

Forecasting Electricity Consumption in Riau Province Using the Artificial Neural Network (ANN) Feed Forward Backpropagation Algorithm for the 2024-2027

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ABSTRACT

Electricity production in Riau Province fluctuates between surplus and deficit, as reported by the Central Statistics Agency. From a peak of 3,758.75 GWh in 2017, production fell to 525.19 GWh in 2019, mainly due to lack of investment in new power plants and dependence on external electricity supply. This study addresses these challenges by using the Artificial Neural Network (ANN) Feed Forward Backpropagation method to forecast electricity demand from 2024 to 2027. This study aims to analyze the accuracy of the prediction through the Mean Absolute Percentage Error (MAPE), evaluate electricity consumption projections, and calculate the annual growth rate. The gap in this study is the inclusion of previously ignored variables, which are the GRDP of Government Buildings and the number of Government Building customers. The methodology used is ANN Feed Forward Backpropagation inspired by the functioning of the human brain. Data simulation was conducted using MATLAB R2014a with a network architecture of 10 input neurons, 20 neurons in the first hidden layer, 10 in the second hidden layer, and 1 output neuron. During the training phase, the MAPE was obtained at 4,315%. The electricity consumption prediction obtained is 8,679 GWh in 2024, 9,690 GWh in 2025, 10,959 GWh in 2026, and 12,681 GWh in 2027. The growth rate is also projected to increase, 5.67% from 2023 to 2024, 11.65% from 2024 to 2025, 13.10% from 2025 to 2026, and 15.71% from 2026 to 2027. The results of this study show the growing electricity demand in Riau Province over the forecast period, which emphasizing the need for better energy planning and targeted investments in power generation.

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1. INTRODUCTION

Over the past century, the energy sector has played a significant role in driving industrial growth [1]. Energy has become a vital resource powering various economic aspects, such as factories, transportation, and technology. Today, all modern-era activities depend on electricity usage [2]. The demand for and consumption of electrical energy has steadily increased globally over time [3]. For instance, in Indonesia, electricity consumption has shown consistent growth annually. In 2022, the electricity consumption in Indonesia reached 273,761.48 GWh [4], while in 2023, it increased to 288,435.78 GWh, representing a 4.11% rise in customers from the end of 2022 [5].

Alongside the rapid growth in electricity consumption, there is a phenomenon of fluctuating imbalances between energy surplus and deficit across various regions, particularly in Riau Province [6]. According to data from the Central Bureau of Statistics, the production of electricity in Riau Province has experienced both surpluses and deficits in recent years. For instance, in 2014, electricity production in Riau was 667.07 GWh, increasing to 3,758.75 GWh by 2017, but then experiencing a production deficit in 2018, with 862.16 GWh, and decreasing further in 2019 to 525.19 GWh [7]-

[12]. From 2020 to 2023, fluctuations were also observed, with production figures recorded at 2,363 GWh, 2,168 GWh, and 2,179 GWh, respectively [13].

Based on data from the Central Bureau of Statistics, 2019 saw the largest drop in energy deficit in Riau Province, amounting to 525.19 GWh [12]. The cause of the electricity deficit in Riau in 2019 from the producer's side was the lack of investment in new power plants, which resulted in existing capacity being insufficient to meet the growing demand [14]. Furthermore, reliance on electricity interconnection from neighboring provinces exacerbated the problem, as supply from external sources could become unstable. On the consumer side, high electricity consumption growth of 8% per year and the construction of new industrial areas requiring large electricity supplies worsened the situation, making the electricity deficit more pronounced in Riau Province. The combination of demand exceeding local supply and the lack of new power plants led to the energy deficit in Riau in 2019 [12][14].

Fluctuations in energy surpluses and deficits in Riau have affected electricity supply stability, leading PLN to struggle with consistently meeting demand [6]. This has caused rotating blackouts during deficits and inefficient supply during surpluses, raising operational costs, especially when additional resources or alternative fuels

are needed [15][16]. The imbalance requires PLN to adopt strategic energy management, with accurate electricity demand forecasting as a key step [17]. Given rapid consumption growth due to population increase and higher activity levels, precise forecasting is essential for efficient power plant operation, optimized distribution, and reduced financial losses from resource misallocation [18][19].

Electricity load forecasting methods, including regression analysis, exponential smoothing, neural networks, adaptive algorithms, and stochastic time series, have been applied to address supply imbalances [20]-[22]. Regression identifies causal relationships for consumption patterns [20], while exponential smoothing estimates trends using historical data [21]. Neural networks, designed to process complex data patterns, are considered the most accurate for forecasting [22]. Among these methods, neural networks are considered superior because they mimic the workings of the human brain's neural network, which more accurately forecasts [22].

Several previous studies have utilized artificial neural networks for forecasting. For instance, a study using the Artificial Neural Network (ANN) Backpropagation method to predict electricity needs with high accuracy showed a MAPE of 0.4% and a growth of 2.7% per year [23]. Another study used ANN to project electricity demand in D.I. Yogyakarta for the period 2016-2025, with an average error rate of 1.89% and electricity consumption growth of 6.90% per year [24]. Another study utilized ANN Backpropagation to improve load forecasting accuracy, with results showing the best training function had a MAPE of 6.24% and 93.75% accuracy [25]. Further research using ANN to forecast electricity load in Jayawijaya Regency, using limited data from PLN, developed a neural network architecture expanded through quadratic interpolation, achieving an error rate of 0.04% after network training [26]. Thus, ANN has proven effective in improving electricity load forecasting and energy demand accuracy [23]-[26].

The ANN forecasting process begins by identifying variables. At PT PLN (Persero) UP3 Semarang, seven variables were used, including population, GRDP, and electricity demand [23]. ULP Sungguminasa employed four variables such as GRDP and electricity consumption [19], while research in D.I. Yogyakarta utilized eight variables, including GRDP across various sectors [24]. This study introduces two new variables gap which are GRDP and the number of customers for Government Buildings, addressing their previously overlooked influence [4][5][16][27]-[34].

This research contributes to PLN, particularly as the state electricity provider in Riau Province, in addressing the imbalance between energy supply and demand in consumption side. By adding new variables such as Government Building GDP and the number of Government Building customers, this study enhances the accuracy of projections regarding energy needs in Riau Province. These projections will undoubtedly assist PLN in devising better energy management strategies,

including infrastructure investment planning and network development. The results of this study provide a foundation for PLN in determining electricity supply policies for Riau Province.

This study designs an Artificial Neural Network (ANN) with the architecture of 10 input variables, 20 neurons in the first hidden layer, 10 neurons in the second hidden layer, and 1 neuron in the output layer for predicting electricity consumption. The data is normalized to the range of [-1, 1] before training and testing using MATLAB's nntool. The accuracy of the forecasts is assessed using the Mean Absolute Percentage Error (MAPE); if MAPE is less than 10%, polynomial linear regression is applied to refine the predictions, followed by denormalization to obtain actual values. The study has three main objectives: (1) analyze the accuracy of MAPE for forecasting energy demand from 2024 to 2027, (2) evaluate the predicted electricity consumption during the same period, and (3) calculate the annual growth percentages of the forecasts.

