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Comparative Analysis of Cubic Spline and PCHIP Using Chebyshev Norm for Household PLN Electricity Access Projection in Indonesia

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ABSTRACT

This study aims to compare Cubic Spline and PCHIP using the Chebyshev norm to construct a projection of household PLN electricity access in Indonesia for 2026. The data used in this study consist of the percentage of households using PLN electricity by province during the 2010-2025 period, obtained from Statistics Indonesia, with 33 provinces having complete time series data. The research method includes analytical function testing, construction of Cubic Spline and PCHIP interpolation functions, calculation of 2026 projections, and evaluation of the Chebyshev norm over the 2025-2026 interval. The main trajectory method is determined based on the smaller maximum function value over this interval. The results show that the average household access to PLN electricity increased from 77.92% in 2010 to 97.60% in 2025, while the standard deviation decreased from 17.01 to 3.44. The 2026 projection indicates that most provinces are already at a high level of electricity access, whereas West Papua, Papua, Central Kalimantan, East Nusa Tenggara, and West Kalimantan remain relatively lower. Based on the Chebyshev norm, PCHIP becomes the main method in 13 provinces, Cubic Spline in 12 provinces, and 8 provinces are classified as comparable.

***Keywords*:** numerical interpolation, function trajectory, household electrification, provincial data, energy equity.

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1. INTRODUCTION

Access to electricity is one of the important indicators of socio-economic development because it is closely related to household quality of life, productivity, education, health, and public welfare. In the context of sustainable development, access to modern energy is also associated with the Sustainable Development Goals, particularly SDG 7 on affordable and clean energy. Studies on energy poverty in Indonesia show that limited access to and affordability of energy remain important issues in household and regional development [1], [2].

Indonesia has experienced an increase in electricity access over the past few decades. In this study, PLN refers to *Perusahaan Listrik Negara*, Indonesia's state-owned electricity company that provides grid-based electricity services to households. However, this improvement has not always been evenly distributed across regions. Geographical conditions, population density, infrastructure availability, regional accessibility, and local development characteristics have caused several provinces to have different levels of PLN electricity access compared with other provinces. Therefore, data on the percentage of households using PLN electricity by province are important to analyze because they can provide an overview of household electricity access development from both spatial and temporal perspectives.

Previous studies have shown that energy access is associated with household welfare and regional development. Sambodo and Novandra [1] positioned energy poverty as an issue related to welfare in Indonesian society. Saputri et al. [2] also showed that household energy poverty in Indonesia is influenced by socio economic characteristics, household expenditure, energy prices, and regional variation. These findings strengthen the view that electricity access data are not merely statistical information, but can also be used to examine the equity of energy development.

In the analysis of annual time series data, numerical methods can be used to construct curve representations from discrete data. One widely used approach is interpolation. Interpolation enables limited annual data to be represented as a continuous function, allowing changes between periods to be observed more clearly. Several previous studies have applied interpolation methods in various fields. Fakhouri et al. [3] compared Cubic Spline, Piecewise Cubic Hermite Interpolating Polynomial (PCHIP), and Akima methods for predicting radiation shielding parameters of materials. Rabbath and Corriveau [4] compared PCHIP, Cubic Spline, and piecewise linear functions for projectile aerodynamics approximation. Karim et al. [5] used Cubic Spline and PCHIP for petroleum engineering data interpolation, while Jaffar et al. [6] compared PCHIP, Cubic Spline, and Makima for filling missing data in river water quality parameters.

In the Indonesian context, Purwani et al. [7] used Cubic Spline to predict the poverty rate in West Java and showed that Cubic Spline could produce smaller errors than Newton interpolation. That study is relevant to the present research because it uses annual statistical data in Indonesia and applies interpolation to examine patterns and make historical-data-based predictions. However, this study differs by comparing Cubic Spline and PCHIP on provincial household PLN electricity usage data and by using the Chebyshev norm as a measure of the maximum function value over the 2025-2026 interval to determine the main trajectory method for each province [8].

Cubic Spline is an interpolation method based on piecewise cubic polynomials that produces a smooth curve with continuity of the function, first derivative, and second derivative. Its advantage lies in its ability to generate smooth curves and to represent data that change gradually [5], [9]. Meanwhile, Piecewise Cubic Hermite Interpolating Polynomial, or PCHIP, is a cubic Hermite interpolation method that preserves the local shape of the data and is widely used when the characteristics of changes between data points need to be maintained [4], [9], [10]. PCHIP is also applied in observational data processing and time series reconstruction, such as nighttime light data and spatio temporal data [11], [12], [13].

This study aims to compare Cubic Spline and Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) in constructing an exploratory projection of the percentage of households using PLN electricity by province in Indonesia for 2026. The comparison is carried out by constructing interpolation functions based on 2010-2025 historical data, calculating the 2026 projection values, evaluating the Chebyshev norm over the 2025-2026 interval, and determining the main trajectory method for each province. The contribution of this study lies in the application of two numerical interpolation methods to examine the development of household electricity access based on provincial data, as well as in the use of the Chebyshev norm as a comparative basis for selecting a more controlled function trajectory over the projection interval. Thus, the results of this study are expected to provide a quantitative overview of household electrification development and help identify provinces whose PLN access levels remain relatively lower than those of other provinces.

