population and was not followed by the development of electrical power sources. Apart from the growth of the human population, the increasing electricity consumption is also influenced by the time of electrical load usage. The electrical load is more used in the morning, evening to night, and leisure time for residential customer types. While the use of electrical energy for industrial scope is more stable although full 24 hours running continuously.

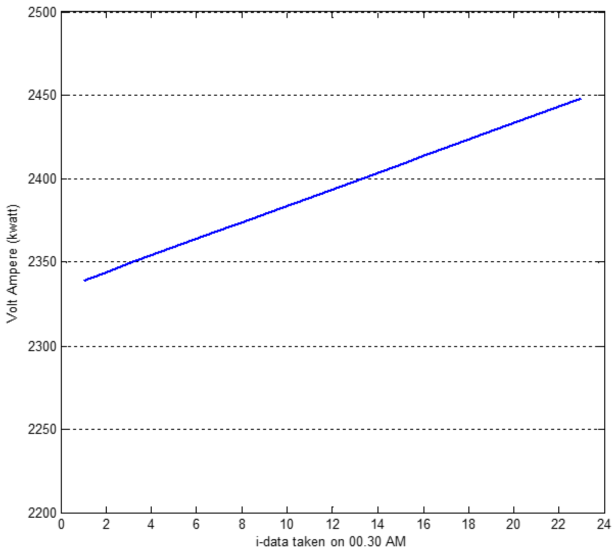

Fig. 3. The characteristics of electrical load use at the same time range.

Figure 4 is the simulation results of the estimated load at 00.30, 01.00, 01.30, and 02.00 using the Regression Analysis. Data 1 to 22 were the historical data, and Data 23 were estimated data using the regression analysis. The clear estimated electrical load usage by using the regression analysis at 00.30 to 02.00 can be seen in Fig. 4.

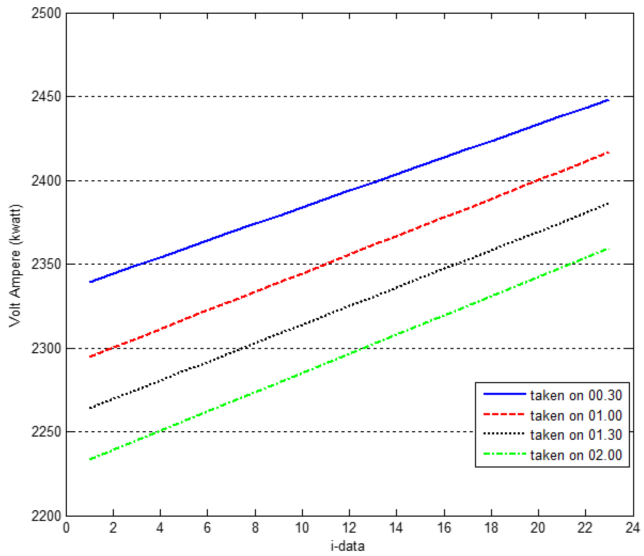

Fig. 4. The characteristics of electrical load use at four different periods.

The estimates of the electrical load carried out by the regression analysis based on Fig. 4 show that the consumption of electrical energy simultaneously increased. The use of electrical load at 00.30 was in the upper position due to the energy consumption, which was still quite high either from the activities of the customers or the industrial machines which were actively working. Energy consumption at 01.00 had begun to decrease because most customers had turned off their electrical appliances and started resting. During the use of electrical load at 01.30 and 02.00, most residential customers were resting, and household appliances were turned off, such as lights, televisions, and other electronic devices.

Figures 5, 6, 7, and 8 show the use of electrical loads from December 31, 2018, to June 3, 2019. The characteristics of electricity used from December 31, 2018, to June 3, 2019. Data taken on June 3, 2019, were the result of the estimation using the Regression Analysis. The simulation data with the regression analysis found that the consumption of electrical energy continuously fluctuated depending on the use of the load used by the customer. The energy consumption of each customer varied and was limited depending on the electrical power capacity installed in the kWh meter. Overall, the consumption of electrical energy consumed by users would increase. The continuously increased electrical energy was influenced by the number of users who was always increasing every time.