2. MATERIALS AND METHOD

The research flowchart is illustrated in Fig.1:

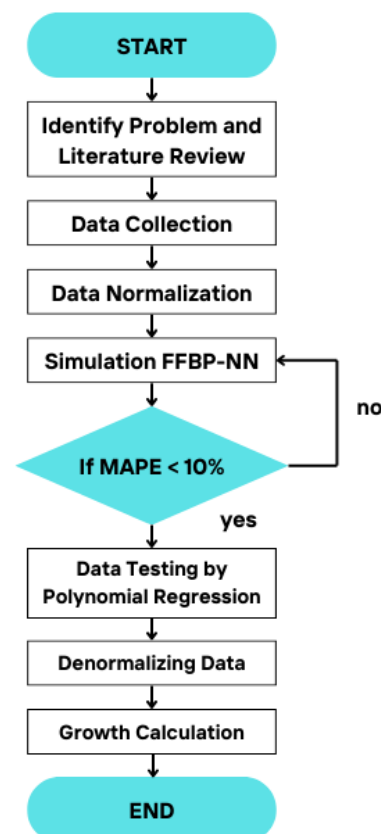


Fig. 1. Research Method

This research begins by identifying the issue of electricity surplus and deficit in Riau Province, followed by a literature review on the Artificial Neural Network (ANN)

Backpropagation method for forecasting. Subsequently, secondary data is collected, including the number of PLN customers, GDRP data, and electricity consumption in Riau Province from 2014 to 2023. The data is normalized and used for forecasting simulations in MATLAB. The forecast results are initially evaluated using MAPE, and if the MAPE value is less than 10%, polynomial linear regression is applied to the test data to generate new input predictions. Once the final predictions are obtained, they are denormalized, and the percentage growth is calculated for each forecasted.

A. Identify Problem and Literature Review

The main issue addressed in this research is the imbalance between the surplus and deficit of electrical energy in Riau Province, where electricity production in Riau rose from 667.07 GWh in 2014 to 3,758.75 GWh in 2017, followed by a decline to 862.16 GWh in 2018 and 525.19 GWh in 2019 [7]-[12]. Fluctuations continued from 2020 to 2023, with production at 2,363 GWh, 2,168 GWh, and 2,179 GWh, respectively [13]. This problem is exacerbated by the significant yearly increase in electricity consumption and the inability of the power generation capacity to meet the growing demand, as seen in 2019 when there was a production deficit of 525.19 GWh [12][14]-[18].

Several studies have utilized ANN for electricity load forecasting. The study Daily Electricity Load Forecasting Using Artificial Neural Network [22] used Cascade Forward Backpropagation, achieving a MAPE of 7.6%. In Forecasting Electricity Demand Using Artificial Neural Networks Backpropagation Method for 2020-2025 [23], Semarang and Kendal's demand was forecasted with a MAPE of 0.4%. Comparison of Backpropagation Neural Network Training Functions for Load Forecasting [25] identified traingdx as the most accurate function, achieving a MAPE of 6.24%. A Jayawijaya study [26]

using feed-forward backpropagation yielded a 0.04% error after nine epochs. In Banjarbaru, a 12-12-1 network predicted demand with MAPEs of 6.597% (training) and 12.366% (prediction) [35]. Similarly, Pontianak's forecast achieved a MAPE of 2.576% [36], and Bandung's long-term prediction for 2022-2023 recorded a MAPE of 8% using TRAIINGDX [37].

B. Data Collection

The next stage is data collection. Several secondary data are required for this research, including the number of PLN customers in Riau Province by sector, the Gross Regional Domestic Product (GRDP) of Riau Province by sector, and the electricity consumption data of Riau Province. Each dataset covers the past 10 years, from 2014 to 2023. In this study, the GRDP variable was selected as one of the input variables in the feed-forward backpropagation artificial neural network (ANN) model because it correlates with electricity demand, as shown in Eq. (1) [38]:

$$GDRP_t = \alpha + \beta KEL_t + \epsilon_t \quad (1)$$

where, $GDRP_t$ represents the change in GRDP value in year- t , α is the intercept, β is slope, KEL_t is the electricity availability in year- t and ϵ is error in year- t .

The following are the required datasets for this research: Table 1 contains the number of PLN customers in Riau Province from 2014 to 2023 [4][5][16][28]-[34], Table 2 provides the Gross Regional Domestic Product (GRDP) of Riau Province by sector, measured in million rupiah, for the same period [39][40]. Table 3 shows the electricity consumption of Riau Province in GWh from 2014 to 2023 [4][5][16][28]-[34], then Table 4 is the projection of the PLN RUPTL for Riau Province from 2024 to 2027 [41]:

Table 1. The number of PLN customers in Riau Province from 2014 to 2023 [4][5][16][28]-[34] [dataset]

Sectors	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Residential	992,413	1,087,916	1,201,666	1,329,838	1,448,980	1,558,844	1,663,114	1,765,513	1,842,357	1,936,633
Commercial	88,842	95,760	105,373	115,847	126,619	133,831	143,731	158,719	177,956	179,138
Public	18,237	20,551	22,822	25,930	29,054	32,641	35,716	39,217	42,115	45,086
Industrial	223	243	274	271	325	343	420	513	633	763
Government Building	3,848	4,073	4,792	5,199	5,652	6,075	6,412	6,693	6,859	7,130

Table 2. The GRDP of Riau Province by sector, measured in million rupiah, from 2014 to 2023 [39][40] [dataset1] [dataset2]

Sectors	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Residential	4,658,529	5,404,854	5,790,843	6,085,292	6,396,204	6,866,314	7,025,355	7,321,896	7,992,862	8,531,360
Commercial	61,490,907	66,992,008	73,742,578	79,142,377	84,960,344	92,886,933	85,471,555	94,965,679	110,793,227	119,867,473
Public	3,715,335	4,443,221	4,683,447	4,962,523	5,288,880	5,859,744	6,347,932	6,773,179	7,119,872	7,591,065
Industrial	141,874,676	155,685,924	168,241,897	178,829,424	185,241,631	194,254,526	207,301,214	235,379,362	270,307,268	282,789,051

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Government Building	9,246,791	10,076,887	10,392,912	10,665,028	10,939,247	11,402,505	11,375,329	11,562,577	12,379,506	13,223,706
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Table 3. The electricity consumption of Riau Province in GWh from 2014 to 2023 [4][5][16][28]-[34] [dataset]

Year	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Consumption	3,338	3,586	3,904	4,069	4,377	4,646	4,967	6,108	7,692	8,213

Table 4. The projection of the PLN RUPTL electricity consumption of Riau Province in GWh from 2021 to 2023 [41] [dataset]

Year	2024	2025	2026	2027
Consumption	7,995	8,982	9,338	9,692

C. Data Normalization

Data normalization is the process of transforming data with varying ranges into a specific scale to meet certain needs, with the goal of reducing it to a smaller range. This process serves as a tool in data mining processing. In this study, the data will be normalized within the range of $[-1, 1]$ using the following Eq. (2) [24]:

$$X_n = 2 \cdot \frac{X_p - \min\{X_p\}}{\max\{X_p\} - \min\{X_p\}} - 1 \quad (2)$$

where, the real data value before normalization is represented as X_p , $\max\{X_p\}$ denotes the maximum real data value, and $\min\{X_p\}$ signifies the minimum real data value.