2. MATERIALS AND METHODS

2.1. Research Data

The data used in this study are secondary data obtained from Statistics Indonesia (Badan Pusat Statistik/BPS), specifically from the statistical table on the percentage of households by province, village classification, and main lighting source from PLN electricity during the 2010-2025 period. The analyzed data consist of provinces with complete time series data throughout the observation period. Based on the data selection process, 33 provinces were included in the analysis.

The main research variable is denoted by $y_{i,t}$, which represents the percentage of households using PLN electricity in province i in year t. The observation year is expressed as $t = 2010, 2011, \dots, 2025$. Each historical data point is represented as the ordered pair:

$$P_{i,t} = \left(t, y_{i,t}\right) \tag{1}$$

where $P_{i,t}$ denotes the discrete point used as the basis for constructing the interpolation function for each province.

2.2. Research Design

This study uses a quantitative computational approach to compare Cubic Spline and Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) in constructing the trajectory of the percentage of households using PLN electricity. The research stages include historical data processing, test function evaluation, interpolation function construction, 2026 projection, function based Chebyshev norm calculation, and comparative interpretation. The research procedure begins with the use of 2010-2025 PLN electricity data as historical points. Next, Cubic Spline and PCHIP functions are constructed for each province. These functions are then used to generate the projected values for 2026. The Chebyshev norm is calculated over the 2025-2026 interval to determine the main trajectory method based on the smaller maximum function value.

2.3. Test Function

Before being applied to the PLN electricity data, both methods are tested using the analytical function:

$$f(x) = \sin(2x) \tag{2}$$

with the discrete points:

$$x_j = j, \;\; j = 0,1,2,3,4,5,6 \tag{3}$$

This function was selected because it has increasing and decreasing patterns as well as changes in direction, making it useful for examining how Cubic Spline and PCHIP construct curves from discrete points. Since the original function values are known, the error between the interpolation results and the true function can be calculated directly.

2.4. Cubic Spline

On each interval $[x_i, x_{i+1}]$, Cubic Spline constructs a cubic polynomial:

$$S_i(x) = a_i + b_i(x - x_i) + c_i(x - x_i)^2 + d_i(x - x_i)^3, \;\; x_i \le x \le x_{i+1} \tag{4}$$

where$i = 0,1, \dots, n - 1$. The coefficients a_i, b_i, c_i, d_i are determined so that the spline function satisfies the interpolation and continuity conditions, namely:

$$\begin{gathered} S_i(x_i) = y_i \\ S_i(x_{i+1}) = y_{i+1} \\ S_i'(x_{i+1}) = S_{i+1}'(x_{i+1}) \\ S_i''(x_{i+1}) = S_{i+1}''(x_{i+1}) \end{gathered} \tag{5}$$

Cubic Spline produces a smooth curve because the function, first derivative, and second derivative are made continuous at the connecting points. Karim et al. [5] explained that Cubic Spline has C^2 continuity, making it commonly used to construct smooth interpolation curves for engineering and observational data.

2.5. Piecewise Cubic Hermite Interpolating Polynomial

PCHIP is an interpolation method based on cubic Hermite polynomials. On the interval $[x_i, x_{i+1}]$, Hermite interpolation can be written as:

$$H_i(x) = h_{00}(\tau)y_i + h_{10}(\tau)\left(x_{i+1} - x_i\right)m_i + h_{01}(\tau)y_{i+1} + h_{11}(\tau)\left(x_{i+1} - x_i\right)m_{i+1} \tag{6}$$

where:

$$\begin{gathered} h_i = x_{i+1} - x_i \\ \tau = \frac{x - x_i}{x_{i+1} - x_i} \end{gathered} \tag{7}$$

The Hermite basis functions are:

$$\begin{gathered} h_{00}(\tau) = 2\tau^3 - 3\tau^2 + 1 \\ h_{10}(\tau) = \tau^3 - 2\tau^2 + \tau \\ h_{01}(\tau) = -2\tau^3 + 3\tau^2 \\ h_{11}(\tau) = \tau^3 - \tau^2 \end{gathered} \tag{8}$$

The parameters m_i and m_{i+1} represent the slopes at the data points. PCHIP determines the slopes locally so that the curve shape follows the data pattern. In previous studies, PCHIP has been used because it can preserve the local characteristics of the data and is suitable for comparison with Cubic Spline [4], [5], [6].

2.6.Projection for 2026

After the functions $S_i(x)$and $H_i(x)$are constructed from the 2010-2025 data, the 2026 projection is calculated as follows:

$$\hat{y}_{i,2026}^{CS} = S_i(2026) \quad (9)$$

$$\hat{y}_{i,2026}^{PCHIP} = H_i(2026) \quad (10)$$

These two values serve as the basis for comparing the Cubic Spline and PCHIP projections for each province.

