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# Prediction of Electrical Energy Needs for Capital City of Central Java Based on Backpropagation and Linear Regression

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**Abstract**

*This study discusses the prediction of electricity needs according to population growth. The model is determined by knowing the population and electricity needs. The parameters determined include: population, number of electricity consumers, energy consumption growth and electricity load factor for eleven years (2012-2023). The back propagation (BP) method and linear regression are used to help predict electricity needs for the next five years (2025-2030) with the BP architecture determined by three hidden layers and the number of neurons 12, 10 and 1. The object of the study was determined to be Semarang City, Indonesia. The results show that BP and linear regression can be used to predict electricity consumption needs in various sectors accurately. This is evidenced by the MAPE value below 10% and the MSE value of 2,65 x10-10 in the household sector, MSE 3,83 x 10-10 in the business sector, MSE 2,41 x 10-7 in the industrial sector, and MSE 3,6 x 10-12 in the public sector. The BP model produces predicted outputs of electrical energy in 2030 in the household sector of 1.104.140 MWH, the business sector of 843.757 MWH, the industrial sector of 1.027.790 MWH and the public sector of 375.974 MWH. The predicted increase in all sectors of electrical energy results in a total percentage of 54.21% for power sufficiency in 2030, so a thorough planning study is needed to meet electrical energy needs in that year.*

## Introduction

Electricity is a form of energy that flows through a network of cables and has become an important element in the advancement of human civilization in various fields, such as economics, technology, social, and culture. Increasing human activity will have an impact on the use of electricity (Gupta et al., 2022; Li & Zhao, 2012; Raimi et al., 2021; Kabeyi & Olanrewaju, 2022). The high demand for electrical energy requires producers to provide sufficient electricity supply to meet consumer needs. The availability of electrical energy is a crucial factor in supporting the success of other sectors (Oito, 2012; Abiodun & Segbenu, 2017). Meeting the right electrical energy needs in a region can encourage the progress of regional development, especially in the technology, industry, and commercial sectors (Rohman et al., 2021; Al-Shetwi, 2022; Çelik et al., 2022; Çeçen et al., 2022). National electricity demand in 2025 will grow by around 11-12% to reach 576,2 TWh (Business As Usual), 537 TWh (Sustainable Development) and 520,7 TWh (Low Carbon) and in 2050 will grow by around 6-7% to reach 2,214 TWh (Business As Usual), 1.917,9 TWh (Sustainable Development) and 1.625,2 TWh (Low Carbon) (Secretary General of the National Energy Council, 2019).



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Electricity demand until 2050 in all scenarios is still dominated by the household sector, then the industrial and commercial sectors (Secretary General of the National Energy Council, 2019). As inSemarang City, which is the capital city of Central Java Province, has an area of 373,78 km2 with a total of 16 sub-districts and 177 villages. Semarang City has high population growth every year with an average of 0,7 percent or around 1.6 million people per year (Central Statistics Agency (BPS) of Semarang City).The electricity system in Semarang City is supplied by PT. PLN (Persero) UP3 Semarang with a formation of 7 Customer Service Units (ULP) serving a total of 12,2 million customers with an average energy sold of 4.131.296,5 MWH in the last five years (PLN Electricity Master Plan (UP3 Semarang).

The electricity problem of Semarang City is how to predict the electricity needs for the next 5 years according to the population growth which results in increasing demand for electricity. Thus, the adequacy of electricity supply can be guaranteed by PLN as a state-owned electricity provider. The solution is the need to make efforts to meet the supply of electrical energy. For this, a prediction of electrical energy needs in Semarang City is needed in the next 5 years (2025-2030).

To meet the need for electrical energy, prediction of future electricity needs needs to be done before the construction of power plants or power supply facilities for customers (Klyuev et al., 2022; Gebremeskel et al., 2021; Strielkowski et al., 2023). Given that the electrical energy sector requires long-term predictions to prepare the power supply infrastructure, these long-term predictions are often difficult to do. The challenges faced are usually related to time and funding factors. In addition, electrical energy is affected by various complex factors, non-linear characteristics, and is easily affected by environmental factors such as weather and economic conditions (Hassan et al., 2022; Ding et al., 2025; Liu e al., 2022; Verma et al., 2024; Mirzayev et al., 2024). Therefore, to anticipate these things, predictions are needed that can estimate the amount of electrical energy consumption (Hernandez et al., 2014; Ruiz et al., 2020; Selvam et al., 2024).

The development of computing technology today leads to artificial intelligence, which produces alternative methods for long-term electrical energy prediction (Rahman et al., 2021; Benti et al., 2023; Chen et al., 2021; Klyuev et al., 2022; Ahmad et al., 2022). The use of computing technology not only facilitates the process, but also produces precise calculations. Then with the advancement of technology and the development of the times, an intelligent system based on Artificial Intelligence (AI) in the form of an Artificial Neural Network (ANN) was discovered which can be used to predict future electrical energy needs with effective results and high accuracy.

Several previous studies on predicting electrical energy needs have been carried out, including: using Artificial Neural Networks, namely by *exponential smoothing* (2016), lagrange multiplayer (2023), simple moving average (2021), weighted moving average (Tsokos, 2008), linear regression (Phan et al., 2024) and backpropagation (Kumar Singla & Gupta, 2018).

The focus of this study discusses the prediction of electricity needs in Semarang City in 2025-2030. Previous studies have not combined two methods by discussing energy per sector and comparing it with existing power from PLN. The backpropagation and linear regression methods were chosen to train the model using the given pattern examples, because both methods are effective in identifying the relationship between nonlinear characteristics of energy and other data. In addition, if the output produced does not match the desired target, the output will be reprocessed (backward) to the hidden layer and forwarded to the input layer unit, providing feedback to validate the output results from the Artificial Neural Network. Artificial Neural Networks also have a high level of accuracy, with the note that the data entered must meet the criteria for high quantity and validity.



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## Methods

### Research Model

The research model used in this study can be seen in Figures 1 and 2.

