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Rainy and dry seasons impact on electricity demand in Indonesia

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Abstract
Electricity consumption has become an integral part of daily life and is pivotal in supporting various aspects of human life. North Aceh Regency, a tropical region in Indonesia, experiences significant seasonal fluctuations between the rainy and dry seasons. This research aims to investigate and analyze the impact of these seasonal differences on electricity consumption patterns by consumers in the region using the IBM SPSS statistical method. Monthly electricity consumption data from consumers in North Aceh Regency over a specific period were collected and analyzed using IBM SPSS software. Descriptive statistical analysis, hypothesis testing, and regression models were employed to identify significant differences in electricity consumption between the rainy and dry seasons and to understand the factors influencing consumption patterns. The results of the analysis indicate a significant difference in electricity consumption between the rainy and dry seasons in North Aceh Regency. The dry season shows an increase in electricity consumption, possibly related to factors such as the use of air conditioning and additional lighting.

Keywords:
Electrical Energy Demand;
Linear Regression Method;
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INTRODUCTION

The demand for electricity in Indonesia continues to increase due to economic growth, population growth, and increased purchasing power [1, 2, 3, 4, 5]. Indonesia has a unique climate due to its tropical location and position between the Pacific and Indian Oceans, which affects climate. Therefore, Indonesia has three climate patterns: monsoon, equatorial, and local [6][7]. During prolonged dry seasons, the temperature increases, requiring electronic devices such as Air Conditioning (AC) or fans to cool the room [8]. The use of AC is one of the causes of increased electricity consumption. Electric consumption forecasting is needed to ensure continuity of service due to increased electricity demand [9][10].

Electricity consumption forecasting is vital in planning electricity production, as it is the starting point in production planning [11, 12, 13, 14]. Overproduction is wasteful or costly for companies, while underproduction allows competitors to enter the market. Therefore, predicting electricity demand is crucial in developing an electricity system in a particular area or region [15][16].

The North Aceh Regency, located in a tropical region, experiences significant seasonal changes between the rainy and dry seasons [17]. These climate variations can impact electricity consumption patterns and consumer needs [18][19].

This study aims to analyze the influence of the differences between the rainy and dry seasons on electricity consumption among consumers in North Aceh Regency. By understanding the variability in electricity consumption patterns during different seasons, this research is expected to provide valuable insights into energy management in the region [20, 21, 22].

Although many studies have examined factors influencing electricity consumption, this research has been motivated by the lack of focus on seasonal variations in tropical regions. By understanding how electricity consumption fluctuates during the rainy and dry seasons, we can identify potential strategies for more effective energy management [23].

In this article, the author presents the influence of climate on electricity demand and forecasts the electricity needs for the next six years in North Aceh Regency during the dry and rainy seasons using IBM SPSS software with a stepwise method in multiple linear regression [24][25]. Previous studies have shown that seasonal variations significantly impact electricity consumption patterns in tropical regions [26][27]. The choice of multiple linear regression using IBM SPSS was motivated by its capability to analyze complex relationships between weather variables and electricity demand patterns [28, 29, 30].

This study uniquely contributes by providing detailed insights into how seasonal variations in North Aceh specifically influence electricity consumption, filling a critical gap in current research on tropical climates. In the conclusion, we will summarize the findings and discuss their implications for energy management strategies in tropical regions with pronounced seasonal changes.

The results of this research are expected to contribute to our understanding of the factors influencing electricity consumption, especially in the context of seasonal variations in tropical regions. These findings can serve as a foundation for developing more adaptive and sustainable energy policies, providing practical guidance for consumers and electricity service providers in dealing with dynamic changes in energy consumption.

This research is relevant for providing new insights into electricity consumption and serving as a basis for further consideration of energy efficiency, sustainability, and energy resource management in regions with significant seasonal variations.