2.7. Chebyshev Norm

The Chebyshev norm evaluation is used as a measure of the maximum function value over the projection interval. The interval used is:

$$I = [2025,2026] \quad (11)$$

The Chebyshev norm for the Cubic Spline function is defined as:

$$\| S_i \|_{\infty,[2025,2026]} = \max_{x\in[2025,2026]} | S_i(x) | \quad (12)$$

The Chebyshev norm for the PCHIP function is defined as:

$$\| H_i \|_{\infty,[2025,2026]} = \max_{x\in[2025,2026]} | H_i(x) | \quad (13)$$

The selection of the main trajectory method based on the smaller Chebyshev norm is grounded in the characteristics of percentage data, which have a natural upper bound. Over the projection interval [2025,2026], the Chebyshev norm represents the maximum function value reached by each trajectory. Therefore, the function with the smaller maximum value is selected as the main trajectory because it produces a more conservative and more controlled path over the projection interval. This criterion is relevant for household electricity access data because most provinces have already approached high values, so a trajectory that does not produce an excessive maximum increase is more appropriate for representing the exploratory projection for 2026.

The main trajectory method for province -i is determined by:

$$m_i^* = \arg\min_{m\in\{CS,PCHIP\}} \| F_i^{(m)} \|_{\infty,[2025,2026]} \quad (14)$$

where $F_i^{(m)}$ denotes the interpolation function used, namely $S_i(x)$ for Cubic Spline and $H_i(x)$for PCHIP. If the Chebyshev norm values of the two methods are equal, the province is classified as comparable. The main projected value is then determined as:

$$\hat{y}_{i,2026}^{*} = F_i^{(m_i^*)}(2026) \quad (15)$$

For the comparable category, the main projected value is reported as a representative value of the two methods.

2.8. Trajectory Stability

The trajectory change from 2025 to 2026 is calculated to examine the movement of the function over the final interval. The Cubic Spline trajectory change is expressed as:

$$\Delta_i^{CS} = | S_i(2026) - S_i(2025) | \tag{16}$$

The PCHIP trajectory change is expressed as:

$$\Delta_i^{PCHIP} = | H_i(2026) - H_i(2025) | \tag{17}$$

This measure is used to support the interpretation of trajectory shapes in provinces with relatively low projected values.

3. RESULTS AND DISCUSSION

3.1. Test Function Result

The test function evaluation was conducted on $f(x) = \sin(2x)$using seven discrete points. The visualization results are presented in Figure 1.

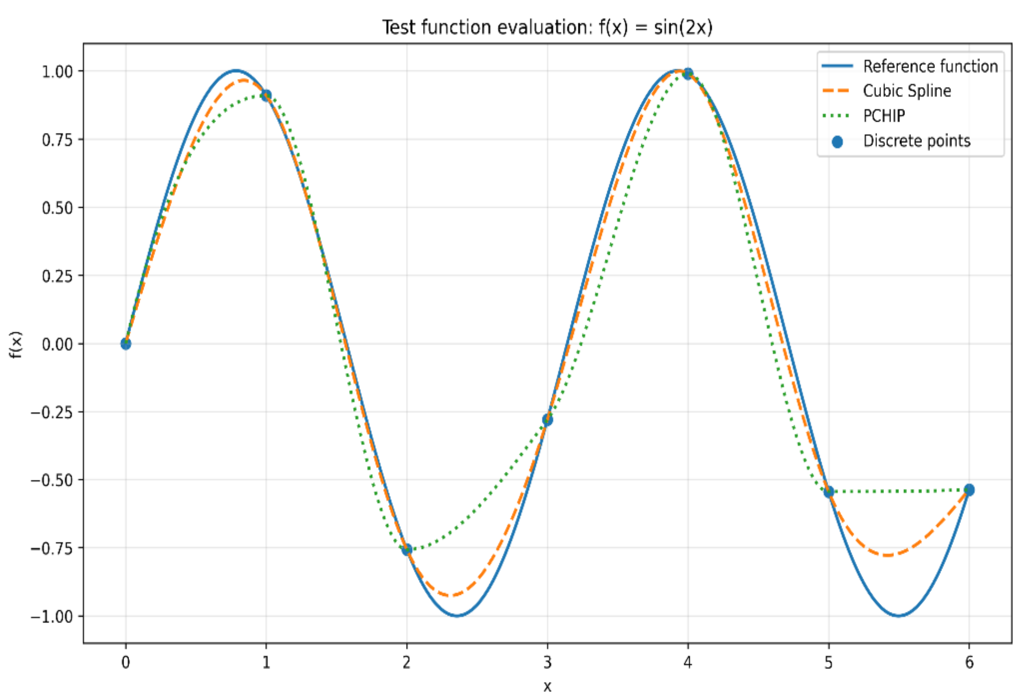


Figure 1. Evaluation of The Test Function $f(x) = \sin(2x)$.

Figure 1 shows that both Cubic Spline and PCHIP form curves that pass through the discrete points. However, the trajectory shapes of the two methods differ between data points. Cubic Spline produces a smoother curve, whereas PCHIP forms a curve that follows local changes between points more closely. This difference is particularly visible in parts of the curve where the function changes direction, namely when it moves from positive to negative values or vice versa. To strengthen the visual results, a summary of the absolute differences between the reference function and the interpolation results is presented in Table 1.

Table 1. Summary of Test Function Results.

Measure	Cubic Spline	PCHIP
Maximum absolute difference	0.2343	0.4569
Mean absolute difference	0.0574	0.1567

Based on Table 1, Cubic Spline produces a maximum absolute difference of 0.2343, whereas PCHIP produces a value of 0.4569. The mean absolute difference of Cubic Spline is also smaller, namely 0.0574 compared with 0.1567 for PCHIP. These results indicate that, for a smooth and oscillatory test function, Cubic Spline constructs a curve approximation that is closer to the reference function. However, the test function result is used only as an initial examination of the behavior of the methods before they are applied to the percentage data of households using PLN electricity.