D. ANN Feed Forward Backpropagation Algorithm

Artificial Neural Network (ANN), commonly known as neural networks, is an information processing model inspired by the functioning of the human brain, particularly in learning and data processing [42]. The backpropagation network model is one of the supervised learning methods [43]. The backpropagation network algorithm consists of 11 steps, including weight initialization, feedforward processing, error calculation, and adjusting the weights and biases [44]. The network weights are initialized randomly with very small values. If the iteration does not meet the criteria, steps 3 to 10 are repeated. For each test data pair, the feedforward and backpropagation steps are executed. Steps 4 to 6 represent the feedforward process, where each input unit ($x_i, i=1, \dots, n$) receives the input signal x_i , which is then propagated to all units in the hidden layer. Each unit in the hidden layer ($z_{j,j}=1, \dots, p$) sums the weighted input signals according to the following Eq. (3) [44]:

$$z_{in_j} = v_{0j} + \sum_{i=1}^n x_i v_{ij} \quad (3)$$

The output signal from the input is then activated using the activation function in the hidden layer, as expressed by Eq. (4) [44]:

$$z_j = f(z_{in_j}) \quad (4)$$

where z_{in_j} represents the output signal from the input layer to the hidden layer, z_j is the activated output signal from the hidden layer, v_{0j} is the bias value from the input layer to the hidden layer, x_i is the input signal, v_{ij} is the weight vector from the input to the hidden layer, and f is the activation function.

The signal is then sent to the output layer through the hidden layer. Each output unit ($y_k, k=1, \dots, m$) sums the weighted input signal according to the following Eq. (5) [44]:

$$y_{in_k} = w_{0k} + \sum_{j=1}^p z_j w_{jk} \quad (5)$$

The signal is activated to calculate the output signal using the following Eq. (6) [44]:

$$y_k = f(y_{in_k}) \quad (6)$$

where y_{in_k} is the accumulated weighted input signal received by unit k , y_k is the actual output value from unit k in the output layer, w_{0k} is the bias for the output unit k , z_j is the activated signal from the hidden layer, and w_{jk} represents the weight between neuron y in the hidden layer and neuron k in the output layer.

Steps 7 and 8 involve error backpropagation. Each output unit ($Y_k, k=1, \dots, m$) receives the target pattern according to the training input. For unit k in the output layer, the error is calculated as follows Eq. (7) [44]:

$$\delta_k = (t_k - y_k) f'(y_{in_k}) \quad (7)$$

where δ_k represents the error at unit k in the output layer, t_k is the target output for unit k , y_k is the actual output of unit k , and $f'(y_{in_k})$ is the derivative of the activation function used in the output layer.

Weight correction is then applied to update w_{0k} with the learning rate α , according to the Eq. (8) [44]:

$$\Delta w_{jk} = \alpha \delta_k z_j \quad (8)$$

where, Δw_{jk} represents the weight correction between neuron y in the hidden layer and neuron k in the output layer, α is the learning rate, δ_k is the error at unit k in the output layer, and z_j is the activated signal from the hidden layer.

The next step involves correcting the bias to update w_{0k} as follows Eq. (9) [44]:

$$\Delta w_{0k} = \alpha \delta_k \quad (9)$$

where Δw_{0k} is the bias correction for output unit k . Consequently, δ_k is sent to the hidden layer. Each unit in the hidden layer ($Z_j, j=1, \dots, p$) sums the delta input from the subsequent layer units, as shown in the following Eq. (10) [44]:

$$\delta_{in_j} = \sum_{k=1}^j \delta_k w_{jk} \quad (10)$$

where δ_{in_j} is the accumulated input from unit k in the output layer to unit j in the hidden layer, δ_k is the error at unit k in the output layer, and w_{jk} is the weight between neuron y in the hidden layer and neuron k in the output layer.

The error information is calculated by Eq. (11) [44]:

$$\delta_j = \delta_{in_j} f'(z_{in_j}) \quad (11)$$

where δ_j is the error at unit j in the hidden layer, δ_{in_j} is the accumulated input from the output layer to unit j , and $f'(z_{in_j})$ is the derivative of the activation function in the hidden layer.

The weight correction to update v_{0j} is given by Eq. (12) [44]:

$$\Delta v_{0j} = \alpha \delta_j \quad (12)$$

where, Δv_{0j} is the bias correction for the hidden layer unit j , and δ_j is the error at unit j in the hidden layer. Steps 9 and 10 involve updating the weights and biases.

Each output unit ($Y_k, k=1, \dots, m$) updates its weight and bias values according to the following Eq. (13) [44]:

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk} \quad (13)$$

where $w_{jk}(new)$ is the updated weight between the hidden layer and output layer, $w_{jk}(old)$ is the previous weight, and Δw_{jk} is the weight correction.

Similarly, each hidden layer unit ($Z_j, j=1, \dots, p$) updates its weight and bias values by Eq. (14) [44]:

$$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij} \quad (14)$$

where $v_{ij}(new)$ is the updated weight between the input layer and hidden layer, $v_{ij}(old)$ is the previous weight, and Δv_{ij} is the weight correction.

The training process continues until the error stabilizes or starts to increase. If the error decreases to a certain limit, the training is stopped. If the error increases, the network is considered overfitting, and training must be stopped to preserve the network's generalization ability.

E. ANN Backpropagation Forecasting Simulation

In this study, the ANN Backpropagation algorithm was simulated using MATLAB R2014a with a network architecture of 10 input neurons, 20 neurons in the first hidden layer, 10 in the second hidden layer, and 1 output neuron. The Gradient Descent with Momentum and Adaptive Learning Rate (traingdx) function was used to adjust weights and biases during training, as guided by Eq.(3)-Eq.(14) [23]-[25][37].

The training is set to run for a maximum of 2000 epochs, during which the network learns from its mistakes and iteratively refines its predictions. The stopping criteria for the training are based on either reaching the maximum number of epochs to achieving a target error of zero or hitting a performance failure after 1000 unsuccessful validation attempts, where the network's performance fails to improve. Additionally, the learning rate is set to 0.001, a very small value that shows slow but precise adjustments to the weights and biases.

