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The Use of Regression Method on Simple E for Estimating Electrical Energy Consumption

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Abstract

The continuous increase in population growth has an impact on the electrical energy supply. Based on this increase, electric power producers serve customers using proper forecasts. Therefore, it is a necessity to select the right calculation method with easy implementation. In this study, the population forecasts and economic growth calculations using the GT (Growth Trend) regression method development on Simple E were obtained for the year 2028. Furthermore, electricity consumption estimation was carried out using the DL (Double Log) regression method with growth trend, R, AR, DW, and t values of 6.63%, 0.993, 0.992, 1.21, and 2.18, respectively. The results show that estimated energy consumption was 6.63% annually, with the achievable amount for 2028 being 19,839.83 GWh.

Keywords: Forecast of Electricity Demand; Energy; Population; Economy and Regression.

1. Introduction

Currently, economic and socially driven community life activities are highly dependent on the availability of electricity supply [1, 2]. This dependence increases annually based on population growth, economic development, technological progress, and other social dynamics [3-5]. Therefore, it can be addressed through the provision of sufficient and reliable electricity supply at an affordable price [6]. A long-term electricity system development plan is required to achieve [7] the electricity demand for the next few years [8, 9] through calculations and forecasting [10-12]. During forecasting, it is better to use the routine method carried out by several electric power companies in the world [13]. This is expected to obtain an accurate, close to realization, and accountable output [14, 15]. Furthermore, outputs that deviate by being extremely high or low are detrimental to companies. Extremely high estimated output with low demand leads to overcapacity and overinvestment. Conversely, the reverse leads to a blackout due to insufficient power supply [16]. This study describes the development of an electrical energy forecasting method from Simple E application using regression calculations for North Sumatra Province, Indonesia, until 2028.

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2. Materials and Methods

Figure 1 shows the study location is North Sumatra, one of the 37 provinces in Indonesia.

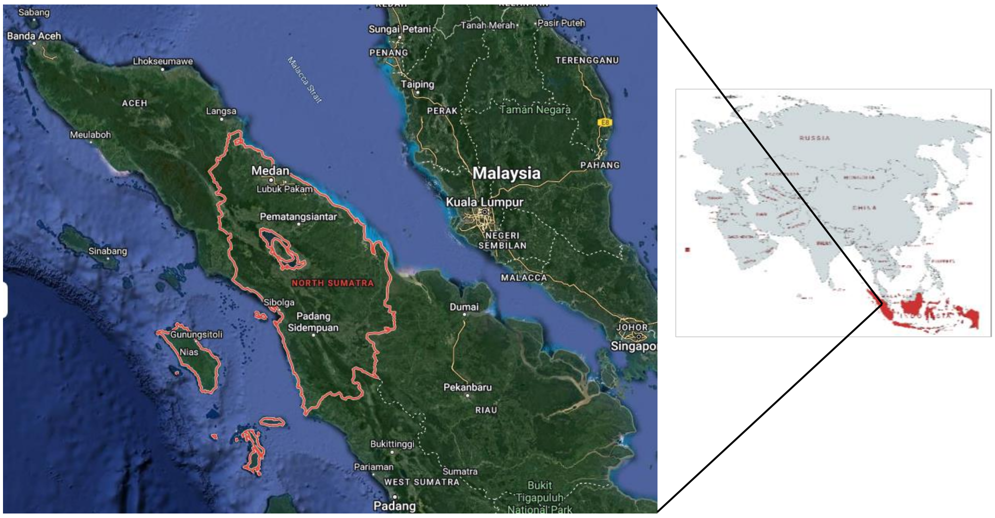

Figure 1. Map of North Sumatra, Indonesia

The study flowchart is presented in Figure 2.