METHOD

The analysis of this research is based on monthly electricity consumption data from consumers in North Aceh Regency during a specific period, namely the data from 2020, 2021, and 2022. The population data for this study were obtained from the Meteorological, Climatological and Geophysical Agency (BMKG) Indrapuri, and electricity load data from State Electricity Company (PLN) North Aceh. Temperature and humidity data were measured thrice a day at 07:00, 13:00, and 18:00, then divided by 3 for the daily results. The types and data sources used in this research are secondary and quantitative. The methodology includes descriptive statistical analysis and multiple linear regression models using IBM SPSS software to understand the differences in electricity consumption between the rainy and dry seasons and the factors that may influence it.

The SPSS software application program features advanced statistical data analysis capabilities. SPSS has a data management system in a graphical environment using descriptive menus and simple dialog boxes, making it easy to operate and understand. SPSS is one of the most popular and widely used application programs by analysts and researchers for processing statistical data [31][32].

Based on weather and power data, where the population values are averaged and divided into 16 months for the rainy season and another 16 months for the dry season, to ascertain that the population data of weather and power can be processed with multiple linear regression, it is necessary to undergo classical assumption tests as follows:

a. Normality Test
b. Autocorrelation Test
c. Multicollinearity Test
d. Heteroskedasticity Test

After conducting classical assumption tests, the analysis of the data continued using multiple linear regression analysis with the stepwise method [33, 34, 35] to examine the extent of influence between independent variables X1 (temperature), X2 (air humidity), X3 (rainfall), X4 (sunshine duration), X5 (wind speed) on the dependent variable Y1 (electric consumption). The aim is also to determine which season significantly influences electricity consumption among electric customers in North Aceh Regency.

Subsequently, the determination coefficient (R2) and correlation coefficient values were calculated [35]. The research flowchart is presented in Figure 1.

The coefficient of determination in multiple linear regression, often referred to as R2 measures how well the regression model can explain the variability of the dependent variable. The coefficient of determination ranges from 0 to 1, and the closer it is to 1, the better the regression model can explain the data variation.

Regression analysis is a statistical tool that explains the relationship pattern (model) between two or more variables [36]. In regression analysis, there are two types of variables: the response variable, also called the dependent variable, whose existence is influenced by other variables and is denoted by Y, and the independent variable, namely the independent variable (not influenced by other variables) and denoted by X [37]. The paradigm of multiple linear regression analysis is shown in Figure 2.

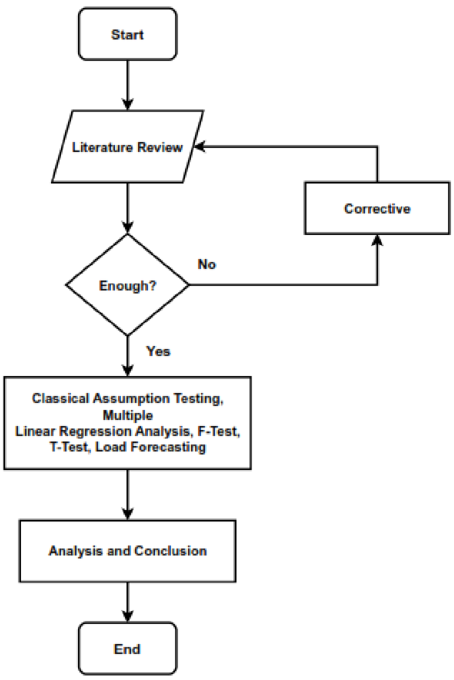

Figure 1. Research Flowchart

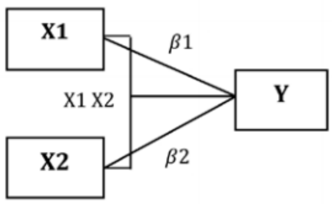

Figure 2. The Paradigm of Multiple Linear Regression Analysis

RESULTS AND DISCUSSION

Presentation of Data Results

In the regressed data, the authors grouped the dry and rainy seasons data, each of which amounted to 18 months from the previous three years (2020, 2021, and 2022). The dry season is seen from the lowest rainfall each month, which can be seen in Table 1 and vice versa in the rainy season data contained in Table 2.