In this study, the activation function used is the bipolar sigmoid function, selected to align with the normalization range of [-1,1]. This function ensures that the output values remain within the desired range, making it suitable for models where data is normalized between -1 and 1. The bipolar sigmoid (*tansig*) function is expressed as Eq. (15) [45]:

$$f(x) = \frac{2}{1+e^{-x}} - 1 \quad (15)$$

where $f(x)$ represents the output value, x denotes the input value, and e is euler's number. Thus, the following is the Table 5 of parameters used for the ANN backpropagation simulation:

Table 5. Parameters Used For Simulation

Parameter	Value
Epoch	2000
Training Time	Infinite
Target Error	0
Failure Criteria	1000
Learning Rate	0.001
Activation Function	Tansig
Architecture	10-20-10-1 (10 neurons in input layer, 20 neurons in first hidden layer, 10 neurons in second hidden layer, 1 neuron in output layer)
Training Function	Gradient Descent with Momentum and Adaptive Learning Rate (traingdx)
Learning Function	Learngdm

F. MAPE

The Mean Absolute Percentage Error (MAPE) is used to assess the accuracy of forecasting results by comparing the predicted values to the actual data. In calculating MAPE, the error is determined by measuring the percentage difference between the predicted values and the actual values. The formula for MAPE is provided as Eq.(16) [44]:

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \cdot 100\% \quad (16)$$

where n represents the total number of data points, Y_t denotes the actual data values, and \hat{Y}_t signifies the forecasted values.

G. Predicting Testing Data By Polinomial Linear

After knowing (MAPE), data testing is predicted for 2024-2027 using polynomial linear regression. This new input using *polyfit* function calculates the slope and intercept from historical data by MATLAB. Predictions are made with the *polyval* function for future years, Eq. (17) is linear regression as shown in below [46]:

$$y = a + bX \quad (17)$$

where y represents the predicted value dependent variable, x is independent variable, a is the slope indicating the rate of change, and b is the intercept.

Polynomial regression is an extension of linear regression that incorporates the influence of each predictor variable (x) raised to the power of up to order k . In many real-world cases, data exhibits more complex patterns than a simple linear relationship. Polynomial can provide more accurate predictions for data showing non-constant growth or decline. In general, the polynomial regression model can be expressed as E.q (18) [47]:

$$Y = b_0 + b_1X + b_2X^2 + \dots + b_kX^k + e \quad (18)$$

In this model, y represents the response variable, b_0 is the intercept, and b_1, b_2, \dots, b_k are the regression coefficients. The variable x denotes the predictor variable, while e accounts for the error term or disturbance factor.

When elaborated in detail, the second-order polynomial regression is generally expressed as follows E.q (19) [47]:

$$\begin{bmatrix} n & \sum x_i & \sum x_i^2 \\ \sum x_i & \sum x_i^2 & \sum x_i^3 \\ \sum x_i^2 & \sum x_i^3 & \sum x_i^4 \end{bmatrix} \begin{Bmatrix} a_0 \\ a_1 \\ a_2 \end{Bmatrix} = \begin{Bmatrix} \sum y_i \\ \sum x_i y_i \\ \sum x_i^2 y_i \end{Bmatrix} \quad (19)$$

where n represents the number of data points. The terms $\sum x_i, \sum x_i^2, \dots, \sum x_i^k$ denote the sums of the independent variables raised to the k -order. The coefficients a_0, a_1, a_2 correspond to the second-order polynomial coefficients, while $\sum y_i$ signifies the sum of the dependent variable.

H. Denormalizing Forecast Data

Denormalizing data is the process of converting previously normalized values back to their original scale [24]. This step is necessary when the results of analysis or modeling, which used normalized data, need to be interpreted in terms of real-world data. The equation used for denormalizing data within the range of $[-1, 1]$ is as follows Eq. (20) [24]:

$$X = 0.5 \cdot (X_n + 1) \cdot (\max\{X_p\} - \min\{X_p\}) + \min\{X_p\} \quad (20)$$

where X represents the real data that has been denormalized, and X_n is the normalized data. The maximum value of the original real data is denoted as $\max\{X_p\}$, while the minimum value is represented by $\min\{X_p\}$.

I. Percentage Growth Forecasting

The percentage growth is a measure used to indicate the change in the value of a quantity over time. The commonly used equation to calculate the percentage increase involves subtracting the initial value from the final value, dividing the result by the initial value, and then multiplying it by 100%.

The equation for calculating percentage growth can be expressed as Eq. (21) [48]:

$$\text{Growth} = \left(\frac{\text{Forecast Year Value} - \text{Previous Year Value}}{\text{Previous Year Value}} \right) \cdot 100\% \quad (21)$$

where *percentage* refers to the rate of growth increase expressed in percentage terms. Then, the forecast year value represents the electricity consumption projected for the forecast year, while the previous year value denotes the electricity consumption recorded in the preceding year.

J. PLN RUPTL

RUPTL is a guiding document prepared to direct the development of the electricity system in PLN's operational areas over the next ten years. In this study, the results of the ANN Backpropagation forecasting will be compared with the PLN RUPTL to calculate the average percentage difference of both projections using Eq. (22) [24]:

$$\text{Comparison} = \left| \frac{X_{ann} - X_{ruptl}}{X_{ruptl}} \right| \cdot 100\% \quad (22)$$

where *comparison* represents the average percentage difference, X_{ann} refers to the projected data from the ANN Backpropagation, and X_{ruptl} denotes the projected data from the RUPTL.

3. RESULTS

A. Data Training

The first step in the results section involves data normalization, after cleaning the data by removing or addressing missing, invalid, or anomalous values. The

data to be normalized includes Table 1, which presents the number of PLN customers in Riau Province from 2014 to 2023 [4][5][16][28]-[34], and Table 2, detailing the Gross Regional Domestic Product (GRDP) of Riau Province by sector, measured in million rupiahs, from 2014 to 2023 [39][40]. These tables will be utilized as input for the simulation, formatted into a 10x10 matrix. Following this,

Table 3, which shows the electricity consumption of Riau Province in GWh from 2014 to 2023 [4][5][16][28]-[34], will also be normalized. The normalization process is performed using Eq. (2). Table 6 and Table 7 shows normalized results.