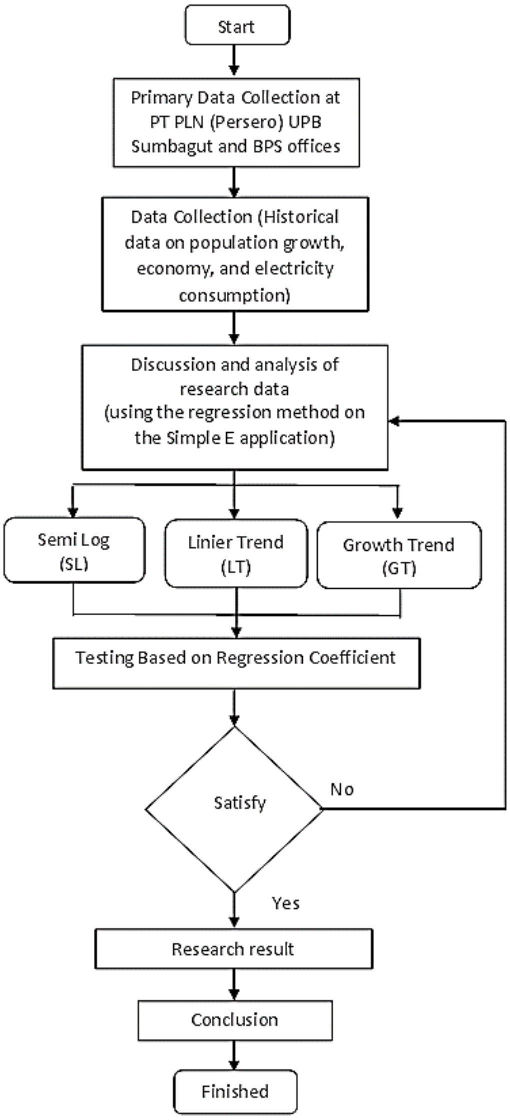

Figure 2. Study flowchart

2.1. Forecasting Method

The forecasting method is a technique for predicting future values based on mathematical and statistical data or information about the past and present [17-19]. In general, this method can be classified into two main groups namely:

- ***Quantitative Method:***

  The quantitative method obtains an estimate based on past quantitative data accompanied by a series of mathematical rules to predict future values for example the regression method [20].

- ***Qualitative Method:***

  The qualitative method obtains an estimate based on past qualitative data. Its forecast results depend on the compiler's intuitive thinking, opinions, knowledge and experiences. This method is usually used due to a lack of representative data for suitable mathematical models [21, 22].

2.2. Regression Method

Regression is a measure of the relationship between two or more variables expressed in terms of an equation or function [23, 24]. To determine this relationship (regression) a strict separation is required between symbol X and Y which represents independent and dependent variables, respectively [25]. Both variables are usually causal or have a causal relationship of mutual influence. Therefore, regression is a function L or the form of a particular function between dependent Y and independent X variables.

$$Y = f(X) \tag{1}$$

According to Cénac et al. (2020) [26], regression methods can be divided into linear and nonlinear:

Linear Regression

In linear regression, the relationship between the independent (X) and dependent (Y) variables in a mathematical equation is a linear or straight line [27]. Linear regression consists of two types, namely:

- Simple Linear Regression:

  The linear or simple linear regression is the simplest straight line or linear relationship between X and Y variables [28, 29]. Its mathematical equation is shown Equation 2:

$$Y = f(x) = a + bx \tag{2}$$

- Multiple Linear Regression:

  For multiple linear regression, there is more than one independent variable (X) in a forecast. Its equation function is shown Equation 3:

$$Y = f(x) = a + b_1x_1 + b_2x_2 + \cdots + b_nx_n \tag{3}$$

Nonlinear Regression

Non-linear regression is a relationship or function in which the independent X and dependent Y variables are factors with a certain rank and can either be denominators (fractional functions) or exponentials.