Table 1. The Dry Season Data Table is seen from The Lowest Rainfall for 3 Years

No	Years	Months	Y	X1	X2	X3	X4	X5
1	2020	March	19048	30.8	84	31.66	57	3.7
2	2020	April	18540	31.2	85	23	67	3.8
3	2020	June	20360	31.9	84	11	66	4.2
4	2020	July	20096	32.1	82	19	65	4.2
5	2020	October	19916	30.9	86	21.66	58	3.7
6	2020	November	18941	30.1	88	24.33	49	3.6
7	2021	February	17971	31.1	83	21	69	4.3
8	2021	Maret	21047	32	82	27	78	4
9	2021	June	22024	32.6	81	17	56	3.6
10	2021	July	21976	32.4	80	10	63	3.9
11	2021	August	22282	32.2	82	25.33	65	3.3
12	2021	December	20294	30.4	86	0	48	3.7
13	2022	January	21842	31.2	87	13.33	69	4.5
14	2022	February	20119	31.6	82	14.33	79	3.4
15	2022	March	23846	32.4	80	13.33	84	3.7
16	2022	April	23391	32.8	81	15	69	4.1
17	2022	June	23565	32.6	83	26.66	58	3.3
18	2022	July	23479	32.8	80	18	71	3.7

Table 2. The Rainy Season Data given The Highest Rainfall for 3 Years

No	Years	Months	Y	X1	X2	X3	X4	X5
1	2020	January	18019	29.5	87	39.33	41	4
2	2020	February	16982	30.3	85	37	63	4.4
3	2020	May	19917	32.2	84	39	57	3.7
4	2020	August	19549	31.7	83	50.33	54	3.8
5	2020	September	19006	30.7	86	36.33	53	3.7
6	2020	December	18669	29.8	88	53	38	3.8
7	2021	January	19044	30.3	87	32.66	46	3.8
8	2021	April	21274	32.5	83	34.66	66	3.6
9	2021	May	22601	31.8	85	57.66	62	4
10	2021	September	21341	31.3	84	29.33	50	3.7
11	2021	October	21174	30.6	87	45.66	48	3.2
12	2021	November	20268	30.7	88	47	47	3.1
13	2022	May	25173	32.2	83	40.33	64	3.9
14	2022	August	23697	32.8	81	27	72	4.1
15	2022	September	23024	31.5	86	35.66	45	4
16	2022	October	22524	30.3	88	41.33	45	2.8
17	2022	November	22389	30.5	88	36.66	50	4
18	2022	December	22405	30.4	86	42.66	50	4.9

Note: Y = PLN monthly load (kW)
X1 = Temperature (^{0}C)
X2 = Humidity (%)
X3 = rainfall (mm)
X4 = Length of Sunlight (hours)
X5 = Wind Speed (knot)

Assumption and Model Validity Testing with Normality Test

Dry season

If the value is asymptotic, the regression model is said to be normally distributed. Sig (2-tailed) is greater than the significance value of 0.05, so the data is normally distributed.

Conclusion: The regression Model is normally distributed.

Based on the Kolmogorov-Smirnov test results as listed in Table 3, the residuals from the regression model can be considered normally distributed. This is an important assumption in regression analysis as it ensures that the results of statistical analyses (such as hypothesis testing and confidence intervals) are reliable.

Rainy season

If the value is asymptotic, the regression model is said to be normally distributed. Sig (2-tailed) is greater than the significance value of 0.05, so the data is normally distributed.

Based on the results of the Kolmogorov-Smirnov test, as listed in Table 4, the standardized residuals from the regression model for the rainy season can also be considered normally distributed. This is crucial to ensure the reliability of statistical analyses conducted on the regression model.

Table 3. Kolmogrov-Smirnov Test Table

		Unstandardized Residual
N		18
Normal Parameters[a, b]	Mean	.0000000
	Std. Deviation	1126.328528
Most Extreme Differences	Absolute	.107
	Positive	.087
	Negative	-.107
Test Statistic		.107
Asymp. Sig. (2-tailed)		.200 [c,d]

Table 4. Kolmogrov-Smirnov Test Table

		Unstandardized Residual
N		18
Normal Parameters[a, b]	Mean	.0000000
	Std. Deviation	1792.608437
Most Extreme Differences	Absolute	.107
	Positive	.094
	Negative	-.107
Test Statistic		.107
Asymp. Sig. (2-tailed)		.200 [c,d]

Multiple Linear Regression Analysis

Multiple linear regression analysis was conducted using the stepwise method to understand the influence of independent variables on electricity load during the dry and rainy seasons. The stepwise method was chosen because it allows for selecting the most significant independent variables in the model, either by adding or removing variables iteratively based on statistical criteria. In this section, the steps taken in the regression analysis using the stepwise method will be explained, starting from describing the process to interpreting the results obtained.