Table 6. Input Data Training Normalization in Matrix 10x10

Input Training	Sectors	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Number of Customers	Residential	-1	-0.798	-0.557	-0.285	-0.033	0.1998	0.4206	0.638	0.8	1
	Commercial	-1	-0.847	-0.634	-0.402	-0.163	-0.004	0.2158	0.548	0.974	1
	Public	-1	-0.828	-0.659	-0.427	-0.194	0.073	0.302	0.563	0.779	1
	Industrial	-1	-0.926	-0.811	-0.822	-0.622	-0.556	-0.27	0.074	0.519	1
	Government Building	-1	-0.863	-0.425	-0.177	0.0993	0.3571	0.5625	0.734	0.835	1
GRDP	Residential	-1	-0.615	-0.415	-0.263	-0.103	0.1401	0.2223	0.375	0.722	1
	Commercial	-1	-0.812	-0.58	-0.395	-0.196	0.0756	-0.178	0.147	0.689	1
	Public	-1	-0.624	-0.5	-0.356	-0.188	0.1066	0.3585	0.578	0.757	1
	Industrial	-1	-0.804	-0.626	-0.476	-0.385	-0.257	-0.071	0.327	0.823	1
	Government Building	-1	-0.583	-0.424	-0.287	-0.149	0.0841	0.0704	0.165	0.575	1

Table 7. Target Data Normalization

Years	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Consumption	-1	-0.8983	-0.7678	-0.7001	-0.5737	-0.4634	-0.3317	0.1364	0.7683	1

B. Training ANN Feed Forward Backpropagation

The Feedforward Backpropagation simulation in ANN involves a learning process where the network adjusts its weights iteratively to map input data to the desired output while minimizing errors. This is achieved through backpropagation, which updates the weights based on the calculated error between predicted and actual values. The training phase ensures that the model can generalize patterns from historical data, improving its predictive accuracy over time. The ANN architecture used in this

study consists of 10 input neurons representing different variables, 20 neurons in the first hidden layer, 10 neurons in the second hidden layer, and a single output neuron for forecasting, as illustrated in Fig. 2. This structure shows the network to capture complex relationships within the dataset and refine its predictions through multiple layers of abstraction. The training process is conducted using MATLAB R2014a.

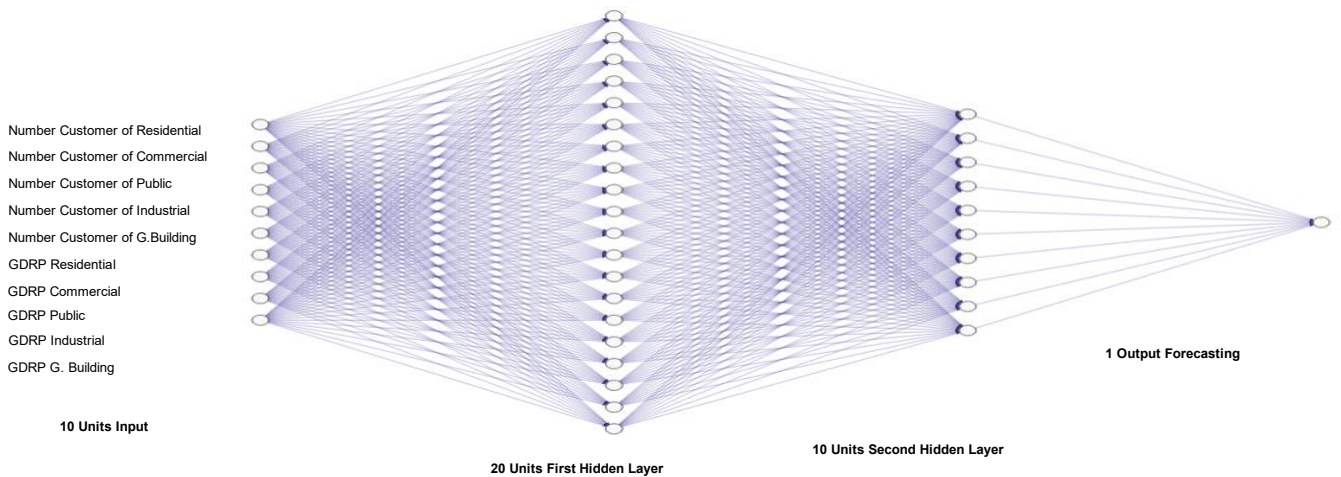


Fig. 2. Designing architecture ANN Feed Forward Backpropagation

The following step in the research involves designing the architecture by Matlab shown in Fig. 3. The architecture also same consists of 10 neurons in the input layer, 20 neurons in the first hidden layer, 10 neurons in the second hidden layer, and 1 neuron in the output layer.

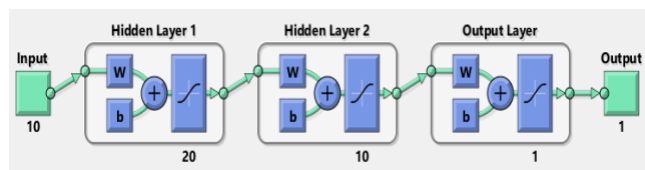


Fig. 3. Architecture ANN Backpropagation by Matlab

After defining the architecture, the simulation parameters in Table 5 were input into MATLAB R2014b, including an epoch value of 2000, infinite training time, target error of 0, failure criteria of 1000, and a learning rate of 0.001. The activation function used was Tansig. The training function was *traindgm*, and *learngdm* was used for learning. Backpropagation training was performed iteratively according to Eq. (3) to Eq. (15), repeated 7 times, as shown in Fig. 4.

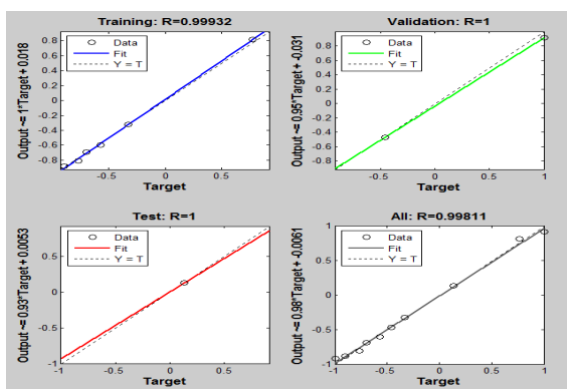


Fig. 4. Training Regression Plot Results

The training regression plot by Fig. 4 illustrates the relationship between the target values and the model's output predictions. It is divided into four sections. The first

section, training, shows a correlation coefficient of $R=0.99932$. The second section, validation, with $R=1$, also the test showing $R=1$. Then, the All section shows an overall $R=0.99811$, confirming that the model achieves high accuracy and a good fit across all phases of training, validation, and testing.

C. Energy Consumption Forecasting

The next step is to calculate the Mean Absolute Percentage Error (MAPE) using Eq. (16) for the forecasting outputs compared to the target data. MAPE is a valuable metric for assessing the accuracy of the model during the training phase, The following is Table 8, which presents the MAPE results from the simulation outputs.

