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Electricity Energy Demand in Banjarnegara District for the Year 2021-2030 Using Linear Regression Method and Leap Software

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ABSTRAK

Kebutuhan listrik Jawa Tengah pada tahun 2013 mencapai 18.205 GWh dengan jumlah pelanggan sebanyak 8.092.964 pelanggan. Permintaan energi ini tumbuh di tahun 2018 menjadi 22.945 GWh dengan jumlah pelanggan sebanyak 10.011.388 pelanggan. Penggunaan listrik secara terus menerus, baik secara langsung maupun tidak langsung, juga akan mempengaruhi kebutuhan ekonomi dan kesejahteraan masyarakat. Diperkirakan penjualan listrik akan terus meningkat seiring pertumbuhan pelanggan dan juga terus meningkat. Untuk memprediksi kebutuhan daya, ada banyak metode peramalan yang biasa digunakan untuk memprediksi kebutuhan daya, seperti metode regresi, metode deret waktu, metode kausal, metode jaringan saraf, metode analisis sistem dinamik dll. Dalam peramalan permintaan energi listrik, metode peramalan memiliki kelebihan dan kekurangan. Berdasarkan data yang ada, penelitian ini menganalisis prakiraan kebutuhan listrik di Kabupaten Banjarnegara dengan metode regresi dan time series yang diterapkan menggunakan perangkat lunak LEAP. Hasil penelitian menunjukkan total kebutuhan energi listrik dengan metode regresi pada tahun 2030 mencapai 50.616 GWh sedangkan menurut software LEAP pada tahun 2030 sebesar 59.677 GWh.

Kata kunci: *Regressi Linear, LEAP, Energi*

ABSTRACT

Electricity demand is expected to increase from year to year. Central Java's electricity demand in 2013 reached 18.205 GWh with a total of 8.092.964 customers. This energy demand has increased in 2018 to 22.945 GWh with a total of 10.011.388 customers. Continuous use of electricity, both directly and indirectly, will also affect economic needs and people's welfare. It is estimated that electricity sales will continue to increase in line with the growth of customers who will also continue to increase. In predicting the need for electrical energy, there are various forecasting methods that are commonly used to predict the need for electrical energy, such as the Regression Method, Time Series Method, Causal Method, Neural Network Method, and Dynamic System Analysis Method. In predicting the need for electrical energy there are advantages and disadvantages of the forecasting method. Based on the availability of data, this research analyzes forecasting the demand for electrical energy in Banjarnegara district using the regression and time series method which is applied using LEAP software. The results show that the total demand for electrical energy using the regression method in 2030 will reach 50.616 GWh while the LEAP software in 2030 will be 59.677 GWh.

Keywords: *Linear regression, LEAP, Energy.*

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1. Introduction

In 2013, Central Java's electricity demand reached 18,205 GWh, serving a total of 8,092,964 customers. By 2018, this demand increased to 22,945 GWh, catering to 10,011,388 customers. (Badan Pusat Statistik Provinsi Jawa Tengah, 2019; Rencana Umum Ketenagalistrikan Nasional 2019-2038, 2019). This rise indicates a continuous yearly growth in electricity demand. Sustainable electric energy consumption directly and indirectly impacts economic development and the quality of life. Additionally, the rise in electricity sales is predicted to align with the increasing customer base(Lestari, 2018)(Lim et al., 2023).

Banjarnegara, a district in Central Java, has experienced significant growth in electricity consumption, reflecting the rising population and Gross Regional Domestic Product (GRDP). (Badan Pusat Statistik Provinsi Jawa Tengah, 2019; Rencana Umum Ketenagalistrikan Nasional 2019-2038, 2019). According to the Central Java Provincial Statistics Agency, the population increased from approximately 892,447 in 2013 to 918,219 in 2018. This population growth correlates with increased economic and electric energy needs. A key consequence of human development is the escalating demand for a continuously available and increasing electric energy supply (Island & Heryana, 2018).

Technical and economic aspects play a vital role in considering the main factors when projecting for electric energy. Accurate forecasting of electricity is crucial, as inaccurate results can lead to insufficient power capacity to handle the load, or conversely, create an unwanted power surplus leading to undesired losses (J. Kastanja & Tupalessy, 2017). To obtain precise and accurate estimations of long-term electric energy demand, several common techniques are often used. These include Regression Techniques, Time Series Methods, Causal Methods, Neural Network Methods, and Dynamic System Analysis Methods, depending on the availability of data(Günay, 2016; Hamed et al., 2022). To evaluate the electric energy needs over a specific time interval, these methods can be utilized as a foundation for projecting future energy requirements.

Furthermore, the outcomes of these projections are not limited to merely calculating energy needs; they also influence the strategy and management of the electric power system. This, in turn, forms the basis for designing the development of new power plants. The precise and adequate availability of electric energy supply will support positive growth in regional development and enhance the quality of life for the community (Oklantama & Suwitno, 2017). This research aims to predict the electric energy needs for the year 2030 using two approaches: the Business as Usual (BAU) scenario of the Long-Range Energy Alternatives Planning System and the Simple Linear Regression Method. The forecasting involves customers, connected power, and an evaluation of the error rate from both methods, with the goal of achieving accurate results for the upcoming years based on previous data (Lim et al., 2023; Nieves et al., 2019).

2. Material And Methods

2.1 BAU Scenario (Business As Usual)

In the BAU (Business As Usual) Scenario, the assumption is that the estimation of electric energy consumption at the end of the period will continue following the same pattern as in the initial year. This is because there are no changes in development policies or forecasts. In this scenario, the projection runs constantly without being influenced by any policies(Liu et al., 2021).