2.3. Statistical Indicators

During the regression method, statistical indicators are used to describe the combined and individual level or degree of closeness between dependent Y and independent $x_1, x_2, x_3, \dots, x_n$ variables. It can also apply to relationships between independent variables alone. Common uses of statistical indicators are described below:

- Correlation Coefficient (R)

  Correlation is a measure of the relationship between two or more variables expressed using the correlation coefficient R as the degree of closeness or relationship level. During analysis, the dependence of one variable on another or vice versa is not important. Correlation methods are used for closeness measurement between independent X and dependent Y variables. According to Wagner (2019) [30], guidelines for providing interpretations of R are as follows:

  R = 0.00 - 0.199: very low;

  R = 0.20 - 0.399: low;

  R = 0.40 - 0.599: moderate;

R = 0.60 - 0.799: strong/close;

R = 0.80 - 1,000: very strong.

- R Square Determination Coefficient (R^2)

A squared correlation coefficient R obtains an R^2 value called the coefficient of determination or determinant index. This states the relationship (percentage) between independent (X1, X2, X3, ... Xn) and dependent Y variables simultaneously. R2 values are between 0 and 1 ($0 \leq R^2 \leq 1$).

- The Coefficient of Determination Adjusted R-Square (AR)

The adjusted R Square (AR) interpretation is the same as R2, however, its value increases or decreases with the addition of a new independent or dependent variable depending on correlation.

A negative AR value is considered 0, which means that the independent variable has absolutely no relationship with the dependent variable. The Adjusted R Square (AR) closeness statistics are:

R = 0.00 - 0.199: very low;

R = 0.20 - 0.399: low;

R = 0.40 - 0.5;

99: moderate;

R = 0.60 - 0.799: strong/close;

R = 0.80 - 1,000: very strong.

- Value of t Statistics

This is often referred to as the t-value for testing the degree of relationship closeness between dependent Y and independent X variables individually or partially (Y with X1), (Y with X2), (Y with X3), etc. The criteria for the degree of relationship closeness are as follows:

$|t| \geqslant 2$: Significant;

$2 > |t| \geqslant 1$: Admissible to use;

$|t| < 1$: Insignificant.

- Durbin-Watson Statistics (DW)

The Durbin-Watson indicator (DW) is used to determine a correlation between independent variables, namely between X1 and X2, X1 and X3, X2 and X3, etc. $1 \leqslant DW \leqslant 3$ is the acceptable DW value, with the following criteria:

DW = 2: No serial correlation;

DW → 0: Positive correlation;

DW → 3: Negative correlation.

2.4. Gross Domestic Product

Gross Domestic Product (GDP) is the total goods and services production output expressed in units of currency from a region of the economy (country) without considering the production factor owner for a given period. The Gross Regional Domestic Product (GRDP) review is limited to a Province or Regency/City, at certain periods (for example 1 year or 1 quarter).

2.5. Simple E Application

The Simple E application is based on statistical methods [31] that take advantage of existing functions [32] in Microsoft Excel. It was developed by Yamaguchi (2000) [33] from the Institute of Energy Economics (IEE) Japan. Furthermore, Simple E was used by the Directorate General of Electricity and the Ministry of Energy and Mineral Resources. It is an inserted Microsoft Excel module [34], placed in an Add-In consisting of three main parts namely:

- Sheet Data

The sheet data is used for input data namely, business (selling energy, contractual power and number of customers), past economic growth, population, and future forecast data. It has data coding or naming which starts at the time of input.

- Sheet Model

The sheet model contains statistical models (time series and regression) selected to calculate the estimated electricity demand. It also shows statistical coefficient indicators (R, R^2, AR, DW, t-Value) due to program execution.

- Sheet Simulation

The sheet simulation contains a complete calculation result with the formed regression equation formulas and average growth rate.

3. Results

3.1. Forecast Stages

Increased electricity consumption is generally influenced by several factors, namely population and economic growth. A forecast for these factors was first obtained before that of electricity consumption was carried out in North Sumatra until 2028. The step table for electricity consumption forecast based on influencing factors can be seen in Table 1.