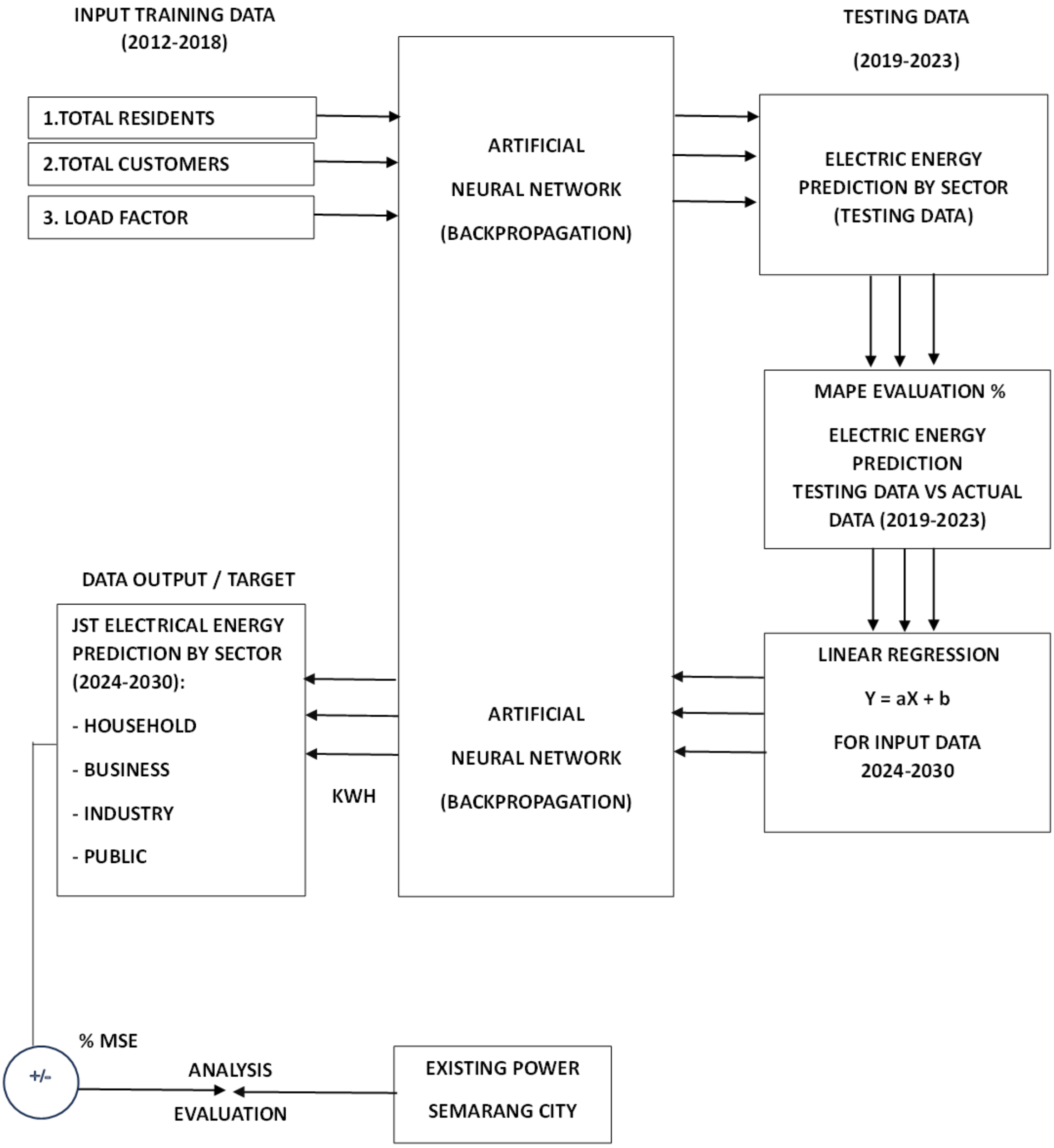


*Figure 1. Research Model*



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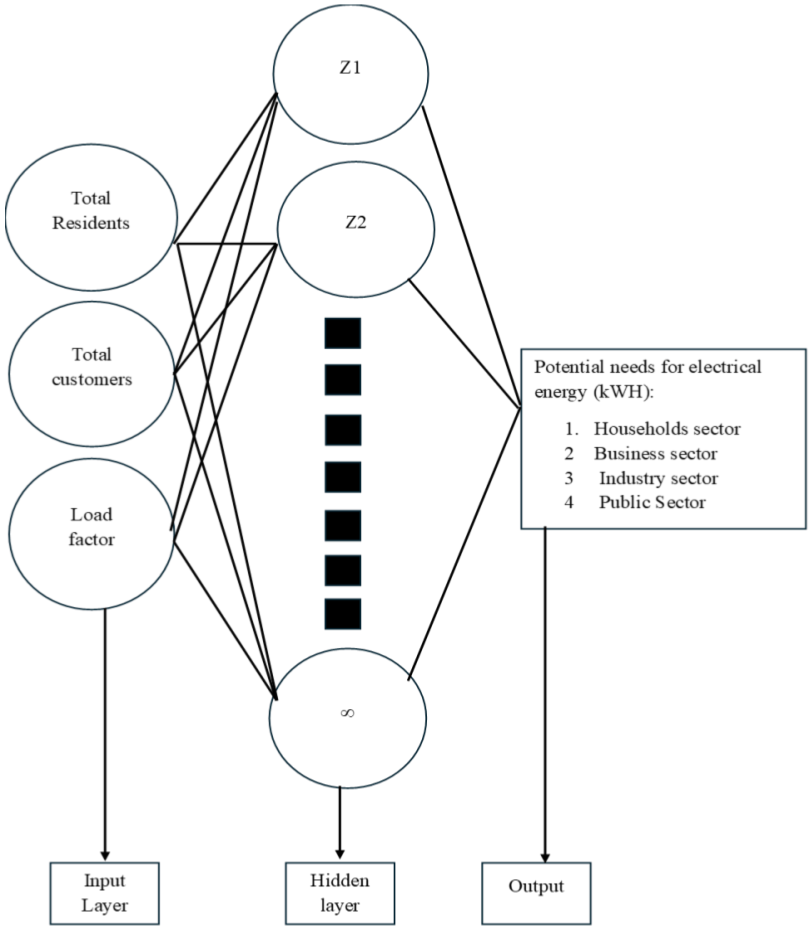


*Figure 2. Research Architecture*

**Linear Regression Prediction Method**

Regression analysis is a statistical technique for modeling and investigating the relationship between two or more variables. In regression analysis, there are one or more independent/predictor variables usually represented by variable x and one response variable usually represented by y. If the number of independent variables is only one, it is often called simple linear regression. While if there is more than one independent variable, it is known as multiple linear regression. The simple linear regression equation is mathematically expressed in equation (1).

$$Y = a + bX \qquad (1)$$

with:$Y$= Dependent variable (bound variable), X = Independent variable (free variable).$a$= Constant (value of Y when X = 0),$b$= Regression coefficient (positive or negative effect).

**Backpropagation Prediction Method**

Backpropagation error propagation algorithm is an algorithmic method for a multiplayer learning system of artificial neural networks. The Backpropagation method has a strong mathematical basis, objective and algorithm to obtain the form of equations and coefficient values in the formula by minimizing the sum of the squares of the error through the developed model.