Energy Intensity Calculation

The data calculations used to run the simulation model with the LEAP application include calculations of energy intensity, annual population growth, and Gross Regional Domestic Product (GRDP) increase. Energy intensity is a parameter used to calculate the energy efficiency of a region, which is the amount of energy consumed as a percentage of the Gross Domestic Product (GDP). The equation for energy intensity is shown in equation (1)(Bartlett et al., 2020)

$$\text{Energy Intensity (EI)} = \frac{Total\ Energy\ Consumption}{Energy\ User} \tag{1}$$

Total Energy Consumption refers to the sum of all energy used within a region over a specific period, measured in Kilowatt-hours (KWh). The calculations for population growth and Gross Regional Domestic Product (GRDP) growth are explained through Equation (1), accompanied by Equation (2) and also Equation (3)(Bartlett et al., 2020)

$$\text{Annual Growth} = \frac{\text{Current Year} - \text{Previous Yea}}{\text{Previous Year}} \times 100 \tag{2}$$

Meanwhile, to calculate the average growth, it is expressed as follows:

$$\text{Average Growth} = \frac{\text{Sum of Growth Data}}{\text{Number of Data Points}} \times 100 \tag{3}$$

Briefly, to calculate the total increase, we can replace the previous equation with its derivative, as illustrated in the Equation (4).

$$\text{Average Grow} = \left(\sqrt[n-1]{\frac{\text{Data Year 2020}}{\text{Data Year 2014}}} - 1\right) \times 100 \tag{4}$$

Energy Elasticity

Elasticity measures the sensitivity level between buyers and sellers to market fluctuations. Demand elasticity assesses how much the demand for a product responds to changes in influencing factors. In the context of energy, elasticity indicates the percentage change in

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energy usage required to produce a 1% change in the Gross Domestic Product (GDP). A lower elasticity figure signifies that economic growth does not significantly affect energy consumption(Suhandi et al., 2018). This concept can be formulaically explained through the Equation (5)(Bartlett et al., 2020; Marriott et al., 1985).

$$\text{Elasticity (E)} = \frac{\text{Growth in Energy Consumption of the Sector}}{\text{Growth in GRDP of the Sector}} \quad (5)$$

Customer Capacity Factor

The customer factor is defined as the ratio of the increase in customers from a particular sector compared to the growth in household sector customers, which is used as a reference. Mathematically, this is explained through Equation (6).

$$\text{Customer factor} = \frac{\text{Growth of customers in the sector}}{\text{Growth of customers in the household sector}} \quad (6)$$

LEAP Software

LEAP (Long-range Energy Alternatives Planning) is an application that serves as a tool for planning or modeling in the energy sector. This application operates based on scenarios hypothesized and selected by the user, such as fuel-to-energy calculations and consumer energy consumption. The LEAP software models end-use energy consumption and can also integrate various technologies in energy use. LEAP was created and developed by the Stockholm Environment Institute in Boston, USA. It was first developed in 1980, with the latest version released in 2008. LEAP is only compatible with computers running the Windows operating system. The LEAP software includes four main modules and three submodules. These main modules are standard components commonly used for energy modeling, encompassing key assumptions, conversion, demand, and resources. The add-on modules are additional components that can be included in the main modules as needed, including differences, changes, and impacts on non-energy sectors(Hutrindo & Kurniawan, 2016).

2.2 Simple Regression Method

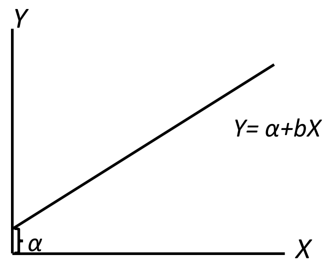

Figure 1. *Illustration of a Linear Regression Line*

In Figure 1 above, the simple linear regression statistical technique is applied to evaluate how an independent variable influences a dependent variable. Regression is often chosen to explore the correlation or relationship between two or more variables. In this instance, the relationship between the independent variable (X) and the dependent variable (Y) is investigated (Hothorn & Everitt, 2006; Putra et al., n.d.; Specht, 1991). In the context of forecasting the load for planning the growth of energy consumption, this will be conducted across five PLN tariff categories, namely Residential, Commercial, Industrial, Public, and Social. The dependent variable (Y) used is the number of customers and the amount of Electrical Power Contracts. The independent variables (X) include Gross Regional Domestic Product and population size. The regression equation can be explained through a mathematical equation (Putra et al., n.d.; Hijriani et al., 2016).

$$\hat{Y} = \alpha + bX \quad (7)$$

which is

$\hat{Y}$ = regression line / response variable

α = constant (intercept), the point where the line crosses the vertical axis

b = regression coefficient (slope)

X = independent variable/predictor

Linear regression is one of the analytical techniques that can be implemented using the Python programming language. Python offers a variety of libraries and tools to perform linear regression with ease. A popular library used for linear regression in Python is scikit-learn. Additionally, Python also has other statistical and data analysis libraries that enable you to perform linear regression, such as statsmodels(Syafruddin et al., 2014).

Table 1. *Customer Data from 2014-2020*

Year	Social Customers	Electricity Consumption (KW)
2014	5.326	593.197
2015	5.768	619.181
2016	6.233	679.437
2017	6.613	769.434
2018	6.841	932.143
2019	7.207	930.540
2020	7.536	930.116

Table 1 represents the input table saved with a CSV extension, resulting from the above code.