Table 1. Stages of forecasts

Years	Population growth	Economic growth	Electric Energy Consumption (GWH)
2004	12,165,423	83,328,948.58	4,450.76
2005	12,297,894	87,897,791.21	4,613.37
2006	12,431,808	93,347,404.39	4,717.81
2007	12,567,180	99,792,273.27	5,163.43
2008	12,704,025	106,172,360.10	5,757.84
2009	12,842,362	111,559,224.81	6,096.89
2010	12,982,204	118,718,902.74	6,636.45
2011	13,103,596	126,587,621.89	7,194.04
2012	13,215,401	134,461,505.43	7,809.32
2013	13,326,307	142,537,121.58	7,917.23
2014	13,556,968	?	8,271.01
2015	13,937,797	?	8,703.66
2016	14,102,911	?	9,240.30
2017	14,262,147	?	9,707.33
2018	14,415,391	?	10,445.02
2019	14,562,549	?	?
2020	?	?	?
2021	?	?	?
2022	?	?	?
2023	?	?	?
2024	?	?	?
2025	?	?	?
2026	?	?	?
2027	?	?	?
2028	?	?	?

Forecast regarding the factors include:

- Forecast of population growth
- Forecast of economic growth
- Electricity consumption forecast

Forecast of Population Growth

The calculation using Simple E application can be seen in Table 2.

Table 2. Test results using Simple E

Years	Population Growth Regression		
	SL	TL	TG
2004	12,165,423	12,165,423	12,165,423
2005	12,297,894	12,297,894	12,297,894
2006	12,431,808	12,431,808	12,431,808
2007	12,567,180	12,567,180	12,567,180
2008	12,704,025	12,704,025	12,704,025
2009	12,842,362	12,842,362	12,842,362
2010	12,982,204	12,982,204	12,982,204
2011	13,103,596	13,103,596	13,103,596
2012	13,215,401	13,215,401	13,215,401
2013	13,326,307	13,326,307	13,326,307
2014	13,556,968	13,556,968	13,556,968
2015	13,937,797	13,937,797	13,937,797
2016	14,102,911	14,102,911	14,102,911
2017	14,262,147	14,262,147	14,262,147
2018	14,415,391	14,415,391	14,415,391
2019	14,562,549	14,562,549	14,562,549
2020	14,725,480	14,725,480	14,741,406
2021	14,888,411	14,888,411	14,922,464
2022	15,051,343	15,051,343	15,105,750
2023	15,214,274	15,214,274	15,291,293
2024	15,377,205	15,377,205	15,479,119
2025	15,540,136	15,540,136	15,669,256
2026	15,703,067	15,703,067	15,861,734
2027	15,865,998	15,865,998	16,056,581
2028	16,028,930	16,028,930	16,253,826

From the calculation data listed in Table 2, it can be described in the form of a graph whose results can be shown in Figure 3.