Dry season

Table 5 shows the steps taken in the regression analysis using the stepwise method for the dry season. The main focus is on the variables included in the model based on the significance criteria of the F-test for entry (probability-of-F-to-enter) and the significance criteria of the F-test for removal (probability-of-F-to-remove).

a) F test

The F-test is used to determine the linear regression model's overall significance. The results of the F-test are obtained from the ANOVA table (Analysis of Variance), as shown in Table 6.

Then, the critical F-value at a significance level of 0.05 is obtained as 3.03. Based on the output above, it is known that the Sig value of the simultaneous influence of variable X on Y is 0.000 < 0.05, and the calculated F-value is 26.896 > the critical F-value of 3.03, indicating that there is a simultaneous influence of variable X on Y.

Table 5. Stepwise Method for Dry Season

Model	Variable Entered	Variables Removed	Method
1	Temperature		Stepwise (criteria: Probability-of-F-to-enter <= 0.050. Probability-of-F-to-remove>=0.100).

Table 6. Anova for Dry Season

Model	Sum. of Square	df	Mean Square	F	Sig.
Regression	36253159.744	1	36253159.744	26.896	0.000
Residual	21566471.201	16	1347904.450		
Total	57819630.944	17			

F table = (k; n-k)
Note: k = Number of Variable X
n = Number of Samples
So, F table = (k; n-k)
= 3.03

Therefore, based on these results, it can be concluded that temperature significantly affects the monthly electricity load in North Aceh District during the dry season based on the analyzed data.

b) T-test

The t-test is used to test the significance of the individual effects of each independent variable on the dependent variable in the regression model. The t-test results are obtained from the regression coefficient table, as shown in Table 7.

T table = T (∝ / 2; n-k-1)

Note: k = Number of variables

∝ = 0.05

n = Number of Samples

T table = T (∝ / 2; n-k-1)

= 2.1788

Based on the output above, it is known that the Sig value for the effect of variable X1 partially on Y is equal to 0.000 <0.05. The value of T count is 5.186> T table 2.1788, so it is concluded that it can reject H0, which means there is a partial influence of variable X1 on Y.

Based on these results, it can be concluded that temperature (Temperature) has a significant partial effect on the monthly electricity load in North Aceh District during the dry season.

c) Coefficient of Determination

The Coefficient of Determination (R-squared) is a statistical measure used in regression analysis to indicate how well the independent variable (in this case, temperature) explains or predicts the variation in the dependent variable (monthly PLN electricity load). R-squared provides information about the percentage of variation in the dependent variable that can be explained by the independent variable in the regression model. The interpretation of the R-squared model results is shown in Table 8.

Table 7. Coefficient for Dry Season

	Unstandardized Coefficients		**Standardized Coefficients**			**Collinearity Statistics**	
Model	B	Std.Error	Beta	T	Sig.	Tolerance	VIF
1 (Constant)	-33841.186	10586.021		-3.197	0.006		
Temperature	1729.782	333.540	0.792	5.186	0.000	1.000	1.000

Table 8. Model Summary for Dry Season

Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of The Estimate**	**Durbin-Watsen**
1	0.792	0.627	0.604	1160.993	1.412

So, from Table 8, looking at the adjusted R2 value of the coefficient of determination (R2), the temperature obtained = 0.604. This means that the effect of temperature in the dry season in the last three years can explain 60.4% of the dependent variable, while other things influence the remaining 39.6%.

In this context, a high R-squared value (0.604) indicates that temperature significantly explains the variation in monthly PLN electricity load in North Aceh District during the dry season, although other factors also contribute to this variation.

d) Correlation Test

This correlation test is a single value that informs how or in what circumstances the variation in one thing varies with another. The correlation coefficient among the sample variables, including power, temperature, air humidity, rainfall, sunshine duration, and wind speed, will also display significant values indicating the significance of the correlation, as shown in Table 9.