**Evaluation**

In evaluating forecasting/predictions can be done by calculating the error accuracy value. Error calculations measure and evaluate the learning ability of the network so that it can be


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identified quickly when compared to new patterns. In this study the techniques used to calculate forecast accuracy are:

$$MAPE = \frac{(A_t - F_t)}{A_t} x\ 100\% \qquad (2)$$

With: At = Actual data at period t, Ft = Predicted data at period t, MAPE = Mean Absolute Percentage Error

$$\text{MSE} = \sum \frac{(Y' - Y)^2}{n} \qquad (3)$$

with: Y' = Predicted value, Y = Actual value, n = Number of training data.

**Electrical Energy Needs Analysis**

After the evaluation is carried out and in accordance with the parameters produced, the next stage is to analyze the percentage of potential electrical energy needs for the next 5 years 2025-2030 which will later be compared with the existing PLN power energy capacity in the current year. The calculation of the analysis of electrical energy needs can be seen in equation (3).

$$\%\ \text{Prediction} = \frac{\sum\text{Electricity Energy Prediction for Year X} - \sum\text{Current Electricity in 2023}}{\sum\text{Current Electricity in 2023}} x100\% \qquad (4)$$

In this study, the descriptive quantitative method is used to describe a certain condition. The approach uses a quantitative approach because it uses numerical parameters, starting from data collection, data interpretation, and the appearance of the results of the approach. This study uses the following supporting tools:

Table 1. Research Support Tools

| No. | **Computer Devices** | **Software** |
|---|---|---|
| 1 | Brand: HP EliteBook 630 G9 | MATLAB |
| 2 | RAM: 16 GB | Edition: R2023a |
| 3 | Processor: Intel (R) Core TM i7 | Publisher: MathWorks, Inc |
| 4 | System Type: Windows 11 Pro – 64 bit | System Type: 64 bit Windows |

To ensure that the data collected is in accordance with the objectives and focus of the study, data collection techniques play a very important role. The following data collection methods were used in this study: 1) Collecting demographic data of the population. 2) Electricity consumption data

## Results and Discussion

Data processing is done by identifying training data and test data, referring to the research model shown in Figure 3.1. This research data uses four indicator parameters from Semarang City. Test data is used for prediction and assessment of network performance, while training data is used to train the network. This study uses 49 energy development data in Semarang City from 2012-2023. Tables 2 and 3 contain these data.

Table 2. Training Data for Artificial Neural Networks (ANN)

| **Year** | **Input Data (X)** | | | **Target Data (Y)** | | | |
|---|---|---|---|---|---|---|---|
| | | | | **Energy Sold (MWH)** | | | |
| | **Resident** | **Load Factor %** | **Customer** | **Household** | **Business** | **Industry** | **Public** |
| 2012 | 1.559.198 | 79,18 | 412.362 | 786.409 | 527.502 | 758.143 | 249.775 |
| 2013 | 1.572.105 | 80,04 | 431.996 | 832.764 | 552.616 | 820.258 | 269.456 |
| 2014 | 1.584.881 | 78,26 | 449.528 | 875.392 | 596.333 | 859.661 | 270.215 |
| 2015 | 1.595.187 | 80,02 | 464.895 | 902.073 | 627.300 | 826.842 | 277.614 |



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| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 2016 | 1.729.428 | 62,62 | 479.134 | 941.384 | 670.362 | 836.578 | 300.522 |
| 2017 | 1.753.092 | 74,93 | 499.741 | 930.436 | 680.287 | 842.548 | 307.504 |
| 2018 | 1.786.114 | 78,64 | 519.828 | 968.895 | 718.843 | 879.122 | 330.267 |

Table 2 explains the input and output parameter data of 49 X and Y variable data, where the data will be used to train the desired JST model so that it can continue processing to the testing stage.

Table 3. Test Data for Artificial Neural Network (ANN)

| **Year (Y)** | **Input Data (X)** | | | **Target Data (Y)** | | | |
|---|---|---|---|---|---|---|---|
| | | | | **Energy Sold (MWH)** | | | |
| | **Resident (X1)** | **Load Factor % (X2)** | **Customer (X3)** | **Household** | **Business** | **Industry** | **Public** |
| 2019 | 1.814.110 | 76,41 | 541.771 | 1.025.578 | 753.913 | 907.137 | 359.176 |
| 2020 | 1.653.524 | 78,32 | 563.552 | 1.090.540 | 686.395 | 837.385 | 332.459 |
| 2021 | 1.656.564 | 77,2 | 583.059 | 1.093.515 | 694.544 | 830.281 | 325.113 |
| 2022 | 1.659.975 | 84,11 | 603.205 | 1.113.094 | 773.762 | 793.812 | 367.464 |
| 2023 | 1.694.743 | 63,33 | 629.360 | 1.192.535 | 833.470 | 781.757 | 437.259 |

Table 3 explains the input and output parameter data of 35 X and Y variable data where the data will be used to test the desired JST model with the JST output target of sold energy which will later be compared with the actual data to obtain small MSE and MAPE error values. After the MSE and MAPE tolerance limits are met, the prediction will be continued in 2025-2030.

To find the optimal network by knowing the number of neurons, training and testing data are carried out several times through trials. After several iterations of training and testing, the optimal configuration is achieved with three hidden layers and twelve to ten neurons. The regression value, or R = 1, is shown in this context, indicating that the actual test variables and the ANN have a very good or even perfect relationship that allows the network to be modeled.

**MAPE Prediction and Calculation on Test Data**

From Table 3, it is known that the test data uses data from 2019-2023 as a test. To calculate the MAPE value, electrical energy prediction (output) data is needed using the JST Backpropagation model using the matlab function shown in Figure 3.

```
%% test ann
testdata=data(:,2:4);
pnewn=tramnmx(datauji',minp,maxp);
anewn=sim(net,pnewn);
anew=postmnmx(anewn,mint,maxt)';
hasil=num2str([yu anew]);

%% MAPE testing
pre_MAPE=abs((your-anew)./your);
MAPE=mean(pre_MAPE(isfinite(pre_MAPE)))
accuracy-100-MAPE
```

*Figure 3. Coding Test Data for Calculating Output Values and MAPE*

From the processing results in Matlab, the predicted output value calculation for electrical energy is produced, which is shown in Table 4.