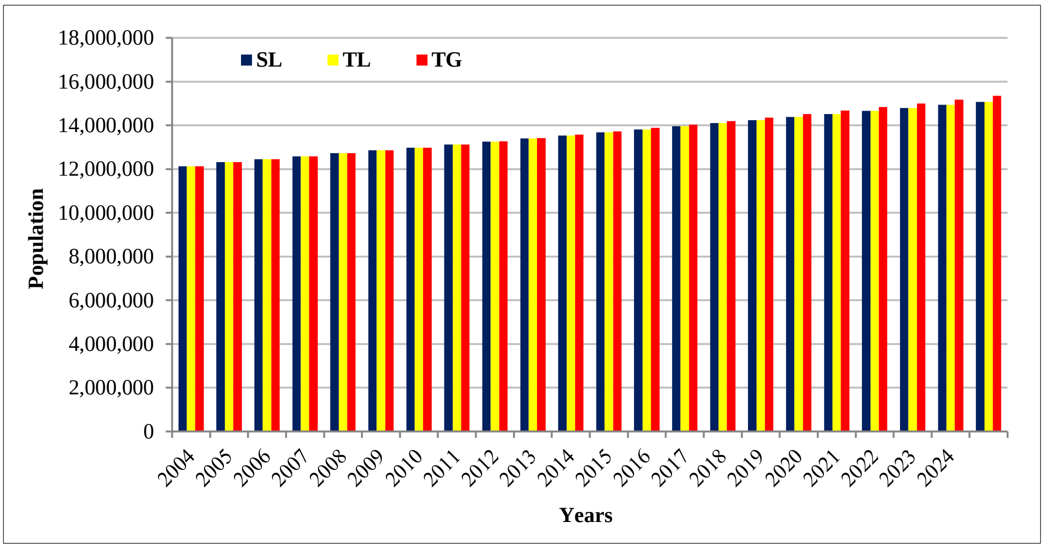

Figure 3. Graph of population test results

The trend coefficient values obtained from the Simple E application are shown in Table 3.

Table 3. Test coefficient values

No	Regression Method		Trend Coefficient (%)
	Name	Cede	
1	Semi Log	SL	1,21 / 1,07
2	Linear Trend	TL	1,21 / 1,07
3	Growth Trend	TG	1,21 / 1,23

From the trend coefficient values obtained, the best regression method used is Growth Trend [35]. This is due to the forecast percentage (1.23%) being close to the real data growth percentage (1.21%). Meanwhile, other methods only have a percentage growth value of 1.07%.

Forecast of Economic Growth

The calculation results using Simple E application can be seen in Table 4.

Table 4. Test results using Simple E

Years	Economic Growth Regression (million Rupiah)		
	SL	TL	TG
2004	83,328,948.6	83,328,948.6	83,328,948.6
2005	87,897,791.2	87,897,791.2	87,897,791.2
2006	93,347,404.4	93,347,404.4	93,347,404.4
2007	99,792,273.3	99,792,273.3	99,792,273.3
2008	106,172,360.1	106,172,360.1	106,172,360.1
2009	111,559,224.8	111,559,224.8	111,559,224.8
2010	118,718,902.7	118,718,902.7	118,718,902.7
2011	126,587,621.9	126,587,621.9	126,587,621.9
2012	134,461,505.4	134,461,505.4	134,461,505.4
2013	142,537,121.6	142,537,121.6	142,537,121.6
2014	149,126,136.1	149,126,136.1	151,352,206.6
2015	155,715,150.6	155,715,150.6	160,712,415.0
2016	162,304,165.2	162,304,165.2	170,651,457.0
2017	168,893,179.7	168,893,179.7	181,205,127.6
2018	175,482,194.2	175,482,194.2	192,411,435.4
2019	182,071,208.7	182,071,208.7	204,310,739.4
2020	188,660,223.3	188,660,223.3	216,945,894.1
2021	195,249,237.8	195,249,237.8	230,362,404.7
2022	201,838,252.3	201,838,252.3	244,608,589.9
2023	208,427,266.9	208,427,266.9	259,735,756.8
2024	215,016,281.4	215,016,281.4	275,798,385.0
2025	221,605,295.9	221,605,295.9	292,854,323.3
2026	228,194,310.4	228,194,310.4	310,964,997.9
2027	234,783,325.0	234,783,325.0	330,195,633.4
2028	241,372,339.5	241,372,339.5	350,615,488.1

From the calculation data listed in Table 4, it can be described in the form of a graph whose results can be shown in Figure 4.