Table 8. MAPE Training Data

Target Value	Forecasting Output	$ \frac{Y_t - \hat{Y}_t}{Y_t} $
-1	-0.92327	0.07673
-0.8983	-0.88305	0.016976511
-0.7678	-0.80681	0.050807502
-0.7001	-0.68789	0.017440366
-0.5737	-0.60034	0.046435419
-0.4634	-0.47008	0.014415192
-0.3317	-0.32211	0.028911667
0.1364	0.13197	0.032478006
0.7683	0.81765	0.064232722
1	0.9169	0.0831
$ \frac{Y_t - \hat{Y}_t}{Y_t} $		0.4135
MAPE		4.315%

Then, after achieving a Mean Absolute Percentage Error (MAPE) of 4.315%, which is below 10%, this indicates a highly accurate prediction. The next step is to predict the test data that will serve as input for future

forecasts. This involves predicting the number of customers and Gross Domestic Regional Product (GDRP) for the years 2024-2027 using polynomial regression with the Matlab functions *polyfit* and *polyval*.

Polyfit is a polynomial of a specified degree to the data, while *polyval* evaluates the polynomial at given points,

Table 9. Predicted Input Testing Sample Number of Customers and GDRP for 2024-2027 Using Linear Polynomial

Input Testing	Sectors	2024	2025	2026	2027
Number of Customers	Residential	1.2888	1.5161	1.7435	1.9708
	Commercial	1.2576	1.492	1.7263	1.9606
	Public	1.2211	1.4502	1.6793	1.9084
	Industrial	0.8005	1.0081	1.2157	1.4234
	Government Building	1.3841	1.6153	1.8465	2.0777
GDRP	Residential	1.1067	1.3067	1.5068	1.7068
	Commercial	0.9771	1.1775	1.3779	1.5782
	Public	1.1964	1.4115	1.6267	1.8418
	Industrial	1.0363	1.2514	1.4665	1.6816
	Government Building	0.957	1.1409	1.3249	1.5088

Upon obtaining sample input testing data from the linear polynomial regression for the period 2024-2027, predictions can be made during the testing phase. It is assumed that the same weights and biases used during training are applied. The next step involves simulating with Matlab's *nnTool* by inputting the test data from Table 9 into the previously trained network. The initial weight input range is adjusted from the range [-1, 1] to match the minimum and maximum values of the test input data. After saving the updated input range and adjusting the weights, the simulation is performed, and the results are presented in Table 10.

Table 10. ANN Feed Forward Backpropagation Results

Year	Results Simulation
2024	1.19108
2025	1.60581
2026	2.12674
2027	2.83289

Simulated predicted values for electricity consumption in Riau Province for the years 2024 to 2027 in Table 10 require post-processing or denormalization of the data using Eq. (20). This process converts the normalized forecasted values back to their original scale. Denormalization is carried out using previous target data, where the minimum is from the year 2014 and the maximum is from 2023, with the minimum value of 3,338 GWh and the maximum value of 8,213 GWh. Table 11,

shows predictions based on the fitted model. These functions are key for performing polynomial regression, as shown in Eq. (18). Table 9 below shows the predicted sample data testing for 2024-2027 using the linear polynomial method with Matlab.

representing the predicted electricity consumption Riau Province.

Table 11. Prediction Electricity for Riau Province 2024-2027

Year	Predicted Electricity Consumption (GWh)
2024	8679
2025	9690
2026	10959
2027	12681

D. Growth Percentage Consumption Electricity

Following the denormalization process, the next step is to calculate the percentage growth of electricity consumption starting from the year 2024. This calculation is performed using Eq. (21), Table 12 presents the results of the percentage growth calculations for electricity consumption from 2024 to 2027.

Table 12. Growth Percentage Consumption Electricity

Year	Growth Percentage (%)
2023-2024	5.67%
2024-2025	11.65%
2025-2026	13.10%

2026-2027

15.71%

E. Comparison Between RUPTL and ANN

Next is the result of the the average percentage difference, between the ANN method and the PLN RUPTL projections, aimed at comparing the performance of both methods. The average percentage difference is derived using the equation in Eq. (22). Below is Table 13, which presents the average difference for both predictions:

Table 13. Average Percentage Difference Methods

Year	RUPTL Consumption (GWh)	ANN Prediction (GWh)	Comparison (%)
2024	7995	8679	8.56
2025	8982	9690	7.88
2026	9338	10959	17.36
2027	9692	12681	30.84
Average Comparison			16.6

4. DISCUSSION

A. Accuracy of Backpropagation ANN Model

The accuracy analysis of electricity consumption predictions in Riau Province for the 2014-2023 period indicates that the Artificial Neural Network (ANN) model performs exceptionally well, with a Mean Absolute Percentage Error (MAPE) of 4.315%, which falls into the very good category (<10%). This suggests that the ANN model is highly accurate, providing predictions that are very close to the actual electricity consumption during this period.

In Fig. 5 below, the largest error is observed for 2023, with an absolute percentage error of 8.31%. This is followed closely by 2014, which has an error of 7.67%. The year 2022 shows an error of 6.42%, and 2016 has a lower error of 5.08%. The total error across the examined years is 4,315% indicating an aggregate measure of the network ANN Feed Forward Backpropagation performance. The model's tendency to show increased prediction errors at both the beginning and the end of the observation period highlights a potential weakness in its ability to adapt to changing conditions. For example, in 2023, the error of 8.31% suggests that the model may not have effectively captured emerging trends in electricity consumption, which could be influenced by recent economic developments or advancements in energy technology. Meanwhile, in years like 2015 and 2018, the errors were relatively small, at 1.70% and 2.89%, respectively, demonstrating that the ANN model works well during years with more stable consumption patterns. This signifies that the model is quite effective at capturing long-term trends in electricity consumption.

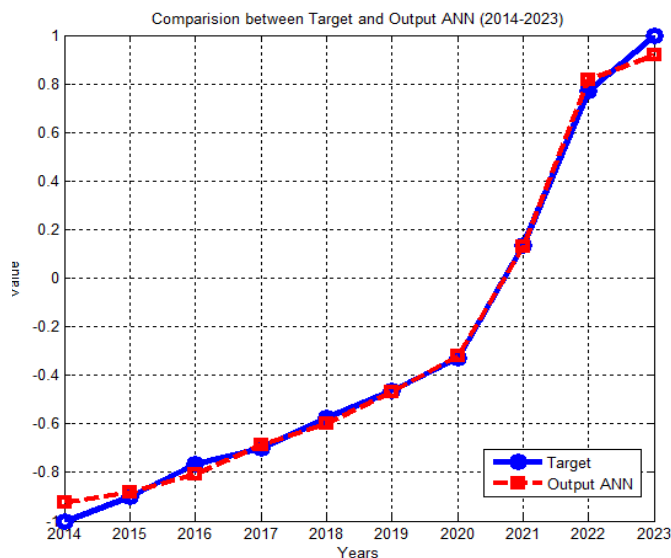


Fig. 5. Comparison between Target and Output ANN

Fig. 6 below, Illustrates the performance of the Artificial Neural Network (ANN) backpropagation model during the training process including the best epoch and MSE of network.