3. Results And Discussion

3.1 Energy Consumption Development

Electric load is influenced by many factors, such as economic fluctuations, weather temperatures, population growth, types of customer loads, and others(Rencana Umum Ketenagalistrikan Nasional 2019-2038, 2019)(Lim et al., 2023) (J. Kastanja & Tupalessy, 2017). In estimating the electrical energy needs for longer periods, actual economic conditions and

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population growth are used as approximations to predict electricity consumption. Data on electric energy consumption and customers from PT. PLN (Persero) in the Banjarnegara region, which includes sectors like Business, Industry, Public Services, Social, and Residential, are available for the period from 2014 to 2020. Subsequently, the data are grouped and can be viewed in Table 2 and Table 3.

Table 2. *Electricity Customers from 2014-2020*

Sector	Year						
	2014	2015	2016	2017	2018	2019	2020
Social	5.326	5.768	6.233	6.613	6.841	7.207	7.536
Household	182.177	195.928	204.281	214.356	224.485	233.323	240.866
Business	3.194	3.452	4.941	5.855	6.665	7.505	8.362
Public	1.974	2.004	2.105	2.177	2.359	2.381	2.341
Industrial	42	45	79	62	72	80	79
Total	192.713	207.197	217.639	229.063	240.422	250.496	259.184

Table 3. *Electricity Energy Consumption Data in Banjarnegara District (GWh)*

Sector	Year						
	2014	2015	2016	2017	2018	2019	2020
Social	593	619	679	769	932	931	930
Household	14.454	15.082	15.819	15.822	16.797	17.359	20.278
Business	1.428	1.544	1.808	1.934	2.255	2.597	2.758
Public	875	884	930	949	997	1.019	998
Industrial	796	716	887	785	844	844	817
Total	18.146	18.845	20.123	20.259	21.825	22.750	25.780

Expenditure from the household sector constitutes the largest portion of the Gross Regional Domestic Product (GRDP) in Banjarnegara (Rini Puspita, n.d.) As can be seen in Table 4.

Table 4. *PDRB and Household Population (2014-2020)(Rini Puspita, n.d.)*

Year	Current Prices (Million Rupiah)	Household (Persons)
2014	11.103.667	898.896
2015	12.171.952	901.814
2016	13.137.717	907.410
2017	14.217.750	912.917
2018	15.355.940	918.219
2019	16.507.200	923.192
2020	16.648.148	1.017.767

3.2 Results of Data Processing in Leap Software

Through the information processing in Tables 2, 3, and 4, we obtained essential variables and assumptions data to calculate the electricity energy demand and electricity customers for the period 2021-2031 in the BaU scenario. The processed data includes electricity energy intensity data, growth variable data, customer factors, and energy elasticity.

Electricity Energy Intensity Data

Energy Intensity in 2016 $= \frac{ENERGY\ CONSUMPTION\ IN\ 2016}{ENERGY\ USERS\ IN\ 2016}$

Household Sector: I_{16} $= \frac{15818775}{204281}$ = 77,436

Social Sector: I_{16} $= \frac{679437}{6233}$ = 109,006

Business Sector: I_{16} $= \frac{1807523}{4941}$ = 365,82

Industrial Sector: I_{16} $= \frac{887208}{204}$ = 17.061,69

Public Secto: I_{16} $= \frac{930081}{2.105}$ = 441,84

The comprehensive results of the energy intensity data can be viewed in Table 5 below.

Table 5. *Electric Energy Intensity Data*

Year	Electric Energy Intensity (KWh/Customer)					
	Social	Household	Business	Industrial	Public	Total
2016	77,436	109,006	365,82	17.061,69	441,84	18.056
2017	73,812	116,352	330,28	12.476,13	435,95	13.432,52
2018	74,825	136,258	338,32	10.897,72	422,54	11.869,66
2019	74,399	129,116	346,04	10.546,41	428,09	11.524,05
2020	84,187	123,423	329,78	10.346,61	426,11	11.310,11

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Customer Factor

The results of the key variable data for customer factors are based on the following calculation:
Equation for calculating the key factors of customers.
Customer Factor = $\frac{\text{Growth of customers in the household sector}}{\text{Growth of customers in the social sector}}$

Example calculation for the customer factor in the household and social sectors.
Household Customer Factor = $\frac{\text{Percentage growth of customers in the household sector}}{\text{Percentage growth of customers in the household sector}}$

$FP_{RT} = \frac{4,21\%}{4,21\%} = 1,00\ \%$

Social Customer Factor = $\frac{\text{Percentage growth of customers in the social sector}}{\text{Percentage growth of customers in the household sector}}$

$FP_{RT} = \frac{4,86\%}{4,21\%} = 1,16\%$

The comprehensive results of the key variable data for customer factors can be viewed in Table 6 below.

Table 6. *Key Variable of Customer Factor*

Variable	Value
Household Customer Factor	1,00%
Social Customer Factor	1,16%
Business Customer Factor	3,34%
Industrial Customer Factor	2,62%
Public Customer Factor	0,64%

Electricity Energy Elasticity

The results of the key variable data for electricity energy elasticity are based on the following calculation:

Equation for calculating the key variable of electricity energy elasticity.
Elasticity = $\frac{\text{Growth of energy consumption in the household sector}}{\text{Growth of PDRB in the household sector}}$

Calculation of household sector elasticity.
$E_{RT} = \frac{6,405\%}{6,32\%} = 1,29\%$

The comprehensive results of the key variable data for customer factors can be viewed in Table 7.