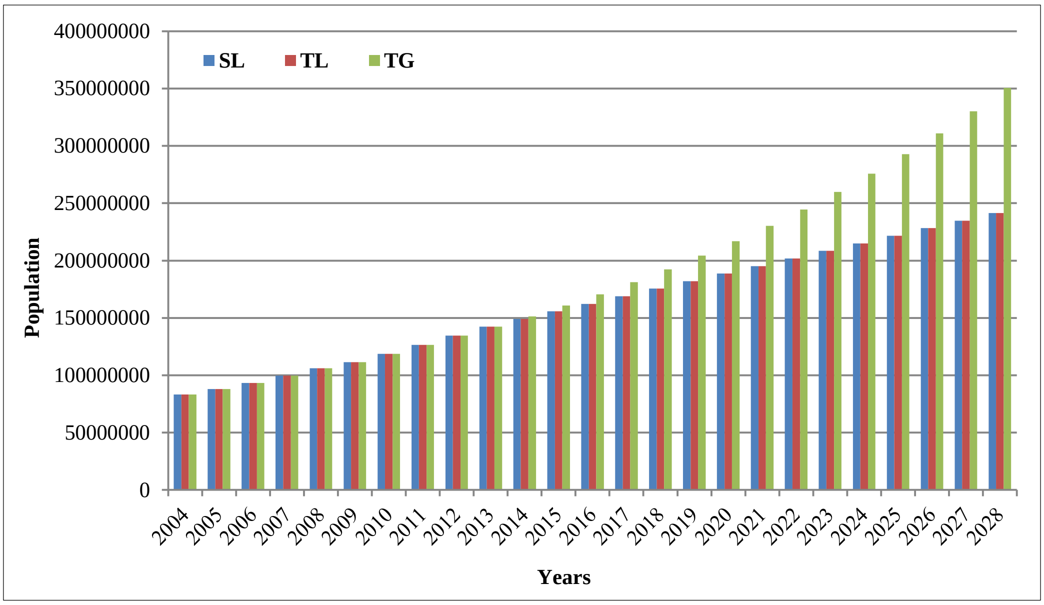

Figure 4. Graph of economic test results

The trend coefficient values obtained from Simple E application are shown in Table 5.

Table 5. Test coefficient values

No.	Regression Method		Trend Coefficient (%)
	Name	Code	
1	Semi Log	SL	6,15 / 3,57
2	Linear Trend	TL	6,15 / 3,57
3	Growth Trend	TG	6,15 / 6,18

From the trend coefficient values obtained, Growth Trend is the best regression method used. This is due to an estimated percentage (6.18%) which approaches the real data percentage growth (6.15%). Meanwhile, other methods only have a percentage growth of 3.57%.

Electricity Consumption Forecast

After obtaining the population and economic growth forecast for up to 2028, electricity consumption was forecasted next as shown in the following Table 6.

Table 6. Forecast of electricity consumption

Years	Population growth	Economic growth	Electric Energy Consumption (Gwh)
2004	12,165,423	83,328,948.58	4,450.76
2005	12,297,894	87,897,791.21	4,613.37
2006	12,431,808	93,347,404.39	4,717.81
2007	12,567,180	99,792,273.27	5,163.43
2008	12,704,025	106,172,360.10	5,757.84
2009	12,842,362	111,559,224.81	6,096.89
2010	12,982,204	118,718,902.74	6,636.45
2011	13,103,596	126,587,621.89	7,194.04
2012	13,215,401	134,461,505.43	7,809.32
2013	13,326,307	142,537,121.58	7,917.23
2014	13,556,968	151,352,206.62	8,271.01
2015	13,937,797	160,712,414.99	8,703.66
2016	14,102,911	170,651,457.00	9,240.30
2017	14,262,147	181,205,127.65	9,707.33
2018	14,415,391	192,411,435.44	10,445.02
2019	14,562,549	204,310,739.35	?
2020	14,741,406	216,945,894.14	?
2021	14,922,464	230,362,404.70	?
2022	15,105,750	244,608,589.93	?
2023	15,291,293	259,735,756.77	?
2024	15,479,119	275,798,384.97	?
2025	15,669,256	292,854,323.30	?
2026	15,861,734	310,964,997.88	?
2027	16,056,581	330,195,633.41	?
2028	16,253,826	350,615,488.09	?