3.2. Descriptive Statistics and Actual Data Pattern

Descriptive statistics of the historical data are used to examine general changes in the percentage of households using PLN electricity at the beginning and end of the observation period. The statistical summary is presented in Table 2.

Table 2. Descriptive Statistics of Household Pln Electricity Data in the Initial and Final Years.

Year	Mean	Minimum	Maximum	Standard Deviation
2010	77.92	32.83	99.59	17.01
2025	97.60	84.16	100.00	3.44

Table 2 shows that the average percentage of households using PLN electricity increased from 77.92% in 2010 to 97.60% in 2025. The minimum value also increased from 32.83% to 84.16%. This increase in the minimum value is important because it indicates that even the provinces with the lowest levels of access experienced improvement during the observation period.

In addition, the standard deviation decreased from 17.01 in 2010 to 3.44 in 2025. This decline indicates that interprovincial variation became smaller. Thus, the historical data show not only an increase in the average level of PLN electricity access, but also a tendency toward more equal achievement across provinces.

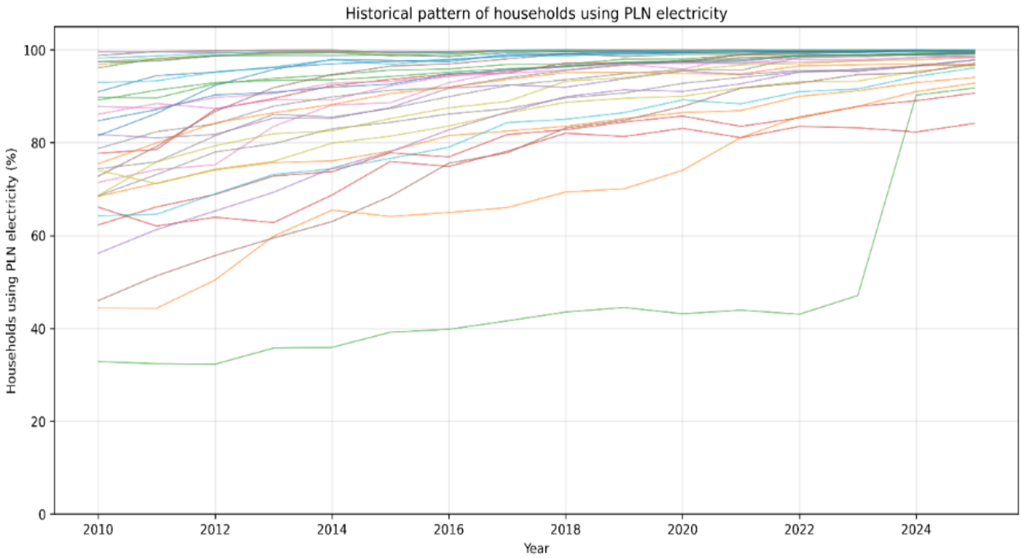
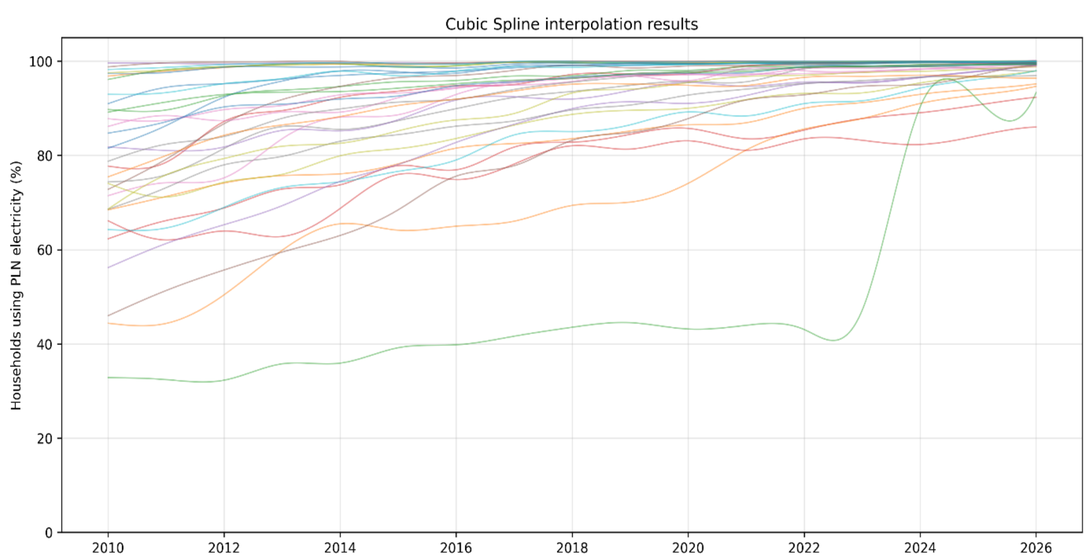


Figure 2. Historical Pattern of The Percentage of Households Using Pln Electricity.