Table 9. Correlation for Dry Season

m	**Power load**	**Temperature**	**Air humidity**	**Rainfall**	**Length of solar irradiation**	**Wind speed**	
Pearson correlation	Power load	1000	.792	-.583	-.197	.300	-.210
	Temperature	.792	1.000	-.865	-.034	.475	-.073
	Air humidity	-583	-.865	1.000	-.057	1.000	.219
	Rainfall	-197	-.034	.057	1.000	-.004	-.254
	Length of solar irradiation	300	475	-.551	-.004	1.000	.219
	Wind speed	-210	-.073	.130	-254	219	1.000
Sig. (1-tailed)	Power load		.000	.006	217	113	201
	Temperature	000		.000	447	023	387
	Air humidity	006	000	.	412	009	303
	Rainfall	217	447	412		494	154
	Length of solar irradiation	113	023	009	494		191
	Wind speed	201	387	303	154	191	

The correlation analysis results in Table 9 indicate significant relationships between various weather factors and electricity load in North Aceh District during the dry season. Temperature shows a strong positive correlation with electricity load (r = 0.792), suggesting that higher temperatures can significantly increase electricity demand. On the other hand, air humidity exhibits a significant negative correlation (r = -0.583), indicating that increased humidity may reduce electricity demand.

Meanwhile, the relationships between other variables such as rainfall, sunshine duration, and wind speed with electricity load show less significant correlations, with correlation coefficients close to zero and p-values greater than 0.05. This analysis provides important insights into how weather factors contribute to fluctuations in electricity load in the region.

Rainy season

Similarly, the stepwise method identified temperature as the most significant variable influencing electricity load during the rainy season. The F-test and T-test results confirmed the significant influence of temperature on electricity load (Tables 10, Table 11, Table 12).

a) F Test

The F-test evaluates the overall significance of the regression model that includes temperature during the rainy season as a predictor of electricity load (variable Y). The results of the F-test are obtained from the ANOVA table, as shown in Table 11. Where: F table = (k; n-k), k is a number of Variable X, and n is a Number of Samples. So, F table = (k; n-k) = 3.03.

Based on the F-test and ANOVA results in Table 11, it can be concluded that the regression model, including temperature as a predictor variable, shows a significant influence on electricity load during the rainy season. The significance value (p-value) of 0.015 from the F-test indicates that the overall model can be considered statistically significant, as this value is smaller than the commonly chosen significance level (0.05). Additionally, the calculated F-value of 7.380 is significantly larger than the critical F-value at the 0.05 significance level (3.03), indicating that the variation in electricity load explained by temperature is statistically significant.

Therefore, these findings confirm that temperature is a primary predictor of electricity load variability during the rainy season in the studied region. This interpretation highlights the importance of considering temperature to predict and manage electricity consumption during varying weather conditions, which can aid in more effective planning and management of electrical infrastructure.

b) T Test

The t-test results are obtained from the regression coefficient table, as shown in Table 12. The T-test is applied to test the influence of temperature variables on electricity load. Table 12, which displays regression coefficients, shows that the temperature variable has a T-value of 2.717 with a significance value (Sig.) of 0.015. The Sig. value less than the established significance level (0.05) indicates a significant partial effect of the temperature variable on the electricity load variable during the rainy season.

Table 10. Stepwise Method for Rainy Season

Model	Variable Entered	Variables Removed	Method
1	Temperature		Stepwise (criteria: Probability-of-F-to-enter <= 0.050. Probability-of-F-to-remove>=0.100).