Table 7. *Key Variable of Electricity Energy Elasticity*

Variable	Value
Household Elasticity	1,29 %
Social Elasticity	0,86 %
Business Elasticity	1,11 %
Industrial Elasticity	0,10 %
Public Elasticity	0,31 %

Intensitas Energy

The data, originating from PT PLN UP3 in the Purwokerto area and presented in Table 5, focuses on the Household sector and the intensity of its growth. The simulation process begins with creating a new worksheet, followed by adding a new branch named "Energy Intensity" in GWH units. For the customer growth branch, the unit of measurement is the number of customers. The subsequent step involves inputting growth and base year values for the simulation. The energy intensity in the simulation data is calculated using Equation (1). An example of calculating the Energy Intensity for the year 2016 is as follows:

$$\text{IE Growth} = \frac{\text{IE for the current year} - \text{IE for the previous year}}{\text{IE for the previous yea}} \times 100\%$$

Energy Intensity 2016 $= \frac{15.818.775 - 15.082.042}{15.082.042} \times 100\%$
$= 4,885\ \%$

The growth of energy and customers in the following year can be viewed in Table 8, where the calculations are performed using the same method.

Table 8. *Table of Energy Intensity Growth Each Year*

IE Year	Electric Energy Growth (%)				
	Household	Social	Industrial	Business	Public
2016	4,88 %	8,06	15,56	43,13	5,04
2017	0,02 %	6,10	19,23	18,50	3,42
2018	6,16 %	3,45	16,13	13,83	8,36
2019	3,34 %	5,35	11,11	12,60	0,93
2020	16,81 %	4,57	-1,25	4,77	11,32
Growth	6,245%	5,97	11,32	7,55	7,14

The average growth or increase listed in Table 8 indicates that energy efficiency improves as energy intensity decreases [6]. The simulation of this data is conducted using the LEAP program. Variables affecting electricity demand in this study include customer types and energy consumption intensity, as detailed in Table 9.

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Table 9. *Table of Customer Growth Each Year*

IE Year	Electric Energy Growth (%)				
	Household	**Social**	**Industrial**	**Business**	**Public**
2016	9,73	4,88	23,87	17,08	5,23
2017	13,25	0,02	-12,81	6,99	2,04
2018	21,15	6,16	1,44	16,60	5,03
2019	-0,17	3,35	7,53	15,17	2,26
2020	-0,05	16,81	-3,12	6,19	-2,13
Growth	8,05	5,93	1,14	11,69	2,24

Energy elasticity, as depicted in Table 9, illustrates how responsive energy demand or consumption is to changes in energy prices. The measure of energy price elasticity indicates the percentage change in energy consumption or demand resulting from a percentage variation in energy tariffs. If the energy elasticity is positive, it means that energy demand tends to increase when energy prices decrease, and vice versa. Conversely, if the energy elasticity is negative, it means that energy demand tends to decrease when energy prices decrease(Ibrahim, 2018).

3.3 Results of the BAU Scenario (LEAP Software)

The Business As Usual (BAU) scenario in the data analysis process is conducted using the LEAP software, where key variables are inputted into the LEAP software to obtain projection data. This analysis yields projection data for both energy consumption and electricity customers.

Projection of Electric Energy Customers

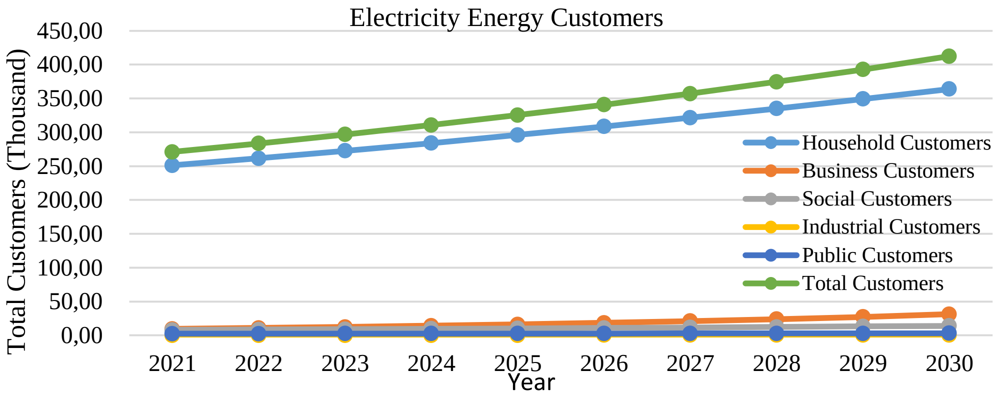

Figure 2. *Results of Electric Customers in Banjarnegara District*

The customer growth projection results shown in Figure 2 indicate that the highest customer growth is in the household sector in 2021, with an increase of 2.06%, totaling 251.01 thousand customers. This growth is expected to continue, reaching a total of 363.81 thousand customers by 2030. Meanwhile, the projected customer numbers for 2030 in other sectors are as follows: the Business sector with 31.2 thousand customers, the Industrial sector with 0.22 thousand customers, the Public sector with 3.05 thousand customers, and the Social sector with 14.01 thousand customers.

Proyeksi of Electric Energy

The growth of these two factors serves as the basis for selecting the year 2021 as the starting point of the simulation. Figure 3 illustrates the estimated needs or consumption of electricity in the Banjarnegara district area.