In this simulation, the estimated result using the Regression Analysis method was obtained, and the smallest MAPE value was 0.08% for the estimation of the use of electrical loads at 08.00. The largest MAPE value for the regression analysis was 3.83% at 18.30 estimation. Meanwhile, using the ANFIS method, the smallest

MAPE value was 0.01% for the estimation at 05.30. Furthermore, the largest MAPE value was 2.55% for 21.00 the day estimation.

Due to the results of the regression estimation of the highest electricity is at 18.00 with a total of 3677.071 kW, and the MAPE value of 2.87%. The estimation of the lowest electricity use through the regression analysis was obtained at 03.30 with a total electrical load of 2316.118 kW and a MAPE value of 3.48%. Overall, based on the regression analysis, the estimation for the use of electrical loads increased stably from 16.00 to 19.30. These hours were spent by the customers to relax or gather with family.

The estimated electrical load carried out by PT PLN, regression technique and ANFIS method have MAPE of 4.47%, 1.92%, and 0.96% respectively. This means that the estimation conducted by PT PLN has the highest error, while the estimation using the regression technique has a smaller error compared to the PT PLN estimation. Meanwhile, estimation with the ANFIS method produced the performances were closer to the real electrical loads. This can be proven when the estimation using ANFIS shows decreasing electrical loads, then the real electrical load data will show the decreasing load. Oppositely when ANFIS shows increasing electrical loads, then the real electrical load data will show the increasing load.

Figure 5 shows the comparison between actual loads and estimations using the regression analysis. The comparison between actual electrical load use and the estimation of the regression analysis can be seen in Fig. 5. Based on Fig. 5, it can be explained that the overall electrical load use increased and decreased according to the customer activities. Estimations made by the regression analysis showed good results with an accuracy close to the actual data from the Public Electricity Company (PT PLN). Estimation results with regression techniques are a collection of data taken from December 31, 2018, to June 3, 2019, by sampling every 30 minutes. The data which is taken every 30 minutes produces an estimated data for every 30 minutes also at the same time range.

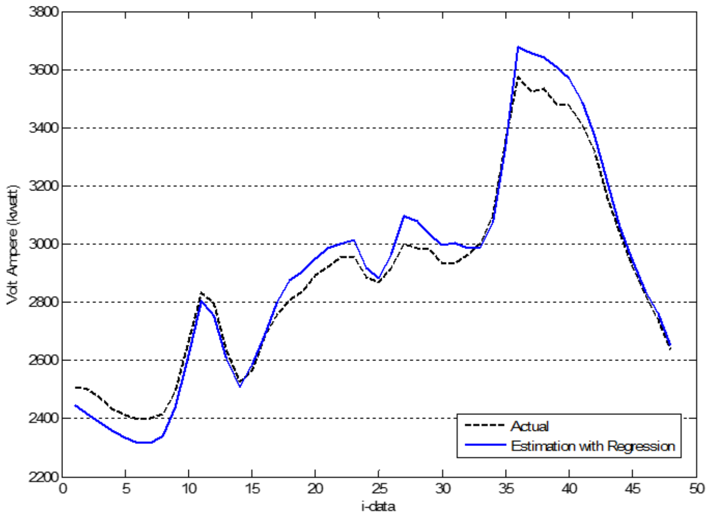

Fig. 5. The comparison between actual loads and estimations using the regression analysis.

Meanwhile, Fig. 6 shows the comparison between actual loads and estimations using ANFIS. A better result was shown in the estimation analysis of the use of electrical loads with ANFIS. The comparison between actual electrical load use and ANFIS estimation can be seen in Fig. 6. Based on Fig. 6, the overall electrical load use experienced a steady increase. Estimations made with ANFIS obtained a better result with a high degree of accuracy compared to the analysis from PT PLN and the Regression Analysis method.