Table. 11 Anova for the rainy season

Model		Sum of Square	df	Mean Square	F	Sig.
1	Regression	25197329.274	1	25197329.274	7.380	0.015
	Residual	54628565.170	16	3414285.323		
	Total	79825894.444	17			

Table 12. Coefficient for Rainy Season

	Unstandardized Coefficients	Standardized Coefficients				Collinearity Statistics	
Model	B	Std.Error	Beta	T	Sig.	Tolerance	VIF
1 (Constant)	-18175.342	14407.949		-1.261	0.225		
Temperature	1259.546	463.646	0.562	2.717	0.015	1.000	1.000

Where:

T table = T (∝ / 2; n-k-1)
Note: k = Number of variables
∝ = 0.05
n = Number of Samples
So, T table = T (∝ / 2; n-k-1)
= 2.1788

Furthermore, because the T-value (2.717) is greater than the relevant critical T-value (approximately 2.1788), the null hypothesis (H0) can be rejected. This suggests that the results indicate a significant influence of temperature on changes in electricity load during the rainy season within the context of the study conducted.

c) Coefficient of Determination

The interpretation of the a) Coefficient of Determination (R-squared) model results are shown in Table 13. From Table 13, the Adjusted R-squared (R^2) value is 0.273. This value indicates that the temperature variable can explain approximately 27.3% of the observed variation in electricity load during the rainy season in that region. In other words, about 27.3% of the changes in electricity load can be directly attributed to the temperature variable. Meanwhile, approximately 72.7% of the variation is influenced by other factors that are either not modeled or not accounted for in this analysis.

Understanding R-squared is crucial as it provides insight into how well our regression model fits the observed data. The higher the R-squared value, the more significant the proportion of variation explained by the model for the dependent variable, in this case, electricity load.

d) Correlation Test

The correlation coefficient among the sample variables, including power, temperature, air humidity, rainfall, sunshine duration, and wind speed, will also display significant values indicating the significance of the correlation, as shown in Table 14.

The correlation table (Table 14) shows the correlation coefficients between sample variables such as power load, temperature, air humidity, rainfall, sunshine duration, and wind speed. The table shows that only the temperature variable has a significance value (sig) less than 0.05 in a one-tailed test. The correlation coefficient for temperature is 0.562, indicating a strong positive correlation. This suggests that if the temperature (X1) is high, the electricity load (Y) also tends to be high.

On the other hand, the other variables have sig values greater than 0.05, indicating that their correlation relationships are not statistically significant in this sample. For instance, air humidity has a correlation coefficient of -0.308 with electricity load, but its sig value is 0.106, which is insignificant at the 95% confidence level.

Understanding these correlation test results is essential as it helps us determine the strength of relationships between the tested variables and whether these relationships are statistically significant in the analysis context.

Table 13. Model Summary for the rainy season

Model	R	R Square	Adjusted R Square	Std. Error of The Estimate	Durbin-Watsen
1	0.582	0.316	0.273	1847.774	0.533

Table 14. Correlation for Rainy Season

		Power load	Temperature	Air humidity	Rainfall	Length of solar irradiation		Wind speed
Pearson correlation	Power load	1000	.562	-.308	-.103	.346		-.007
	Temperature	.562	1.000	-.865		-.213	.792	-.021
	Air humidity	-308	-.853	1.000		-.325	-.833	-.292
	Rainfall	-.103	-.213	.325		1.000	-.255	-.124
	Length of solar irradiation	.346	.792	-.833		-.255	1.000	.258
	Wind speed	-.007	-.021	.292		-.124	.258	1.000
Sig. (1-tailed	Power load		.008	.106		.342	.080	.489
	Temperature	.008		.000		.198	.000	.467
	Air humidity	.106	000	.		.094	000	.120
	Rainfall	.342	.198	.094		.	.154	.312
	Length of solar irradiation	.080	.000	.000		.154	.	151
	Wind speed	.489	.467	.120		.312	.151	.

Forecasting Using Linear Equations

This method refers to using regression models to predict future values based on historical data and the regression coefficients generated. Predictions for the dry and rainy seasons are derived from the regression equation produced by SPSS output or similar statistical analysis tools. The prediction coefficients are presented in Table 15 and Table 16. The linear equation graph for forecasting the next six years of the dry season is depicted in Figure 3, and the linear equation graph for forecasting the next six years of the rainy season is depicted in Figure 4.