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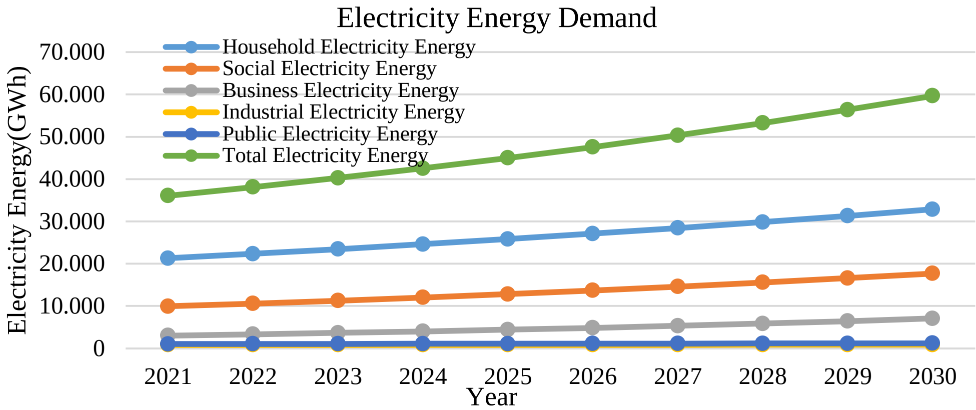

Figure 3. *Results of the Electricity Demand for Banjarnegara District 2021-203*

The simulation results for electricity demand shown in Figure 3 indicate that the highest projected electricity consumption in the Household sector in 2021 increased by 10.73% per year, reaching a total of 21,281 GWh. This is expected to rise further by 2030, reaching a total of 32,873 GWh. For the year 2030, the projected electricity demand in the Business sector is 7,062 GWh, in the Industrial sector 848 GWh, in the Public sector 1,203 GWh, and in the Social sector 17,690 GWh. Consequently, the total electricity demand across all sectors in 2030 is estimated to be 59,677 GWh.

3.4 Linear Regression Analysis

The Simple Linear Regression method is applied to assess the impact or correlation between one dependent variable and one independent variable. This method is used to forecast long-term electricity consumption in Banjarnegara district, employing a linear regression model with specific parameters. The first model aims to predict the Number of Customers, using the Year and the number of Electric Energy Customers as parameters. Meanwhile, the second model is used to predict electricity consumption, with Electric Energy Customers and the Total Electricity Consumption as parameters, aided by the use of Python programming.

Prediction of Electric Energy Customers

The prediction of customers is conducted using the year as the dependent variable and the total number of customers as the independent variable. Data on electricity customers from the years 2014 to 2020 can be viewed in Table 2.

```
   Year  Business Customer  Electric Energy Consumption KWh
0  2014               3194                          1427852
1  2015               3452                          1543836
2  2016               4941                          1807523
3  2017               5855                          1933811
4  2018               6665                          2254867

coefficient of determination: 0.987654601325150б
intercept: -1819242.2142857148
slope: [904.78571429]
-------  ----  -------  -------  -------  -------  -------
2014     2015  2016     2017     2018     2019     2020
2996.21  3901  4805.79  5710.57  6615.36  7520.14  8424.93
-------  ----  -------  -------  -------  -------  -------
```

Figure 4. *Results of Regression Parameter Output*

In Figure 4, the output of the regression parameters reveals an intercept value of -1,819,242.21, representing variable α, and a slope value of 904.78, representing variable β. These are derived using the regression Equation (7). Based on variable x, the number of customers in 2014 is 2,996.21, whereas for variable x in the year 2020, it is 8,424.93 customers. In regression analysis, the independent variable (X), which in this case is time (year), is considered the determining factor for the dependent variable (Y), that is, the number of customers. By using the year as variable X and the number of customers as variable Y, the aim is to analyze how the number of customers changes from year to year. This approach aids in understanding the trends and patterns of customer count variation over time(Aihunan et al., 2023) (Suhandi et al., 2018). In linear regression, the intercept value is the number obtained when all the inputs of the model (the X variables) are set to zero, giving us the starting point of the regression line on the vertical axis. However, when our X variable is time, a zero value often does not make sense (since we cannot go back to "year zero")(Suhandi et al., 2018). Therefore, it is more insightful to focus on how the number of customers increases or decreases over time, which is indicated by the slope or the tilt of the line. The slope tells us how much the number of customers changes each year. In the analysis, focusing on this slope and how well the regression line fits the data (measured by R-squared) will provide more useful information than the intercept value itself(Aihunan et al., 2023)(Trianggana, 2020). The results of the regression parameters for other sectors are shown in the table.

Table 10. *Electric Customer Regression Parameters*

Sector	Coefficient Of Determination	Intercept	Slope
Business Customer	0.98	-1819242.2	904.8
Industrial Customer	0.96	-14417.5	7.2
Public Customer	0.90	-149731.7	75.3

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Household Customer	0.99	-19312441.9	9680.7
Social Customer	0.99	-722209.85	361.3

The Coefficient Of Determination table indicates that for the Business Customer sector, the model explains approximately 98% of the variability in the number of social customers. In contrast, for the Industrial Customer sector, it explains 99%, for the Public Customer sector 90%, for the Household Customer sector 99%, and for the Social Customer sector 99%. The projection of customer numbers for the years following 2020 suggests that if the current trend continues, the number of customers is expected to keep increasing annually until the year 2030.