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Table 4. Test Data for Electrical Energy Prediction Results for 2019-2023

| Year | Input Data (X) | | | JST Prediction Result Data | | | |
|---|---|---|---|---|---|---|---|
| | Resident (X1) | Load Factor % (X2) | Customer (X3) | Electrical Energy (MWH) | | | |
| | | | | Household | Business | Industry | Public |
| 2019 | 1.814.110 | 76,41 | 453.468 | 1.018.010 | 778.609 | 935.064 | 350.747 |
| 2020 | 1.653.524 | 78,32 | 469.910 | 1.062.011 | 824.385 | 943.428 | 367.209 |
| 2021 | 1.656.564 | 77,2 | 485.292 | 1.110.646 | 849.900 | 1.028.237 | 374.997 |
| 2022 | 1.659.975 | 84,11 | 500.869 | 1.063.129 | 805.792 | 1.009.044 | 355.866 |
| 2023 | 1.694.743 | 63,33 | 520.781 | 1.130.089 | 866.466 | 1.023.788 | 367.364 |

From the results of the JST electrical energy prediction, the values of each electrical energy sector are obtained, for the next step is to compare each electrical energy sector with actual data in 2019-2023 to obtain the MAPE value according to equation (2.4). The smaller the MAPE value and accuracy, the test data is suitable for use and continued to the prediction stage to the next year 2025-2030.

The MAPE value for each electricity sector in 2019-2023 can be seen in Table 5.

Table 5. MAPE Values on Test Data for 2019-2023

| Year | MAPE Value (%) | | | |
|---|---|---|---|---|
| | Household | Business | Industry | Public |
| 2019 | 0,07 | 0,03 | 0,03 | 0,02 |
| 2020 | 0,02 | 0,20 | 0,12 | 0,10 |
| 2021 | 0,01 | 0,22 | 0,23 | 0,15 |
| 2022 | 0,04 | 0,04 | 0,27 | 0,03 |
| 2023 | 0,05 | 0,03 | 0,30 | 0,15 |
| **Average** | **0,03** | **0,10** | **0,19** | **0,09** |

From the results of the MAPE calculation in Table 5, it was found that the MAPE value has a very small percentage below 10% so it is very accurate to be used as a prediction model.

**Linear Regression Model for 2025-2030**

A statistical technique called linear regression uses the creation of mathematical relationships between variables to make predictions. One of the techniques used in this study to make predictions is linear regression. The Linear Regression approach is applied to predict input data for the next five years, which will then be tested in the same year to obtain the smallest error value through the JST process.

The training data in Table 2 and the test data in Table 3 are calculated using simple linear regression with the toolbox function in Matlab software, so that the input data will get a constant variable value ($a$) and the regression coefficient ($b$). These variables are shown in Table 6.

Table 6. Input Data Regression Variables for 2024-2030

| Regression Variables | Resident | Customer | Load Factor |
|---|---|---|---|
| Constant (a) | -24.636707 | -38733681 | 841,8 |
| Coefficient (b) | 13044 | 19454 | -0,37 |

The data in Table 6 is processed in JST regression on Matlab software to obtain the predicted results of the number of residents, customers and load factors of Semarang City in 2024-2030. The process of processing regression and prediction data using JST can be shown in Figure 4 and Table 7.