From Table 15, the regression coefficients are given as a constant coefficient (B0) of 18,406.033 and a coefficient for the time variable (t) of 277.359. The regression equation obtained is $Yt = 18{,}406.033 + 277.359\ t$. where Y_t represents the predicted value of electricity demand during the dry season at a time (t). To forecast electricity demand for the next six years (2023 to 2028), the value of (t) starts from 19 and continues sequentially up to 54, following the relevant time range. Using this regression equation, the forecasted values Y_t can be calculated for each future year based on the observed linear relationship from historical data used in the regression analysis. This method enables analysts to anticipate demand changes by leveraging identified historical patterns.

Table 16 displays the forecast coefficients for the rainy season, derived from regression analysis using historical data. The regression coefficients in this table include the constant coefficient (B0) of 17,809.418 and the coefficient for the time variable (t) of 330.330. The resulting regression equation is Y_t = 17,809.418 + 330.330.t, where Y_t represents the predicted value of electricity demand during the rainy season at a time (t). To forecast electricity demand for the next six years (2023 to 2028), the value of (t) starts from 19 and continues sequentially up to 54, corresponding to the relevant period. Using this regression equation, the forecasted values Y_t can be calculated for each future year based on the linear trend observed from the historical data used in the regression analysis. This process enables the projection of electricity demand while considering seasonal patterns and significant time factors in forecasting.

Figure 3 and Figure 4 depict the linearization graph of the data to be forecasted, where the scattered points represent the output data to be forecasted. This study uses linear regression to linearize the scattered points, resulting in a linear line (diagonal). The function of this linear line is to determine the forecasted values of electricity load usage in the future.

Comparison of Electricity Demand Between Dry and Rainy Seasons Over the Next 6 Years

Table 17 compares electricity demand between the dry and rainy seasons over the next six years based on the description above. Table 17 presents the average monthly electricity demand during the dry and rainy seasons from 2023 to 2028. This data illustrates the fluctuation pattern in electricity demand between these two seasons. During the dry season, the average electricity demand per month tends to be lower than the rainy season, although variation is observed yearly. For example, in 2023, the average monthly electricity demand during the dry season is approximately 24,369.2515 kW. During the rainy season, it slightly increases to about 24,911.513 kW. This increase may be attributed to increased heating use or additional lighting during the rainy season.

Table 15. Forecasting Coefficients for Dry Season

	Unstandardized Coefficients		Standardized Coefficients		
Model	B	Std.Error	Beta	T	Sig.
1 (Constant)	18406.033	557.288		33.028	0.000
t	277.359	51.485	0.803	5.387	0.000

Table 16. Forecasting Coefficients for Rainy Season

	Unstandardized Coefficients		Standardized Coefficients		
Model	B	Std.Error	Beta	T	Sig.
1 (Constant)	17809.418	638.323		27.900	0.000
t	330.330	58.971	0.814	5.602	0.000

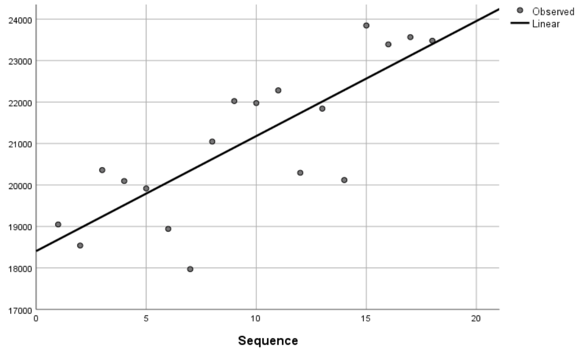

Figure 3. Linear Equation Graph for Forecasting the Dry Season Over the Next 6 Years

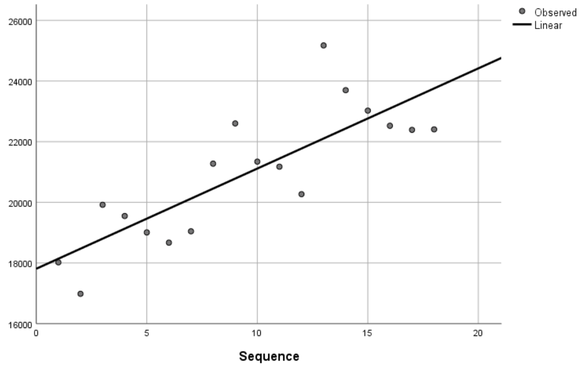

Figure 4. Linear Equation Graph for Forecasting the Rainy Season Over the Next 6 Years