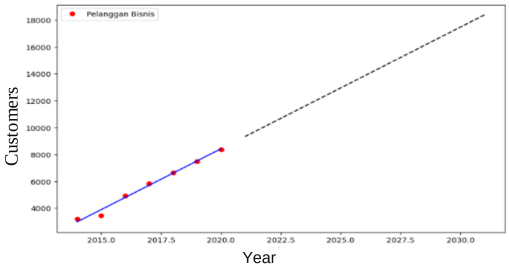

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Figure 5. *Results of Line Regression Plot Y Year 2014-2030*

The output shown in Figure 5 provides information about the regression line. The red points represent the electricity customer data from 2014 to 2020. The blue line displays the regression plot for the customers from 2014 to 2020 based on the existing data. Meanwhile, the dashed black line represents the predicted regression line for the years 2021 to 2030. The next step to determine the customer predictions for 2021 to 2030 involves changing the x-variable to 2021-2030. Figure 6 shows the results of these projections.

```
X_new = np.arange(2021, 2032).reshape((-2, 1))

y_new = model.predict(X_new)
y_new
table1 = X_new, y_new
print(tabulate(table1))
```

2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
9329.71	10234.5	11139.3	12044.1	12948.9	13853.6	14758.4	15663.2	16568	17472.8

Figure 6. *Output of the Business Customer Program for the Year 2021 – 2030*

In sectors such as Residential, Industrial, Public Services, and Social, a uniform analysis method is employed. This involves using the total number of customers as the dependent variable and the total electricity consumption as the independent variable in the electricity consumption data. The results of the electricity energy projection can be viewed in Figure 7.

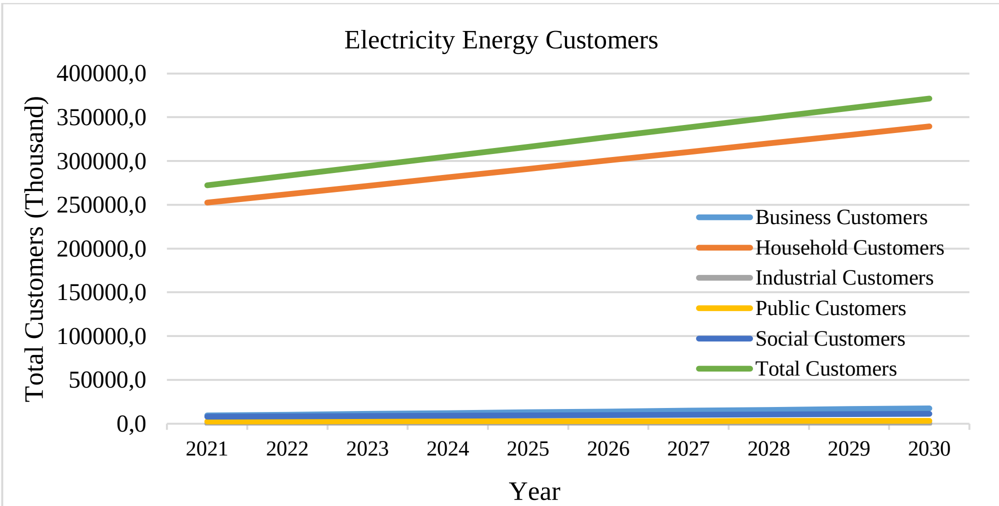

Figure 7. *Demand of Electric Energy Customers 2021-2030*

Sectors is as follows: Business sector at 17.47 thousand customers, Industrial sector at 0.16 thousand customers, Public sector at 3.17 thousand customers, and Social sector at 11.20 thousand customers. Consequently, the total electricity customer count across all sectors in 2030 is estimated to reach 371.48 thousand.

Prediction Electricity Energy

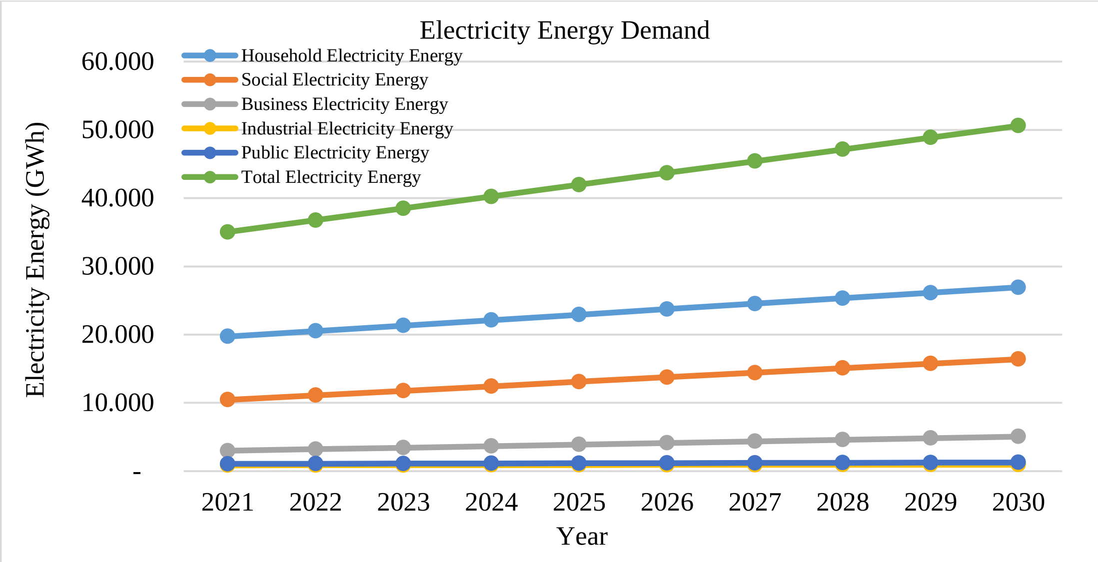

Figure 8. *Graph of Electric Energy Projection 2021-2031*

The electricity demand results using linear regression method depicted in Figure 8 show that the highest projected electricity consumption is in the Household sector. In 2021, the total consumption in this sector increased by 1.28% per year, reaching 19,721 GWh, and is expected to rise further to 26,933 GWh by 2031. For the year 2031, the Business sector is projected to consume 5,052 GWh, the Industrial sector 948 GWh, the Public sector 1,275 GWh, and the Social sector 16,408 GWh. Consequently, the total electricity demand across all sectors in 2031 is estimated to reach 50,616 GWh.