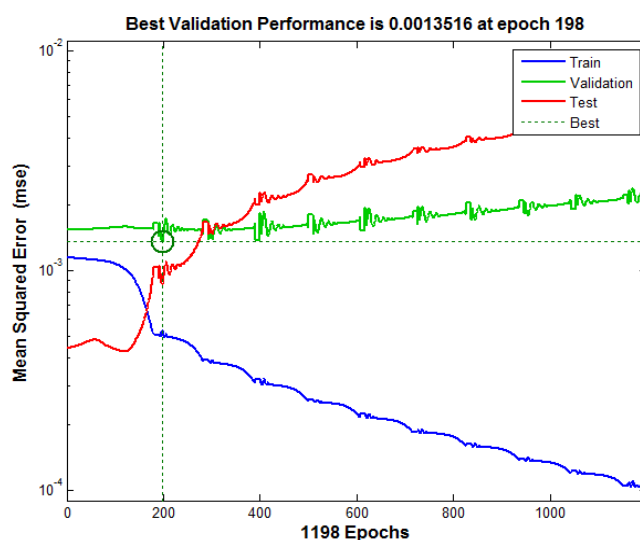


Fig. 6. Performance ANN Backpropagation Training Process

The performance of the Artificial Neural Network (ANN) model, as shown in the Fig.6, demonstrates how the model learns over time. The training process spans 1198 epochs, with the blue line indicating the training set's performance, which steadily decreases in Mean Squared Error (MSE). This shows that the model is effectively learning and improving. The best validation performance is observed at epoch 198, where the validation error reaches its lowest point, marked by the green circle. This indicates the model's most accurate predictions on the validation set at this stage.

B. Forecast Analysis of Electricity Consumption Using ANN in Riau Province (2024-2027)

In forecasting electricity consumption from 2024 to 2027, the polynomial linear regression method was used to inputs testing such as the number of PLN customers and Gross Domestic Regional Product (GDRP). In Fig. 7, the growth of the number of customers of data testing with linear polynomials below, it can be seen that in the prediction for 2024 to 2027, all sectors are expected to continue to experience growth. The residential sector is predicted to reach 1.9708 customers in 2027, which shows a positive increase reflecting the increasing demand for electricity services among households. The commercial and public sectors also show a positive trend with a figure approaching 2, indicating stable growth in electricity use for business and public services. The Government Building sector is predicted to reach 2.0777, indicating high growth potential in electricity consumption in government buildings. However, the Industrial sector still shows the slowest growth, with a prediction of only reaching 1.4234 customers in 2027.

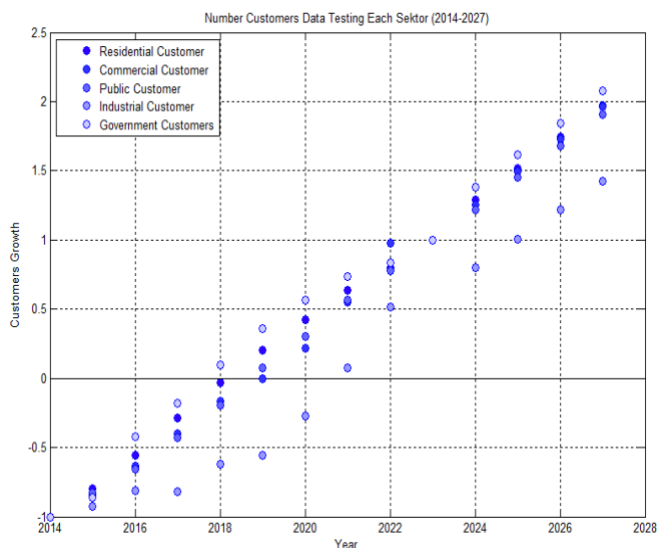


Fig. 7. Customers Growth per Sektor By Linear Polynomial Regression

Then in Fig. 8 below, it can be seen that for GDRP, the residential sector is predicted to grow from 1.1067 in 2024 to 1.7068 in 2027, indicating positive growth. The commercial and public sectors also experienced an increase, although not as fast as the residential sector with a positive growth trend. The industrial sector again showed slower growth in GDRP.

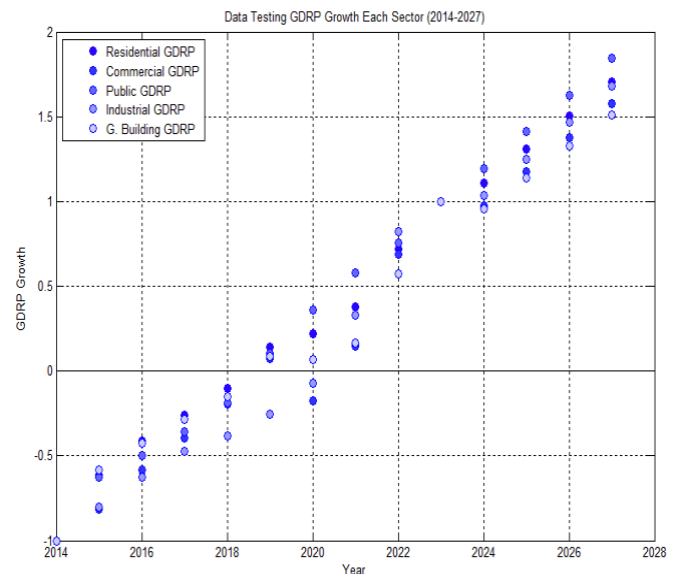


Fig. 8. GDRP Growth per Sektor By Linear Polynomial Regression

In Figure 9, the forecast for 2024 till 2027 shows an increase in electricity consumption for Riau Province:

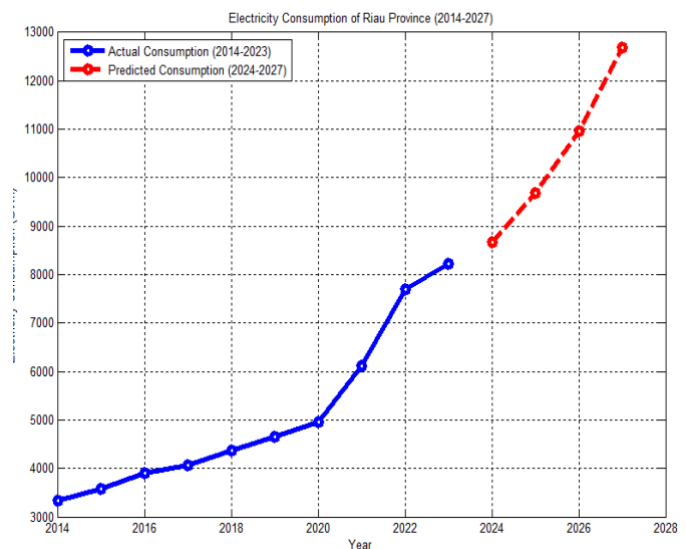


Fig. 9. Comparison of actual electricity consumption data from 2014 to 2023 and forecasted consumption from 2024 to 2027

First, in 2024, the electricity consumption increase to 8,679 GWh, compared to actual consumption of 8,213 GWh in 2023. This represents a growth of around 5.67% indicating positive growth in electricity usage. The larger increase in consumption can be driven by factors such as increasing demand in the residential, industrial, commercial, public and government building sectors. The forecast for 2025 shows a continued upward trend reaching 9,690 GWh further reinforcing the ever-increasing energy demand. The forecast continues to increase with consumption expected to reach 10,959 GWh in 2026 and 12,681 GWh in 2027. This projection shows strong growth with an average annual increase of around 11.5% from 2024 to 2027. This accelerated growth

can be attributed to several factors including increased industrial activity, expansion of the commercial sector and population growth, all of which contribute to increased electricity demand.