Table 17. Comparison of Average Growth of Electricity Demand in the Rainy and Dry Seasons Over the Next 6 Years

Years	Dry season (kW)	Rainy season (kW)
2023	24,369.2515	24,911.513
2024	26,033.4055	26,893.493
2025	27,697.5595	28875.473
2026	29,361.7135	30857.453
2027	31,025.8675	32839.433
2028	32,690.0215	34821.413

Table 18 and Table 19 provide an overview of the percentage increase in electricity demand during the dry and rainy seasons from 2017 to 2025. Table 18 shows a total increase of 47% during the dry season, with specific years showing significant increases in electricity power load. In comparison, Table 19 indicates a total increase of 42% during the rainy season, albeit with a more stable rate of increase from year to year. This data is crucial for planning electricity infrastructure to anticipate the continuously rising demand, especially during the dry season, which requires greater energy capacity to meet societal needs. Table 19 and Table 20 show the percentage increase in electricity demand between the dry and rainy seasons over the next six years.

Table 18. Percentage Increase in Electricity Demand During the Dry Season Over the Next 6 Years

Years	Power Load (kW)	Percentage (%)
2023	19,483.500	0
2024	22,707.000	17
2025	20,932.3333	-8
2026	24,369.2515	16
2027	26,033.4055	7
2028	27,697.5595	6
	Total **Percentage**	**47**

Table 19. Percentage Increase in Electricity Demand During the Rainy Season Over the Next 6 Years

Years	Power Load (kW)	Percentage (%)
2023	18,690.3333	0
2024	20,950.3333	12
2025	23,202.000	11
2026	24,911.513	7
2027	26,893.493	8
2028	28,875.473	7
	Total **Percentage**	**42**

Table 20. Table of Comparison Multiple Linear Regression Methods with Arima and Fuzzy Methods

Methods	Error	Accurate	MAP
Regression	9.38%	98.9%	1%
ARIMA	-	97.64%	2.36%
Fuzzy	20.74%	-	-

This data is crucial for infrastructure planning and electricity distribution management. It enables energy providers to allocate resources efficiently and ensure adequate electricity availability throughout the year.

This research was carried out using one method, namely multiple linear regression, researchers have compared it with other methods. Previous research stated that the multiple linear regression error value was 9.38% smaller than the average error value for the fuzzy method of 20.74%. They also stated that using SPSS software for the multiple linear regression method was faster and easier than fuzzy logic, which uses Matlab. Research related to other forecasting was carried out by comparing the multiple linear regression and ARIMA methods. They stated that the multiple linear regression equation model results showed the highest accuracy value of 98.9% and a MAPE value of 1% compared to the ARIMA forecasting method, with an accuracy value of 97.64 % and MAPE value of 2.36% [38]. Then, research conducted by Sahrul et al. using a combined method in predicting energy needs was suggested using the linear regression method [39][40].

A comparison table of forecasting methods that previous researchers have carried out to show that the multiple linear regression method is better than other methods is listed in Table 20.

CONCLUSION

This research concludes that the weather factor that has the most significant influence on electricity loads in North Aceh Regency in 2020, 2021, and 2022 is temperature, as seen from the correlation value (r), which is 79.2% in the dry season, and 56.2% in the rainy season. The rainy season and the season that has the most influence on the electricity load in North Aceh Regency in 2020, 2021, and 2022 is the dry season, seen from the adjusted R2 value = 60.4% for the dry season, while the rest is the dry season. Influenced by other things and adjusted R2 = 27.3% for the rainy season, while other things influence the rest. The percentage increase in electrical energy demand in the dry season is 47% until 2028, and the increase in the percentage of electrical energy demand in the rainy season is 42% until 2028. On the other hand, this research still needs to improve, namely, the need to add several more X variables to become factors for Y, considering that population growth factors also influence electrical energy consumption.

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