The calculation results using Simple E application can be seen in Table 7.

Table 7. Test results using Simple E

Years	Electric Energy Consumption (Gwh) Based on the Method				
	Semi Log (SL)	Linear Trend (TL)	Growth Trend (GT)	Double Log (DL)	Least Square (LS)
2004	4,450.76	4,450.76	4,450.76	4,450.76	4,450.76
2005	4,613.37	4,613.37	4,613.37	4,613.37	4,613.37
2006	4,717.81	4,717.81	4,717.81	4,717.81	4,717.81
2007	5,163.43	5,163.43	5,163.43	5,163.43	5,163.43
2008	5,757.84	5,757.84	5,757.84	5,757.84	5,757.84
2009	6,096.89	6,096.89	6,096.89	6,096.89	6,096.89
2010	6,636.45	6,636.45	6,636.45	6,636.45	6,636.45
2011	7,194.04	7,194.04	7,194.04	7,194.04	7,194.04
2012	7,809.32	7,809.32	7,809.32	7,809.32	7,809.32
2013	7,917.23	7,917.23	7,917.23	7,917.23	7,917.23
2014	8,271.01	8,271.01	8,271.01	8,271.01	8,271.01
2015	8,703.66	8,703.66	8,703.66	8,703.66	8,703.66
2016	9,240.30	9,240.30	9,240.30	9,240.30	9,240.30
2017	9,707.33	9,707.33	9,707.33	9,707.33	9,707.33
2018	10,445.02	10,445.02	10,445.02	10,445.02	10,445.02
2019	12,577.98	10,879.48	11,139.16	11,257.94	11,396.83
2020	14,050.86	11,313.95	11,878.49	11,989.56	12,194.77
2021	15,820.59	11,748.41	12,665.94	12,768.71	13,051.97
2022	17,963.38	12,182.88	13,504.64	13,598.47	13,972.23
2023	20,579.28	12,617.34	14,397.93	14,482.14	14,959.56
2024	23,800.96	13,051.81	15,349.37	15,423.21	16,018.24
2025	27,806.19	13,486.27	16,362.74	16,425.41	17,152.81
2026	32,835.85	13,920.73	17,442.06	17,492.72	18,368.10
2027	39,220.11	14,355.20	18,591.64	18,629.36	19,669.21
2028	47,417.16	14,789.66	19,816.04	19,839.83	21,061.59

The statistical coefficient values obtained from Simple E application are shown in Table 8.

Table 8. Test coefficient values

No.	Regression Method		Regression Indicators				Trend Coefficient
	Name	Code	R	AR	DW	t-value	
1	Semi Log	$SL	0.959	0.952	0.29	2.18	6.28/16.33
2	Linier Trend	$TL	0.989	0.988	0.65	2.18	6.28/3.54
3	Linier Growth	$TG	0.989	0.988	0.65	2.18	6.28/6.61
4	Double Log	$DL	0.993	0.992	1.21	2.18	6.28/6.63
5	Least Square	$LS	0.989	0.988	0.65	2.18	6.28/7.27

From the statistical coefficient values, the Double Log is the best regression method used. This is shown in the coefficient values obtained, namely growth trend, R, AR, DW and t values of 6.63%, 0.993, 0.992, 1.21 and 2.18 respectively.

3.2. Comparison of Forecast Using Simple E Application and Forecast Obtained from PT PLN (Persero)

A comparison of the PT PLN (Persero) forecasts and those obtained from Simple E application was carried out [36]. The data obtained is used for the realization of electricity consumption in North Sumatra region from 2016 to 2018 based on RUPTL PT PLN (Persero) during 2016-2025, and the Simple E application.

Time series data is used to obtain forecasts, namely data on the realization of population, economic, and electricity consumption growth in the North Sumatra region from 2004 to 2015. A comparison of the forecast values from PT PLN (Persero) [37] and the Simple E application can be seen in Table 9.