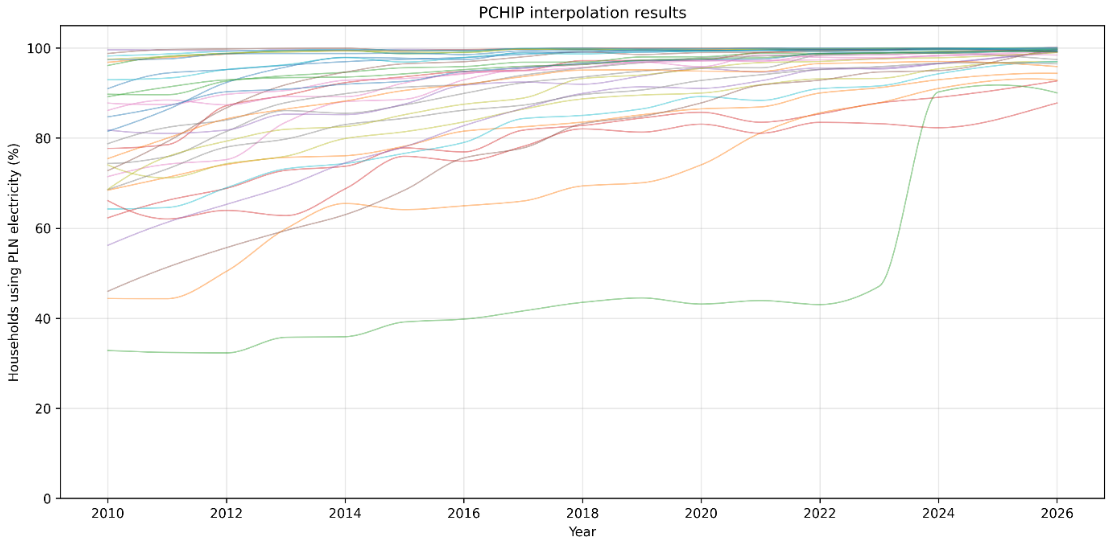
Figure 2 shows that most provinces experienced an increase in PLN electricity access during the 2010-2025 period. Provinces that already had high values at the beginning of the period tended to move steadily toward 100%. Meanwhile, several provinces with lower initial values showed larger increases, particularly toward the end of the observation period. This pattern explains why the mean value increased and the standard deviation decreased, as shown in Table 2.

3.3. Cubic Spline and PCHIP Interpolation Results

The results of the Cubic Spline and PCHIP function construction are presented in Figure 3.



(a) Cubic Spline Interpolation Results



(b) PCHIP Interpolation Results

Figure 3. Cubic Spline and Pchip Interpolation Results.

Figure 3(a) presents the interpolation results using Cubic Spline, while Figure 3(b) presents the interpolation results using PCHIP. In general, both methods are able to construct functions that follow the historical data pattern of each province. The main difference lies in the trajectory shape between data points. Cubic Spline forms a smoother trajectory because the function is constructed with first- and second-derivative continuity. In contrast, PCHIP forms a trajectory that is more strongly influenced by local changes between points.

For provinces with gradual increasing patterns, the results of the two methods appear close to each other. However, for provinces with sharp changes, the differences in curve shape become more visible. This indicates that the response of each method to the historical data structure differs across provinces. Therefore, the selection of the main trajectory method is not carried out generally for all provinces, but is determined based on the function values over the projection interval for each province.

3.4. Projection for 2026 and Chebyshev Norm

The 2026 projection results for all provinces are presented in Table 3 and Figure 4. The main projection is determined based on the method with the smaller Chebyshev norm value over the 2025-2026 interval.

Table 3. Projection For 2026 and Main Trajectory Method.

Province	CS 2026	PCHIP 2026	Norm CS	Norm PCHIP	Method	Main Projection
Gorontalo	100.17	100.23	100.17	100.23	Cubic Spline	100.17
Central Java	100.06	100.08	100.06	100.08	Cubic Spline	100.06
Bali	100.06	100.06	100.06	100.06	Comparable	100.06
West Java	100.02	100.06	100.02	100.06	Cubic Spline	100.02
DI Yogyakarta	100.00	100.00	100.00	100.00	PCHIP	100.00

East Java	99.93	99.96	99.93	99.96	Cubic Spline	99.93
Banten	99.81	99.79	99.81	99.80	PCHIP	99.79
DKI Jakarta	99.71	99.59	99.84	99.84	Comparable	99.65
North Sulawesi	99.89	99.65	99.89	99.78	PCHIP	99.65
South Kalimantan	99.59	99.69	99.59	99.69	Cubic Spline	99.59
Bangka Belitung Islands	99.54	99.32	99.60	99.60	Comparable	99.43
West Sumatra	99.37	99.45	99.37	99.45	Cubic Spline	99.37
West Nusa Tenggara	99.57	99.15	99.73	99.73	Comparable	99.36
Bengkulu	99.59	99.11	99.67	99.67	Comparable	99.35
West Sulawesi	99.21	99.68	99.21	99.68	Cubic Spline	99.21
North Sumatra	99.33	99.20	99.33	99.28	PCHIP	99.20
Aceh	99.25	99.13	99.49	99.49	Comparable	99.19
Riau	99.14	99.33	99.14	99.33	Cubic Spline	99.14
Lampung	99.43	99.13	99.43	99.32	PCHIP	99.13
Riau Islands	99.23	99.09	99.23	99.09	PCHIP	99.09
East Kalimantan	99.04	99.16	99.04	99.16	Cubic Spline	99.04
Southeast Sulawesi	98.81	98.98	98.81	98.98	Cubic Spline	98.81
South Sulawesi	98.83	98.43	98.83	98.56	PCHIP	98.43
Jambi	97.90	97.44	98.40	98.40	Comparable	97.67
North Maluku	97.97	96.97	97.97	96.97	PCHIP	96.97
Maluku	97.95	96.93	97.95	96.99	PCHIP	96.93
Central Sulawesi	96.94	96.47	96.94	96.77	PCHIP	96.47
South Sumatra	96.38	95.88	96.70	96.70	Comparable	96.13
West Kalimantan	95.17	94.37	95.17	94.40	PCHIP	94.37
East Nusa Tenggara	94.65	92.89	94.65	93.15	PCHIP	92.89
Central Kalimantan	92.34	92.70	92.34	92.70	Cubic Spline	92.34
Papua	93.32	90.03	93.32	91.78	PCHIP	90.03
West Papua	86.01	87.79	86.01	87.79	Cubic Spline	86.01