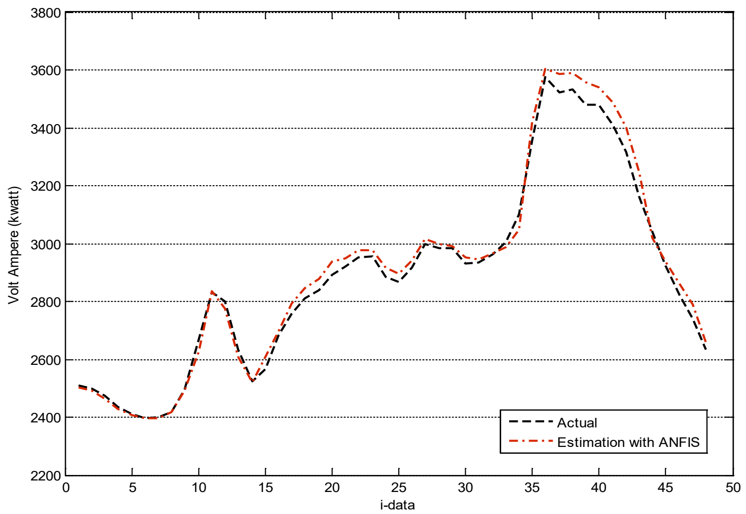

Fig. 6. The comparison between actual loads and estimations using ANFIS.

The previous study on electrical load estimation with the ANFIS method conducted by Mishra and Gupta [18] yielded a MAPE of 2.23%. While this study has estimated the use of electrical loads using ANFIS with MAPE of 0.96%. This study has produced better performances compared to previous studies.

Figure 7 illustrates the comparison between actual data and the results of estimations made by PT PLN. Figure 8 shows the results of the comparison between actual load data, Regression Analysis estimations, ANFIS estimations, and PT PLN estimations. In general, the comparison of analysis results of the estimated electrical load use can be seen in Fig. 8. The estimation results by ANFIS and Regression were better than those of PT PLN.

Based on the simulation results, it can be stated that the Regression Analysis method was quite good to estimate the electrical load with a MAPE error value of 1.92%. The simulation results were better when compared to the estimates made by PT PLN which resulted in the MAPE error value of 4.47%. The final results of the simulation obtained evidence that the accuracy of the estimated MAPE value of the electrical load with the regression analysis was still not as good as that by using ANFIS. The MAPE error value obtained by the ANFIS simulation was 0.96%. Thus, the ANFIS method was the best technique in this study, because it was the most accurate compared to the regression and estimation methods from PT PLN.

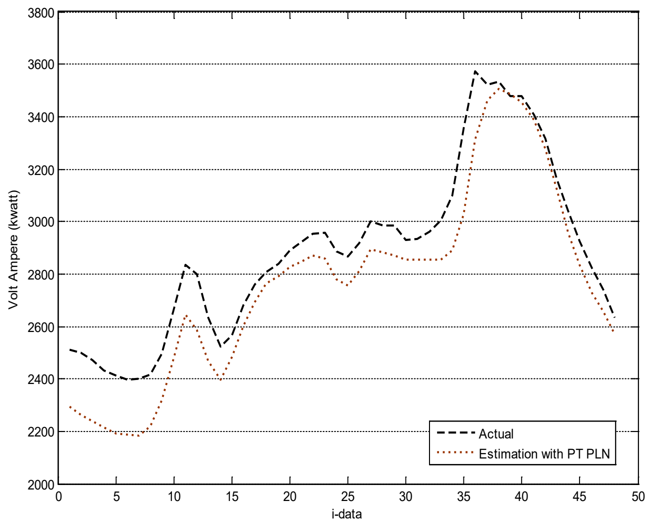

Fig. 7. The comparison between actual data and the estimation results made by PT PLN.