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```
%% estimate 2024:2030
dataUi=2024:2030;
dataujimape=[];
regression_constant=[];
regression_coefficient=[];
dat=[data; data];
trainingdata=data(:,2:4);
for g=1:size(datalit, 2)
    P=polyfit(dat(:,1), data(:,g),1);
    b=P(1);
    m=P(2);
    linefit = polyval(P,dataUi');
    dataujimape=[dataujimape,linefit];
    regression_constant=[regression_constant;m];
    regression_coefficient=[regression_coefficient;b];
end
regression_constant=num2str(regression_constant)
regression_coefficient=num2str(regression_coefficient)
```

*Figure 4. Regression Prediction Coding in Matlab*

Table 7. Linear Regression Prediction of Input Parameters 2024-2030

| Year | Regression Prediction Result Data | | |
|---|---|---|---|
| | Resident | Load Factor % | Customer |
| 2024 | 1.766.316 | 73,62 | 641.321 |
| 2025 | 1.779.361 | 73,24 | 660.775 |
| 2026 | 1.792.406 | 72,86 | 680.229 |
| 2027 | 1.805.451 | 72,48 | 699.683 |
| 2028 | 1.818.496 | 72,10 | 719.137 |
| 2029 | 1.831.541 | 71,72 | 738.591 |
| 2030 | 1.844.586 | 71,34 | 758.045 |

**Backpropagation JST Model for Electrical Energy Prediction in 2025-2030**

Artificial neural networks with the backpropagation method are used to predict needs according to the outline of the research objectives. One of the learning techniques used in multi-layered artificial neural networks is backpropagation. The best model parameters used in this study are shown in Table 8.

Table 8. Best Model Parameters of Artificial Neural Network

| Parameter | Sector Type | | | |
|---|---|---|---|---|
| | Household | Business | Industry | Public |
| Learning Rate | 0,01 | 0,01 | 0,01 | 0,01 |
| Hidden Layer | 3 layers | 3 layers | 3 layers | 3 layers |
| Number of Neurons | 12 - 10 - 1 | 12 - 10 - 1 | 12 - 10 - 1 | 12 - 10 - 1 |
| Epoch | 2000 | 2000 | 2000 | 2000 |
| Iterations | 6 | 6 | 6 | 7 |
| MSE Goals | 1e-6 | 1e-6 | 1e-6 | 1e-6 |
| R value | 1 | 1 | 1 | 1 |

The results of the JST Backpropagation predictions in each electrical energy sector are explained as follows.

**Backpropagation JST Model for Electrical Energy Prediction in Household Sector**

Training was carried out using the Levenberg–Marquardt Algorithm (trainlm) using the parameters in Table 8. The network training modeling process can be seen in Figure 5.



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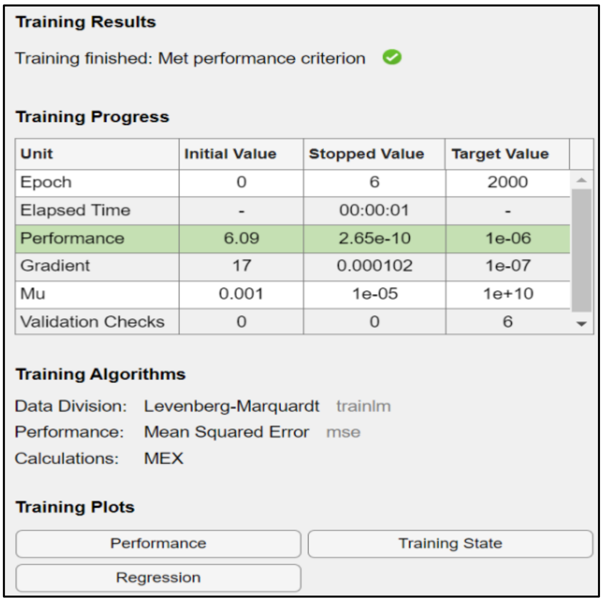


*Figure 5. Household Sector JST Architecture*

Figure 6 explains that the backpropagation JST training ends when its performance reaches the best validation performance of 2.65e-10 with the regression graph shown in Figure 4 that the correlation coefficient (R) between the output and the target is 1.

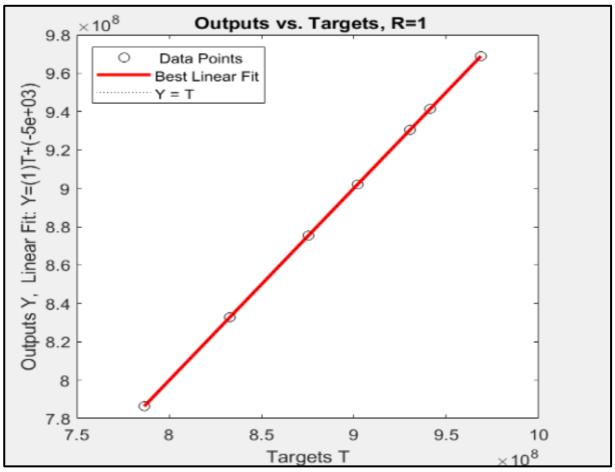


*Figure 6. Comparison Chart of Output Data and Household Sector Target Data*

Figure 7 shows the MSE value obtained from using this model, which is 2.65e-10.

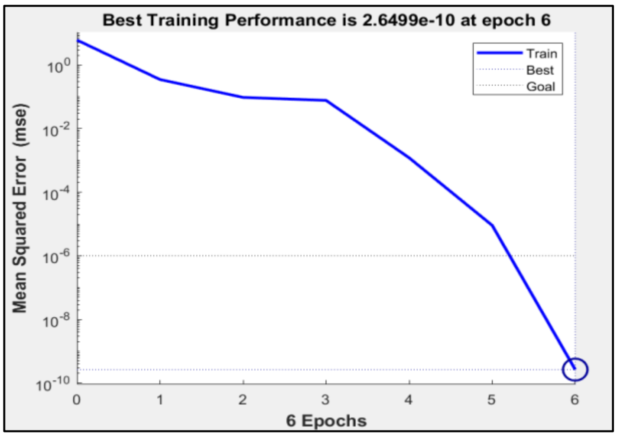


*Figure 7. MSE Graph on Household Sector JST*

JST prediction data for the next five years can be seen in Table 9.



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Table 9. Results of Prediction of Household Sector Electricity Needs 2024-2030

| Year | Prediction of Household Sector Electricity Needs (MWH) |
|---|---|
| 2024 | 1.102.228 |
| 2025 | 1.102.497 |
| 2026 | 1.102.778 |
| 2027 | 1.103.061 |
| 2028 | 1.103.366 |
| 2029 | 1.103.717 |
| 2030 | 1.104.140 |

**Backpropagation JST Model for Electrical Energy Prediction in Business Sector**

Using the parameters in Table 8, Figure 6 shows the ANN training modeling for predicting business sector electrical energy.

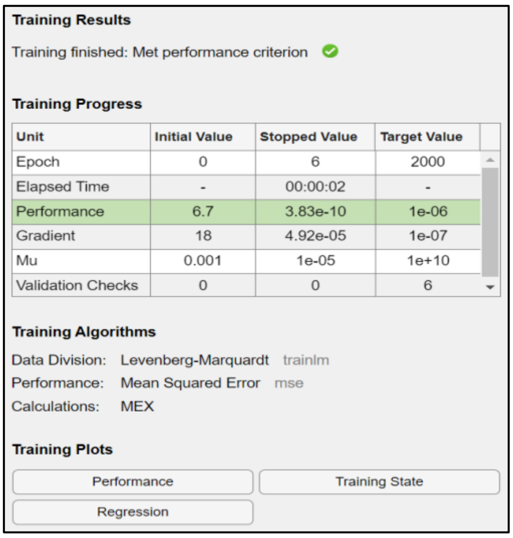


*Figure 8. Business Sector JST Architecture*

The regression plot shows that the JST modeling carried out on the prediction of electrical energy in the business sector is appropriate, as shown in Figure 9, the R value is 1 (R=1).

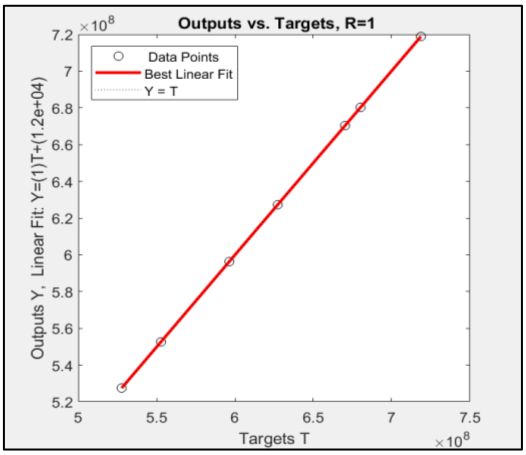


*Figure 9. Comparison Chart of Output Data and Target Data for Business Sector*

Figure 10 shows the MSE value of 3.83e-10 obtained from the JST model for predicting electrical energy in the business sector.



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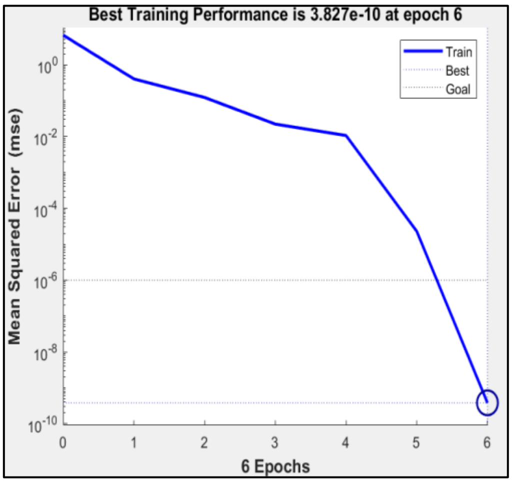


*Figure 10. MSE Graph on JST Business Sector*

Table 10 shows the predicted electricity needs for the business sector.

Table 10. Results of Prediction of Electrical Energy Needs in the Business Sector for 2024-2030

| Year | Prediction of Business Sector Electricity Needs (MWH) |
|---|---|
| 2024 | 840.413 |
| 2025 | 840.917 |
| 2026 | 841.388 |
| 2027 | 841.859 |
| 2028 | 842.379 |
| 2029 | 842.996 |
| 2030 | 843.757 |