4. Conclusion

The projection of electric energy customers using the linear regression method at the beginning of 2021 was quite high, and the trend method simulated using LEAP software tended to rise. The total number of customers using the Linear Regression method in 2021 reached 272.21 thousand, whereas the total from the LEAP software simulation, based on the year 2020, showed an increase of 2.06%, totaling 271.05 thousand customers in 2021. The total number of household sector customers is projected for the year 2030.

The projection of total electricity consumption at the beginning of 2021 was quite high, utilizing both linear regression and trend methods simulated using LEAP software, which indicated an upward trend. The total projection of electricity consumption using the linear regression method in 2021 showed an increase of 1.28%, amounting to 35,039

GWh. In contrast, the results from the LEAP software simulation, based on the year 2020, exhibited an increase of 2.06%, totaling 36.07 GWh in 2021.

The rising trend in electricity energy projections can be attributed to several reasons:

1. Increasing Customers: The growth in customers seen in both methods can be linked to population growth in an area. As the population increases, the number of electricity customers tends to rise.
2. Population Growth: An increasing population in a region typically boosts the demand for electricity, as more people use electricity for their daily needs.
3. Per Economic Growth: When the economy of a region or country grows, economic activities also increase, meaning more businesses and industries require electricity for operations.
4. Technological Advancement: Technological developments can lead to increased use of more efficient electrical equipment. However, often the sheer volume of these devices can end up increasing the total electricity demand.
5. Lifestyle and Consumption Patterns: Changes in lifestyle and consumption patterns can also affect the increased need for electricity, such as the growing use of electronic devices, electric vehicles, and so forth.

Both methods have their respective strengths and limitations. Linear regression can provide an initial depiction of linear trends in historical data but does not account for many external factors that could affect future energy consumption. The LEAP software, on the other hand, is more complex and can more accurately model various factors affecting energy consumption. If the necessary data is available and in-depth analysis is required, LEAP is a better choice for long-term energy projections. However, it should be noted that electricity energy forecasting using linear regression is not a definitive prediction but an estimate based on current trends and data. Unaccounted factors or significant changes in society and technology can render such

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predictions inaccurate or alter the estimates. Therefore, it is important to monitor developments and make adjustments to electric energy projections as changes occur.

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References

Aihunan, M. S., Latupeirissa, H. L., & Kastanja, A. J. (2023). PERAMALAN BEBAN PENYULANG WAYAME 2 PT. PLN (PERSERO) AREA AMBON MENGGUNAKAN METODE LEAST SQUARE. *Jurnal ELKO (Elektrikal Dan Komputer)*, *2*(2). https://doi.org/10.54463/je.v2i2.47

Badan Pusat Statistik Provinsi Jawa Tengah. (2019). Provinsi Jawa Tengah Dalam Angka 2019. In *Badan Pusat Statistik Provensi Jawa Tengah*. *https://jateng.bps.go.id/publication/2019/08/16/fcb9efa7796cdbc491325688/provinsi-jawa-tengah-dalam-angka-2019.html*

Bartlett, P. L., Long, P. M., Lugosi, G., & Tsigler, A. (2020). Benign overfitting in linear regression. *Proceedings of the National Academy of Sciences*, *117*(48), 30063–30070. *https://doi.org/10.1073/pnas.1907378117*

Günay, M. E. (2016). Forecasting annual gross electricity demand by artificial neural networks using predicted values of socio-economic indicators and climatic conditions: Case of Turkey. *Energy Policy*, *90*, 92–101. *https://doi.org/10.1016/J.ENPOL.2015.12.019*

Hamed, M. M., Ali, H., & Abdelal, Q. (2022). Forecasting annual electric power consumption using a random parameters model with heterogeneity in means and variances. *Energy*, *255*, 124510. *https://doi.org/10.1016/J.ENERGY.2022.124510*

Hijriani, A., Muludi, K., & Ain Andini, E. (2016). Implementasi Metode Regresi Linier Sederhana Pada Penyajian Hasil Prediksi Pemakaian Air Bersih Pdam Way Rilau Kota Bandar Lampung Dengan Sistem Informasi Geofrafis. *Jurnal Informatika Mulawarman*, *11*(2), 37. *https://doi.org/http://dx.doi.org/10.30872/jim.v11i2.212*

Hothorn, T., & Everitt, B. S. (2006). *A Handbook of Statistical Analyses Using R*. Chapman and Hall/CRC. *https://doi.org/10.1201/9781420010657*

Hutrindo, E., & Kurniawan, F. (2016). Manual Book Leap Model (Versi Bahasa Indonesia) : Modul Diklat 2016 / Erick Hutrindo. *Perpustakaan Pusat Pengembangan Sumber Daya Manusia KEBTKE*, viii, 84 ;29. *http://perpus.ppsdmkebtke.esdm.go.id/inlislite3/opac/detail-opac?id=2122*

Ibrahim, M. (2018). Peramalan Dengan Menggunakan Dua Metode Regresi Dan Tren. *Universitas Islam Indonesia*, *2018-03–07*, ii–32. *https://dspace.uii.ac.id/handle/123456789/6110*

Island, M., & Heryana, N. (2018). for Small Island in Indonesia. *Conference on Power Engineering and Renewable Energy (ICPERE)*, 1–5.