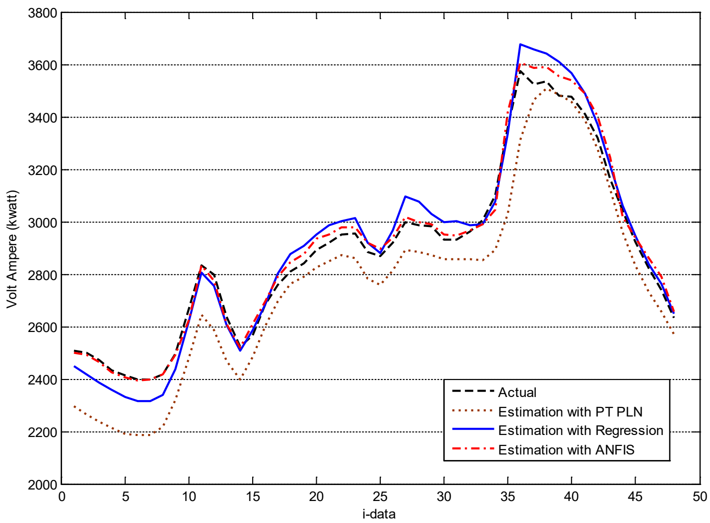

Fig. 8. The comparison between actual load data, Regression Analysis estimations, ANFIS estimations, and PT PLN estimations.

Furthermore, it is necessary to do a comparative analysis to validate the analysis of the estimation results. Here, an analysis of the estimated results and the actual value is also carried out using the Root Mean Square Error (RMSE) technique. Due to the analysis using the RMSE technique, the results using the PT PLN, regression, and ANFIS approaches are 144.31, 63.89, and 37.26 respectively. Thus, it appears that the estimation using the ANFIS approach shows the smallest RMSE value. This shows the same results as the performance using the MAPE technique. It can be concluded that the estimation using the ANFIS approach shows better performance compared to the two other approaches.

The obtained results with ANFIS approaches show a good estimation with a small MAPE, this is in line with the previous studies [18]. Furthermore, ANFIS approaches have been used in short, medium and long-term load estimation. Further work can be applied by including load data on the previous season, precipitation, holiday, and wind speed.

This study can serve as a reference for PT PLN in estimating electrical load. ANFIS approaches show a more accurate MAPE compared to the regression and estimation methods from PT PLN. Furthermore, the previous estimation approach by PT PLN should immediately move to ANFIS approaches.

Future studies should be done with a focus on the load estimation based on the demand side. Future works also can involve market price as an important variable on electrical load estimation.

4. Conclusion

This study estimates the use of electrical loads using the Linear Regression Analysis and ANFIS methods. The data estimation is based on the electrical load data at the same periods in the same days, which are then used to forecast the next day's electrical load at the same time. On the other hand, the data grouping based on the data characteristics shows linear curves. With the recorded data patterns, the estimation of the electrical load use can be obtained through the linear regression analysis. Based on the simulation results of electrical load forecasts, the ANFIS method shows the smallest MAPE error value which is less than 1.0%, suggesting that the accuracy of the forecast is more accurate. Meanwhile, the estimated electrical load using the linear regression shows a smaller MAPE error value of 1.92% when compared to the ANFIS method. Meanwhile, the results of estimations made by PT PLN show an error value of 4.47%. Therefore, it can be ascertained that the ANFIS estimation results show the highest accuracy of the actual value.

Nomenclatures

a, b, c	Adaptive premise parameters
F_t	Estimated value at time t
n	Number of observations
O_1	Degree of membership of each input
p, q, r	Consequent adaptive parameters
w_i	Normalized weight
x , y	Input at node i
X_t	Actual value at time t

Greek Symbols

μ_{Ai}	Membership functions of each node

Abbreviations

ANFIS	Adaptive Neuro Fuzzy Inference System
MAPE	Mean Absolute Percent Error
PT PLN	Perseroan Terbatas Perusahaan Listrik Negara

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