Based on Table 3, most provinces have main projected values for 2026 above 95%. The provinces with the highest projected values are Gorontalo, Central Java, Bali, West Java, DI Yogyakarta, and East Java. The values in this group are close to 100%, indicating numerically that the trajectory of PLN electricity access has reached a very high level. In contrast, the provinces with relatively lower main projections are West Papua, Papua, Central Kalimantan, East Nusa Tenggara, and West Kalimantan. West Papua has the lowest main projection at 86.01%, followed by Papua at 90.03%, Central Kalimantan at 92.34%, East Nusa Tenggara at 92.89%, and West Kalimantan at 94.37%. This group is important because it indicates that although most provinces have already reached high access levels, several provinces still have trajectories that have not approached the achievements of other provinces.

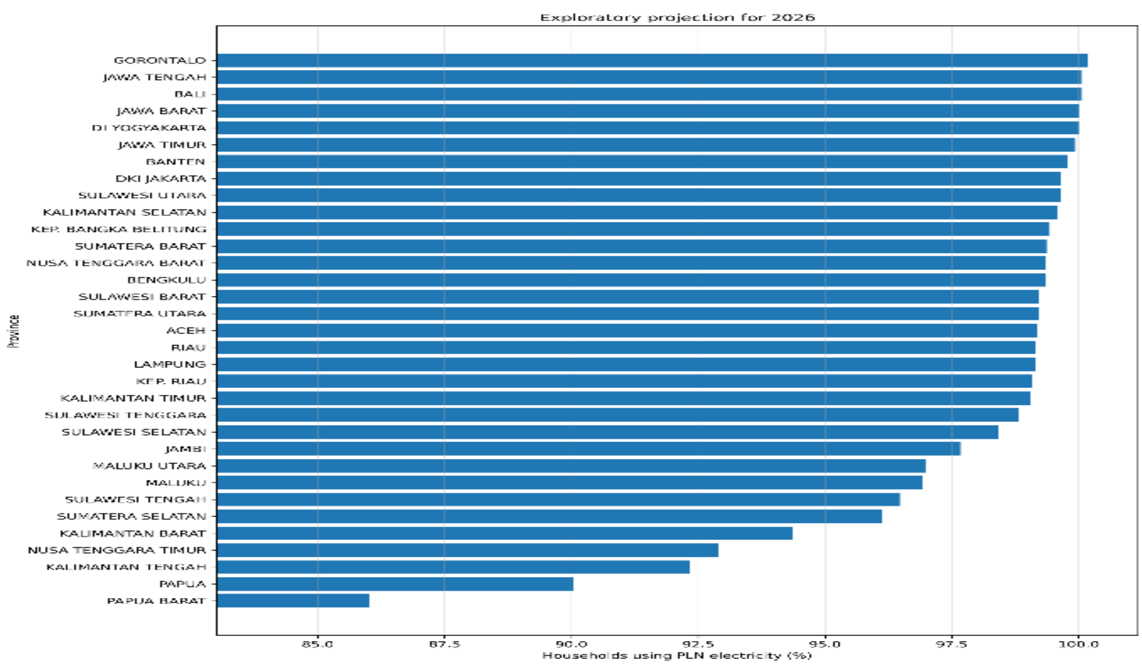


Figure 4. Exploratory Projection for 2026

Figure 4 clarifies the distribution of the main projected values for 2026 across provinces. The bars in the highest positions indicate provinces with achievements approaching full access, while the lower bars indicate provinces with relatively lower projected values. This visualization shows that interprovincial differences are still visible, although the gap between values has become smaller than at the beginning of the observation period. Projection values that slightly exceed 100% in several provinces are interpreted as computational results of the function over the projection interval. In the context of percentage variables, these values indicate that the function trajectory is already very close to the upper bound of household electricity access.

3.5. Trajectory Stability from 2025 to 2026

Trajectory stability from 2025 to 2026 is presented in Figure 5. This visualization focuses on provinces with relatively low main projections so that changes within this group can be observed more clearly.