J. Kastanja, A., & Tupalessy, J. (2017). Peramalan Beban Listrik Kota Ambon Tahun 2016 – 2022. *Jurnal Simetrik, Vol. 7 No. 1 (2017)*, 41–46. *https://doi.org/https://doi.org/10.31959/js.v7i1.177*

Lestari, CV. S. (2018). Kebutuhan Energi Provinsi Jawa Tengah 2018. *Badan Pusat Statistik Provensi Jawa Tengah*, viii + 44 pages. *https://jateng.bps.go.id/publication/2020/12/25/e9d86d3d5fee8b7438ea4ef8/kebutuhan-energi-provinsi-jawa-tengah-2018.html*

Lim, D. H., Na, W. J., Hong, W. H., & Bae, Y. H. (2023). Development of a fire prediction model at the urban planning stage: Ordinary least squares regression analysis of the area of urban land use and fire damage data in South Korea. *Fire Safety Journal*, *136*. *https://doi.org/10.1016/j.firesaf.2023.103761*

Liu, G., Hu, J., Chen, C., Xu, L., Wang, N., Meng, F., Giannetti, B. F., Agostinho, F., Almeida, C. M. V. B., & Casazza, M. (2021). LEAP-WEAP analysis of urban energy-water dynamic nexus in Beijing (China). *Renewable and Sustainable Energy Reviews*, *136*(December 2019), 110369. *https://doi.org/10.1016/j.rser.2020.110369*

Marriott, F. H. C., Neter, J., Wasserman, W., & Kutner, M. H. (1985). Applied Linear Regression Models. *Biometrics*, *41*(2), 596. *https://doi.org/10.2307/2530893*

ISSN PRINT : 2302-500X
ISSN ONLINE : 2477-3786

Nieves, J. A., Aristizábal, A. J., Dyner, I., Báez, O., & Ospina, D. H. (2019). Energy demand and greenhouse gas emissions analysis in Colombia: A LEAP model application. *Energi*, *169*, 380–397. *https://doi.org/10.1016/j.energy.2018.12.051*

Oklantama, R., & Suwitno, S. (2017). Prakiraan Kebutuhan Energi Listrik Di Wilayah Pt. Pln (Persero) Rayon Bangkinang Menggunakan Prangkat Lunak Leap (Long-Range Energy Alternatives Planning System). *Jom FTEKNIK*, *4*(2), 1–8. *https://www.neliti.com/id/publications/199785/prakiraan-kebutuhan-energi-listrik-di-wilayah-pt-pln-persero-rayon-bangkinang-me*

Putra, A. A., Nayusrizal, N., Untari, U., Wibisono, G., & Hudaya, C. (n.d.). Prediction of Electricity Load Growth of Tangerang City using SIMPLE-E. *2019 IEEE International Conference on Innovative Research and Development (ICIRD), Jakarta, Indonesia*, *2019*, 1–6. *https://doi.org/10.1109/ICIRD47319.2019.9074760*.

Rencana Umum Ketenagalistrikan Nasional 2019-2038. (2019). Kementerian Energi Dan Sumber Daya Mineral. In *Kementrian Energi dan Sumber Daya Mineral JAKARTA*. *https://jdih.esdm.go.id/storage/document/Kepmen-esdm-143-Thn%202019%20RUKN%202019.pdf*

Rini Puspita, N. (n.d.). *Produk Domestik Regional Bruto Kabupaten Banjarnegara Menurut Pengeluaran 2014-2018* (A. Priyono & N. Puspita Rini, Eds.). Badan Pusat Statistik Kabupaten Banjarnegara. *https://doi.org/33040.1903*

Specht, D. F. (1991). A general regression neural network. *IEEE Transactions on Neural Networks*, *2*(6), 568–576. *https://doi.org/10.1109/72.97934*

Suhandi, N., Yuliawati, I., & Charista, I. (2018a). Analisis Pengaruh Faktor Kebutuhan Energi Listrik Tahun 2015 Terhadap Daya Yang Tersambung Dan Energi Yang Terjual Menggunakan Regresi Linear Sederhana (Studi Kasus Pada PT. PLN (Persero) Unit Area Pelayanan Dan Jaringan (APJ) Palembang). *Jurnal Ilmiah Informatika Global*, *9*(1). *https://doi.org/10.36982/jiig.v9i1.439*

Syafruddin, M., Hakim, L., & Despa, D. (2014). Metode Regresi Linier untuk Prediksi KebutuhanEnergi Listrik Jangka Panjang (Studi Kasus Provinsi Lampung). *Jurnal Informatika Dan Teknik Elektro Terapan*, *2*, 1–9. *https://doi.org/http://dx.doi.org/10.23960/jitet.v2i2.237*

Trianggana, D. A. (2020). A PERAMALAN JUMLAH SISWA-SISWI MELALUI PENDEKATAN METODE REGRESI LINEAR. *JURNAL MEDIA INFOTAMA*, *16*(2). *https://doi.org/10.37676/jmi.v16i2.1149*