**Backpropagation JST Model for Electrical Energy Prediction in Industrial Sector**

Using the parameters in Table 8, Figure 11 shows the ANN training modeling for predicting electrical energy in the industrial sector.

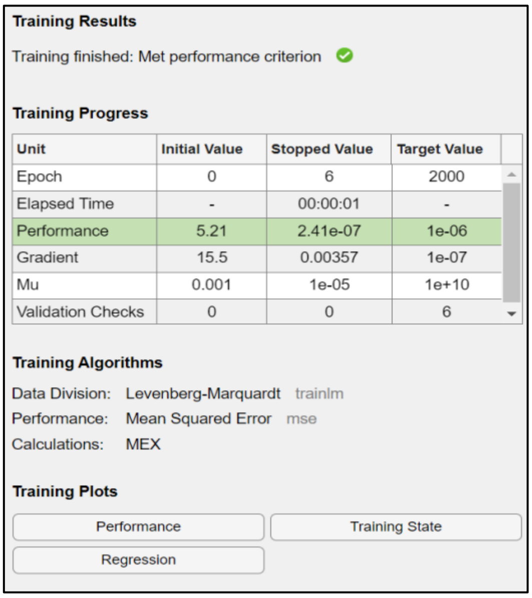


*Figure 11. Industrial Sector JST Architecture*


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The regression plot shows that the JST modeling carried out on the prediction of electrical energy in the industrial sector is appropriate, as shown in Figure 12, the R value is 1 (R=1).

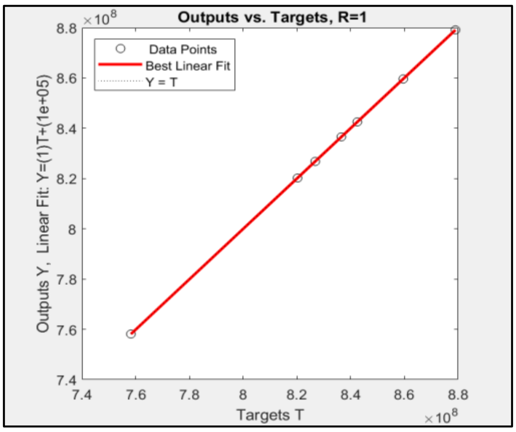


*Figure 12. Comparison Chart of Output Data and Target Data for Industrial Sector*

Figure 13 in the performance menu shows that the MSE value is 2.41e-07.

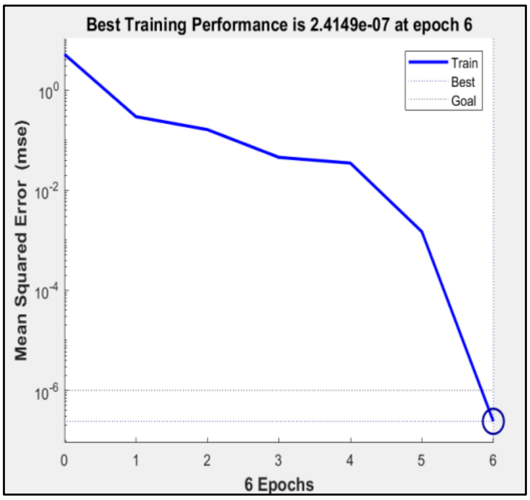


*Figure 13. MSE Graph on Industrial Sector JST*

Table 11 shows the estimated electricity requirements for the public sector.

Table 11. Results of Prediction of Electrical Energy Needs in the Industrial Sector in 2024-2030

| Year | Prediction of Industrial Sector Electrical Energy Needs (MWH) |
|---|---|
| 2024 | 1.026.068 |
| 2025 | 1.026.441 |
| 2026 | 1.026.723 |
| 2027 | 1.026.964 |
| 2028 | 1.027.205 |
| 2029 | 1.027.473 |
| 2030 | 1.027.790 |

**Backpropagation JST Model for Electrical Energy Prediction in Public Sector**

Using the parameters in Table 8, Figure 14 shows the ANN training modeling for public sector electricity prediction.



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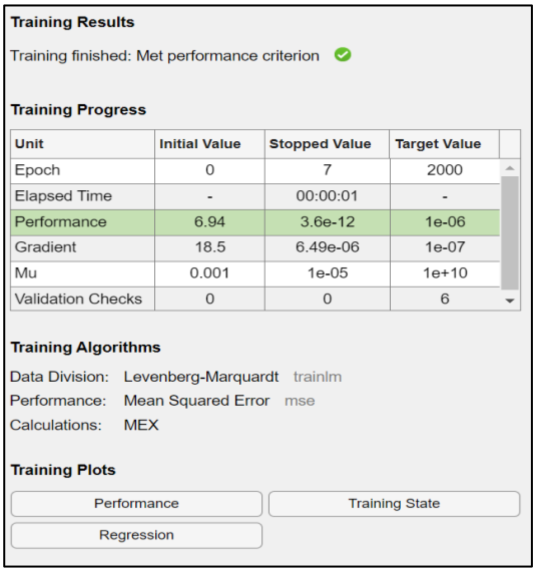


*Figure 14. Public Sector JST Architecture*

The regression plot shows that the JST modeling carried out on public sector electricity energy prediction is appropriate, as shown in Figure 15 with an R value of 1 (R=1).

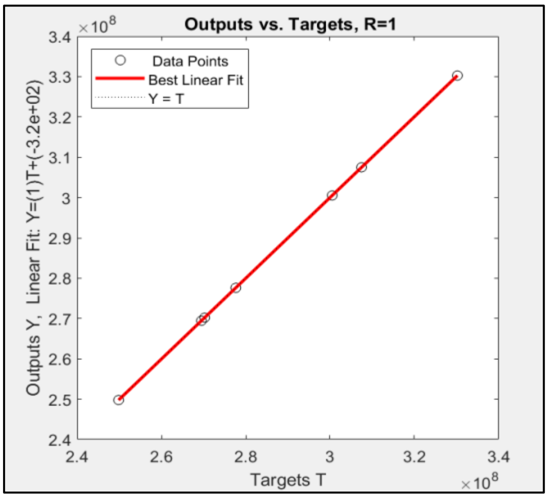


*Figure 15. Comparison Chart of Output Data and Target Data for the Public Sector*

Figure 16 in the performance button shows the MSE value is 3.6e-12.


*Figure 16. MSE graph on Public Sector JST*

Table 12 shows the findings of the predicted electricity needs of the public sector.



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Table 12. Results of Prediction of Public Sector Electricity Needs 2024-2030

| Year | Prediction of Public Sector Electrical Energy Needs (MWH) |
|---|---|
| 2024 | 375.585 |
| 2025 | 375.600 |
| 2026 | 375.644 |
| 2027 | 375.703 |
| 2028 | 375.775 |
| 2029 | 375.864 |
| 2030 | 375.974 |

**Analysis**

***Analysis of Prediction of Household Sector Electrical Energy Needs***

The predicted need for electrical energy in the household sector in 2030 is 924.547 MWH. The percentage of household electricity needs to electricity sold in 2023 can be calculated using equation (4). Prediction of Percentage of Household Sector Electricity Needs:

= (924.547 – 1.646.210) / (1.646.210) x 100 %

= -0,07 x 100 %

= -7 %

The predicted electricity needs of the business sector in 2030 is 843.757 MWH. The percentage increase in the business sector's electricity needs in relation to electricity sold in 2023 can be calculated using equation (4). Prediction of Percentage Increase in Electricity Needs in the Business Sector:

= (843.757 – 833.470) / (833.470) x 100 %

= 0,012 x 100 %

= 1,2%

***Analysis of Prediction of Industry Sector Electrical Energy Needs***

The predicted need for electrical energy in the industrial sector in 2030 is 1.027.790 MWH. The percentage increase in the need for electrical energy in the industrial sector relative to the electrical energy sold in 2023 can be calculated using equation (4). Prediction of Percentage Increase in Electricity Needs in the Industrial Sector:

= (1.027.790 – 781.757) / (781.757) x 100 %

= 0,31 x 100 %

= 31%

***Analysis of Prediction of Public Sector Electrical Energy Needs***

The predicted need for public sector electricity in 2030 is 375.974 MWH.The percentage increase in public sector electricity needs relative to electricity sold in 2023 can be calculated using equation (4). Prediction of Percentage Increase in Public Sector Electricity Needs:

= (375.974 – 437.259) / (375.974) x 100 %

= - 0,14 x 100 %

= - 14 %



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***Analysis of Predicted Electricity Needs with Existing Power in Semarang City***

Based on the analysis calculations that have been carried out for the need for electrical energy in 2030, the industrial sector is still the largest contributor to energy needs followed by the business sector. As seen in Figure 17.

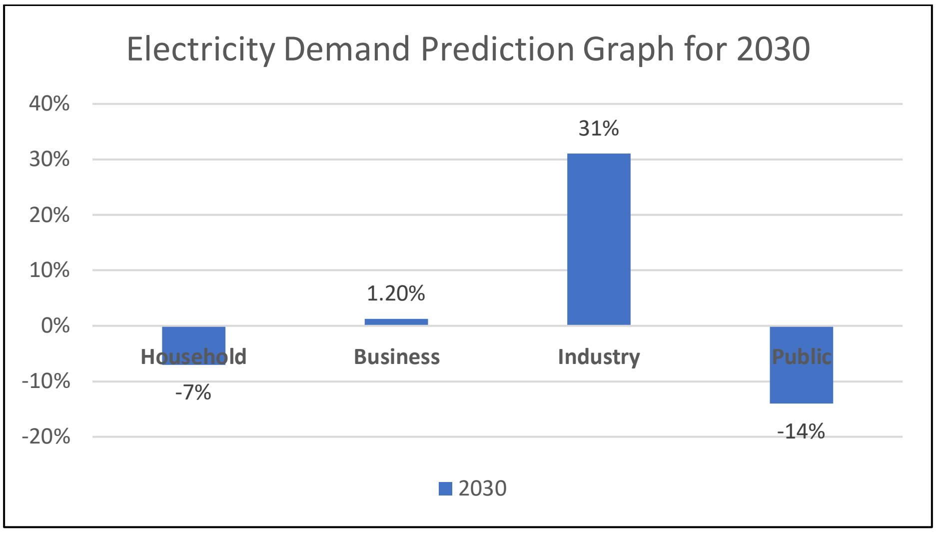


*Figure 17. Prediction Graph of Percentage of Potential Energy Needs Per Sector in Semarang City*