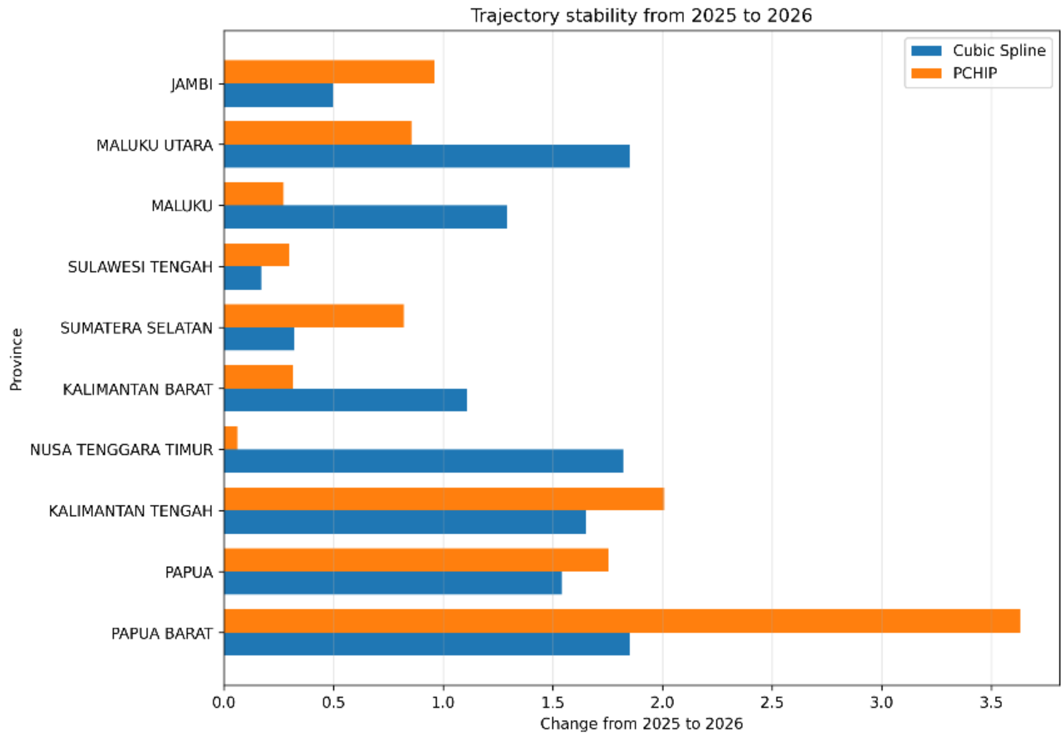


Figure 5. Trajectory Stability from 2025 to 2026

Figure 5 shows that the trajectory changes from 2025 to 2026 differ across provinces and methods. West Papua has a larger PCHIP change than Cubic Spline. This is consistent with the method selection result, as Cubic Spline becomes the main trajectory method for West Papua. In Papua, PCHIP produces the main trajectory because its Chebyshev norm value is smaller than that of Cubic Spline. East Nusa Tenggara and West Kalimantan show smaller changes under PCHIP than under Cubic Spline. Meanwhile, Central Kalimantan shows relatively close changes between the two methods, but Cubic Spline remains the main trajectory method because its Chebyshev norm value is smaller. Thus, trajectory stability helps describe the magnitude of functional change over the final interval, while the main method selection remains based on the Chebyshev norm.

3.6. Chebyshev Norm in Provinces with Relatively Low Projections

The Chebyshev norm over the 2025–2026 interval is used to compare the maximum function values of Cubic Spline and PCHIP in provinces with relatively low main projections. The comparison results are presented in Figure 6 and Table 4.

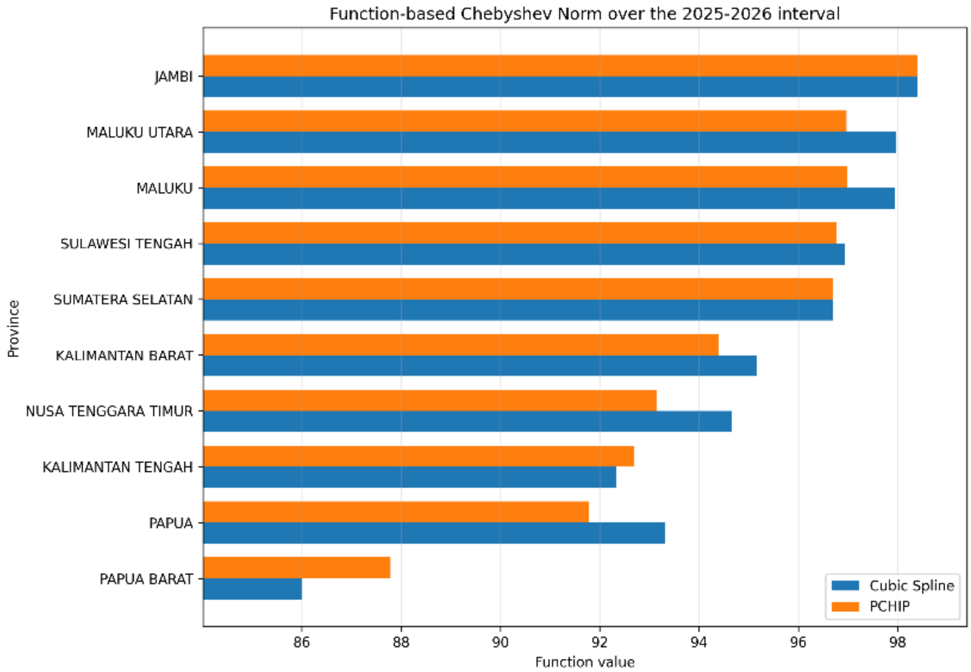


Figure 6. Function Based Chebyshev Norm Over the 2025-2026 Interval.