The Double Log Regression (DL) method was used for Simple E application above and obtained R, AR, DW and t values of 0.986, 0.982, 1.03 and 2.31, respectively. From Table 9, the results are closer to the realization data with an average percentage value of 7.04%. Meanwhile, the PT PLN (Persero) forecast results had an average deviation of 13.31% from the realization data.

Table 9. Comparison of forecast results

Years	Realization of Electric Energy consumption (Gwh)	Comparison of Forecast Values (Gwh)		Comparison of Forecast Percentages (%)	
		RUPTL 2016-2025	Simple E	RUPTL 2016-2025	Simple E
2016	9,240.30	9,918	8,527.42	7.33%	7.71%
2017	9,707.33	11,046	9,089.96	13.79%	6.36%
2018	10,445.02	12,410	9,709.98	18.81%	7.04%
Average				13.31%	7.04%

Table 10 describes the forecast for electricity consumption in North Sumatra, Indonesia until 2028. It can be seen that there is almost no difference between using the 2019-2028 RUPTL and Simple E. The only difference in the forecast starts from 2020 to 2028, which according to Simple E calculations is lower.

Table 10. Electricity consumption forecast

Years	Electricity Consumption Forecast (GWh)	
	RUPTL 2019-2028	Simple E
2004	4,450.76	4,450.76
2005	4,613.37	4,613.37
2006	4,717.81	4,717.81
2007	5,163.43	5,163.43
2008	5,757.84	5,757.84
2009	6,096.89	6,096.89
2010	6,636.45	6,636.45
2011	7,194.04	7,194.04
2012	7,809.32	7,809.32
2013	7,917.23	7,917.23
2014	8,271.01	8,271.01
2015	8,703.66	8,703.66
2016	9,240.30	9,240.30
2017	9,707.33	9,707.33
2018	10,445.02	10,445.02
2019	11,361.00	11,257.94
2020	12,210.00	11,989.56
2021	13,286.00	12,768.71
2022	14,656.00	13,598.47
2023	15,979.00	14,482.14
2024	17,007.00	15,423.21
2025	18,105.00	16,425.41
2026	19,381.00	17,492.72
2027	20,742.00	18,629.36
2028	22,194.00	19,839.83

4. Conclusion

This study considers electricity demand until 2028 with a Simple E application using Regression in North Sumatra Province, Indonesia. There was a focus on three trends in forecasting, namely semi-logs, linear, and NAT trends. A model was calibrated with historical data from 2004 to 2018. Furthermore, during the regression process using double logs, the coefficient values obtained include growth trend, R, AR, DW, and t values of 6.63%, 0.993, 0.992, 1.21, and

2.18, respectively. Application using the Double Log Regression (DL) method obtained R, AR, DW, and t values of 0.986, 0.982, 1.03, and 2.31, respectively. This was closer to the realization data, with an average percentage value of 7.04%. Meanwhile, the forecast results carried out by PT PLN (Persero) had an average deviation of 13.31% from the realization data.

Using a value of "t = 2", it can be concluded that the relationship between electricity consumption, with population and economic growth was significant. The estimated energy consumption growth in North Sumatra was 6.63% annually, with a total of 19,839.83 GWh in 2028. Finally, further studies may be required to validate the model accuracy for different periods or extended sample sets. This is carried out by applying the model to different energy markets. In this study, the load demand accounted for expandable variables such as weather forecasting measures, renewable energy impact on power grids, production technology, new trends in distributed energy generation, and market incorporation.

5. Declarations

5.1. Author Contributions

Conceptualization, A.H.; methodology, A.H., W.V.S., and E.W.; formal analysis, W.V.S., and M.; investigation, E.W.; data curation, R.F.; writing—original draft preparation, A.H., W.V.S., M.I., E.W., R.F., and M.; writing—review and editing, A.H., and M.I. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available in article.

5.3. Funding

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5.5. Ethical Approval

Not applicable.

5.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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