For existing power data in Semarang City in 2024, it has reached 43% of the available transformer supply capacity. So with the predicted increase in the potential for electrical energy by 11,21%, for use in 2030 it will be 54,21%. The increase in electrical energy is shown in Table 13 and Figure 18.

Table 13. Prediction of Electrical Energy in 2030 with Existing Power in 2024

| **Electricity Sector Prediction 2030** | | | | **Note** | **Existing Power in 2024** | **Total Electricity Energy Prediction 2030** |
|---|---|---|---|---|---|---|
| **Household** | **Business** | **Industry** | **Public** | **Total** | | |
| - 7% | 1,2% | 31% | -14% | 11,21% | 43% | 54,21% |

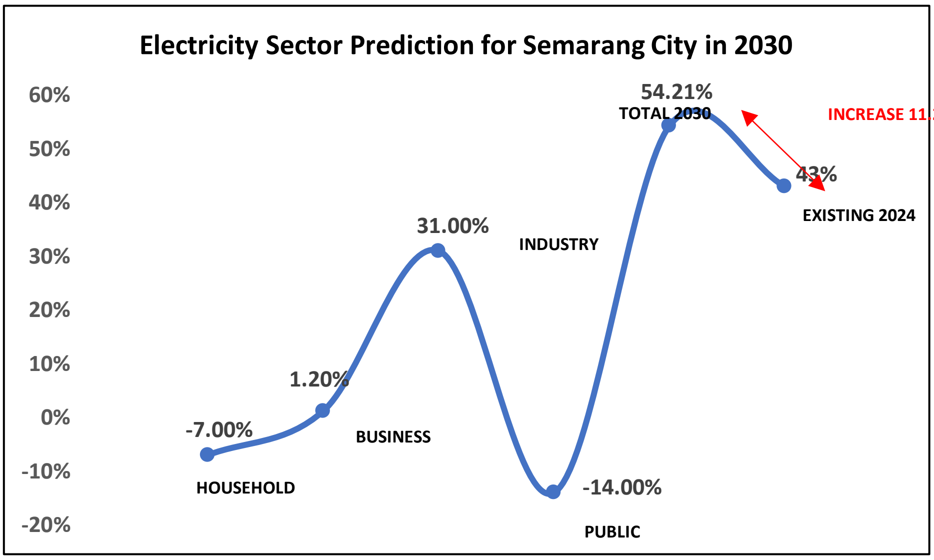


*Figure 18. Comparison Chart of Electric Energy Predictions in 2030 vs. Existing Power in 2024*

The next system updates should include a combination of modular features that enable separate maintenance which is essential when adding telehealth services or implementing AI-based health risk assessments.



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The system successfully implemented in Payaman Village serves as a model design for various communities that operate similar Posyandu structures in rural and semi-urban areas. The program's long-term success depends on the combination of consistent funding along with training for digital literacy and healthy institutional support from local government health sectors. The future successful expansion of posyandu systems will require database integration that connects them to provincial health offices and national electronic health records systems for better patient care and public healthcare services.

The research reveals both Backpropagation Neural Network (BPNN) and Linear Regression (LR) produce dependable and accurate electricity demand predictions for Semarang City across various economic sectors spanning 2025–2030. The forecasting method demonstrates strong reliability because test results show Mean Absolute Percentage Error (MAPE) values at less than 10% while some sectors reach 0.03%. These results verify modern energy forecasting academics that AI-based models become increasingly dependable for resource planning together with public policy (Chen et al., 2021; Klyuev et al., 2022; Pimenow et al., 2024; Saheb et a., 2022; Safari et al., 2024; Rojek et al., 2023).

The implementation of BPNN parallel to LR overcomes fundamental issues discovered in solo-model research methodologies (Phan et al., 2024; Kumar Singla & Gupta, 2018). Linear Regression effectively evaluated three elements such population growth and customer expansion and load factor that exhibit linear patterns (Li & Zhao, 2012; Akadiri et al., 2022; Chen et al., 2021). Electrical power demand manifests nonlinear behavior because economic developments combine with technological advancements and seasonal fluctuations (Ding et al., 2025; Gebremeskel et al., 2021). This application showed how BPNN actually provided an effective solution to interpret the non-linear energy consumption patterns based on existing research by Rahman et al. (2021) and Benti et al. (2023).

This analysis demonstrates various growth patterns between the different sectors. According to forecast projections the industrial sector will expand by 31% until 2030 showing major economic recovery potential for manufacturing alongside other urban centers in Southeast Asia (Al-Shetwi, 2022). The business sector advances at a slow rate (1.2%) due to possibly energy efficiency programs alongside saturation within the commercial real estate market (Çelik et al., 2022). The expected decreases in household (-7%) and public (-14%) areas may stem from better energy efficiency together with changing populations and possible structural governmental decisions (Raimi et al., 2021; Ruiz et al., 2020). Analysis of urban policy adjustments and consumer behavior impacts as well as energy subsidy distribution patterns on future demand projection becomes essential because of these recorded shifts.

The ANN architecture's quality is confirmed by the small MSE values which reach $2.65 \times 10^{-10}$ in the household sector when using a 3-layer neural network with 12–10–1 neurons while controlling the learning rate at 0.01. Strielkowski et al. (2023) note that this neural network design follows best methods in neural architecture optimization. All regression models showed perfect linear performance because they obtained an R value of 1 which is a rare achievement with real-world data indicating excellent model calibration. The accomplished results from the models should be evaluated due to their potential overfitting issues caused by the limited training data points (49). The literature presents warnings about ANN applications stressing the need to prevent buildings that become excessively dependent on specific models because they might fail in unforeseen conditions (Hassan et al., 2022; Selvam et al., 2024; Trach et al., 2025; Qu et al., 2025).