From Figure 10, it can be seen that the electricity consumption forecast between the ANN Backpropagation model and PLN's RUPTL for Riau Province shows an average difference of 16.6% during the period 2024-2027.

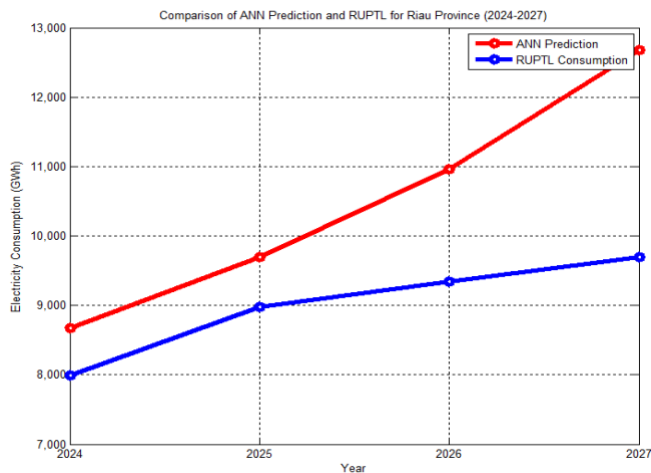


Fig. 10. Comparison of Predicted ANN Feed Forward Backpropagation and RUPTL PLN for Riau Province (2024-2027)

This difference shows differences in the forecasting approach, not inherent inaccuracies in the ANN model. Based on RUPTL approach; for example, in 2023, the RUPTL projects consumption of 6998 GWh, far below the actual 8213 GWh with an error of 14.79%. In contrast, the ANN model forecast for 2024 is 8679 GWh which is very much in line with the recent historical trend before 2023, indicating its capacity to anticipate more realistic growth patterns.

C. Analysis of Growth Forecasts for Electricity Consumption Riau Province (2024-2027)

The projection of electricity consumption growth in Riau Province from 2024 to 2027, based on Fig. 11, shows a stable upward trend. In the early period from 2023 to 2024, the growth rate is estimated at 5.67%, there is an increase in electricity demand. This growth increases again between 2024 and 2025 which reaches 11.65%. Entering 2025-2026, growth continues to increase with a rate of 13.10% which further strengthens the trend of increasing demand. Last, from 2026 to 2027, the growth rate peaks at 15.71% which indicates a continuous and strong expansion of electricity consumption.

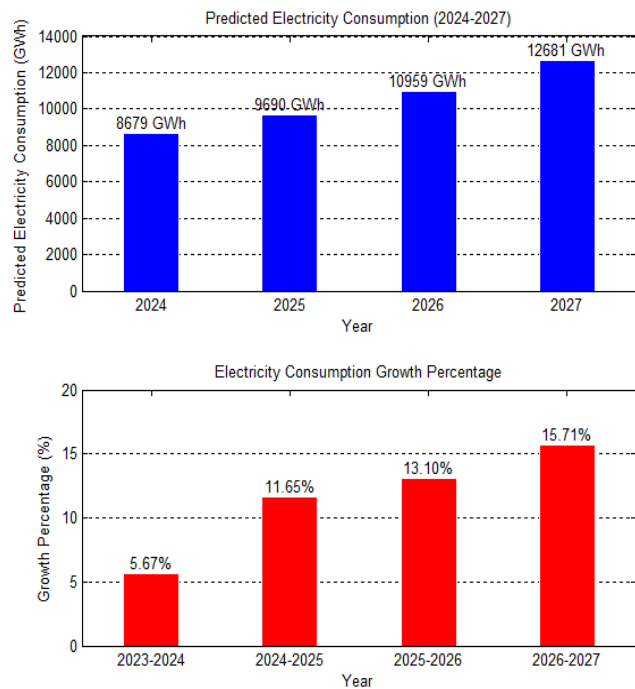


Fig. 11. Growth forecasts of electricity consumption in Riau Province using ANN Backpropagation

The current model demonstrates superior performance compared to other similar studies. For instance, the study by [22] reported a MAPE of 7.6% using Cascade Forward Backpropagation, while this research achieved a MAPE of 4.315% with Feed Forward Backpropagation. Similarly, the study by [25] recorded a MAPE of 6.24%, and [26] achieved lower errors after 9 iterations, whereas this study reached comparable results in just 7 iterations. Furthermore, the study by [35] utilizing LSTM integration reported a MAPE of 6.5%-7%, and [37] obtained 8%, both higher than this study's consistently sub-5% MAPE. However, a notable limitation of this method is its vulnerability to overfitting, which necessitates repeated trials to ensure optimal accuracy.

Despite this, the findings of this study provide valuable insights for PT. PLN in planning electricity production levels to meet the growing demand of consumers in Riau Province effectively.

5. CONCLUSION

This research aimed to assess electricity consumption forecasts in Riau Province using the Artificial Neural Network (ANN) Feed Forward Backpropagation method for the 2024-2027 projection. The analysis revealed a Mean Absolute Percentage Error (MAPE) of approximately 4.315%, indicating a high degree of accuracy in predicting energy demand. The predicted electricity consumption values for Riau Province demonstrate a steady increase across the forecast period, with projected values as follows: 8679 GWh in 2024, 9690 GWh in 2025, 10,959 GWh in 2026, and 12,681 GWh in 2027. The growth percentage analysis shows an

accelerating trend in electricity consumption growth over time. The growth rate begins at 5.67% between 2023 and 2024, increases to 11.65% from 2024 to 2025, rises further to 13.10% from 2025 to 2026, and reaches 15.71% from 2026 to 2027. Therefore, this study provides valuable insights for PT. PLN in planning electricity production in Riau Province. For forecasting accuracy improvements, implementing robust data cleaning processes is highly recommended. Data cleaning shows the removal of inconsistencies, outliers, and missing values that could adversely impact model performance. Future research should explore comparisons with other neural network methods available in the *nntool* GUI of MATLAB. This would provide a broader perspective on model performance and identify alternative approaches that may offer further improvements in accuracy and efficiency.

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