Through the consolidated projection energy needs will increase 11.21% until 2030 which will boost the current transformer capacity utilization rate in Semarang from 43% in 2024 to 54.21% in 2030. The current buffer capacity establishes enough reserves for short-to-medium duration periods. The future energy plans need to include provisions for industrial market



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energy variations alongside possible modifications in public and residential energy consumption patterns. The planning of adaptive modular power grid infrastructure together with demand-side control programs should be funded to ensure buffer capacity survives economic or environmental fluctuations (Çeçen et al., 2022; Oito, 2012; Khalid et al., 2021; Ghafoor et al., 2024). The city's energy supply integration with renewable sources will strengthen its resilience while supporting the national energy goals of Indonesia (Secretary General of the National Energy Council, 2019).

The authors contribute to regional energy forecasting methodology by uniting LR and ANN in a forecasting model specific to energy sectors while remaining a rarely explored concept in this field (Rohman et al., 2022; Strielkowski et al., 2023). The study adds value to urban energy modeling research by integrating analytical predictors from demographics and customer behavior which prove ML-algorithm optimized macro-demographic information delivers purposeful understanding (Benti et al., 2023). The implementation of MATLAB-based regression and BPNN modeling establishes an example for researchers and planners across mid-sized cities to replicate their own predictions dealing with comparable population growth patterns.

The study demonstrates strong aspects but still has specific boundaries. The model draws most of its information from historical data spanning 2012 until 2023 while neglecting potential developments in economic transformations and emerging power technology innovations. The research did not incorporate environmental and weather-related factors that strongly affect load variability (Hassan et al., 2022). Future investigations should add varied predictors to their analyses while examining neural network-fuzzy logic and ensemble learning combination models (Strielkowski et al., 2023; Rahman et al., 2021; Hurriyati et al., 2023). The simulation of policy changes together with climate-driven effects and economic disturbances would strengthen robustness through a scenario-based approach.

## Conclusion

The research proved successful for implementing BPNN combined with LR to forecast electric power usage by Semarang City sectors from 2025 through 2030 while showing which method performed best under real-world conditions. Hybridization between Linear Regression and Backpropagation Neural Networks provided a powerful methodology by utilizing precise linear trend applications of LR to population data points and customer growth patterns and BPNN's ability to uncover hidden relationships among energy consumption patterns in household and business and industrial and public sector operations.

The prediction model used a three-layer design featuring a neuron distribution of 12–10–1 and a learning rate set to 0.01 which produced outstanding results indicated by sector-wide R values of 1 and MAPE readings under 10% where the household sector reached 0.03. The BPNN model demonstrates proactive value as a versatile forecasting instrument primarily due to its ability to process well-prepared data and its participation with conventional regression methods.

The projected rise in electricity consumption for 2030 exceeds 11.21% of existing transformer capacity and the industrial sector leads this expansion at 31%. Research demands industrial energy infrastructure improvement investments as well as accurate demand-side management policy development. The predicted electricity demand data from both the public and household sectors point towards future decreases yet these trends warrant more study of policy and behavioral elements. The result of this work contributes theoretical advancements to energy forecasting through evidence that hybrid modeling techniques generate improved accuracy when planning regions for the long term. The sector-based approach enhances granularity, offering practical insights for utility planners, municipal authorities, and national energy policymakers.



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