Figure 6 shows that the selection of the main trajectory method differs across provinces. In West Papua and Central Kalimantan, Cubic Spline produces a smaller Chebyshev norm than PCHIP, so it is selected as the main trajectory method. In contrast, in Papua, East Nusa Tenggara, West Kalimantan, Central Sulawesi, Maluku, and North Maluku, PCHIP produces a smaller Chebyshev norm. This indicates that PCHIP is more controlled in several provinces with stronger local changes.

Table 4. Chebyshev norm in provinces with relatively low projections.

Province	Norm CS	Norm PCHIP	Method	Main Projection
West Papua	86.01	87.79	Cubic Spline	86.01
Papua	93.32	91.78	PCHIP	90.03
Central Kalimantan	92.34	92.70	Cubic Spline	92.34
East Nusa Tenggara	94.65	93.15	PCHIP	92.89
West Kalimantan	95.17	94.40	PCHIP	94.37
South Sumatra	96.70	96.70	Comparable	96.13
Central Sulawesi	96.94	96.77	PCHIP	96.47
Maluku	97.95	96.99	PCHIP	96.93
North Maluku	97.97	96.97	PCHIP	96.97
Jambi	98.40	98.40	Comparable	97.67

Based on Table 4, West Papua has the lowest main projection, namely 86.01%, with Cubic Spline as the main method. Papua, East Nusa Tenggara, and West Kalimantan have main projections of 90.03%, 92.89%, and 94.37%, respectively, with PCHIP as the main method. Meanwhile, South Sumatra and Jambi are classified as comparable because the Chebyshev norm values of the two methods are equal.

Thus, these results show that provinces with relatively low projections do not always have the same best performing method, but depend on the function trajectory shape of each province.

3.7. Distribution of the Main Trajectory Method

The distribution of the main trajectory method based on the Chebyshev norm is presented in Table 5.

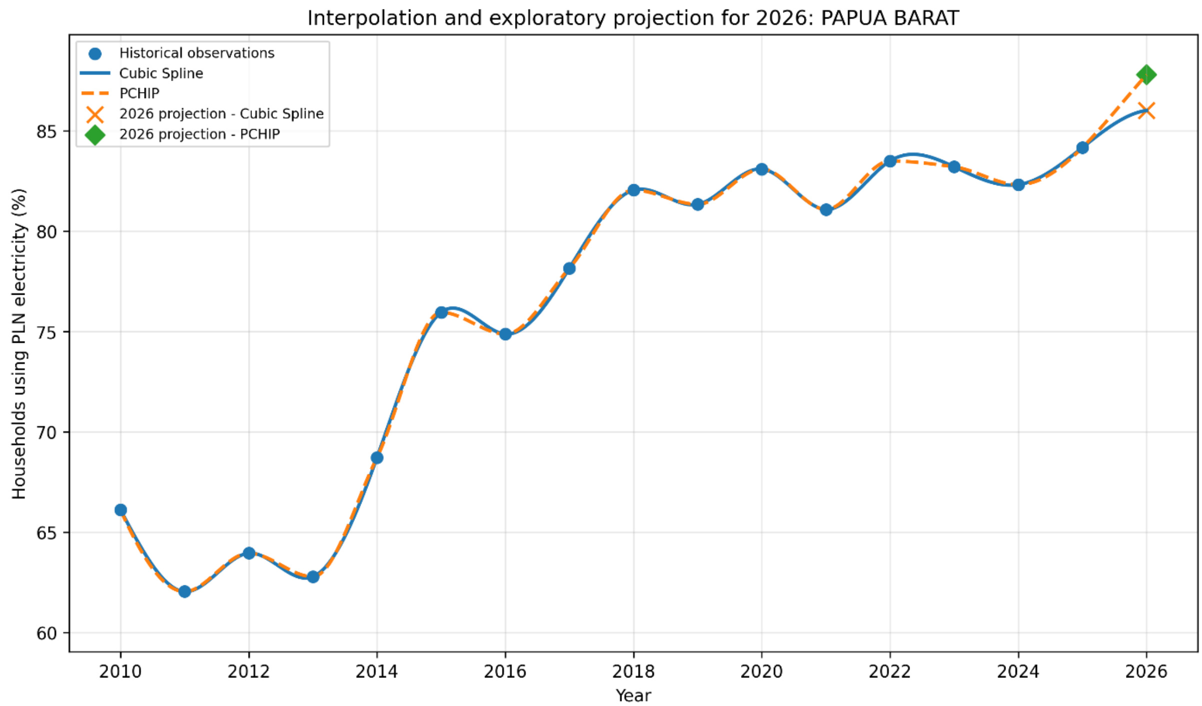
Table 5. Distribution of the Main Trajectory Method.

Method	Number of Provinces
PCHIP	13
Cubic Spline	12
Comparable	8

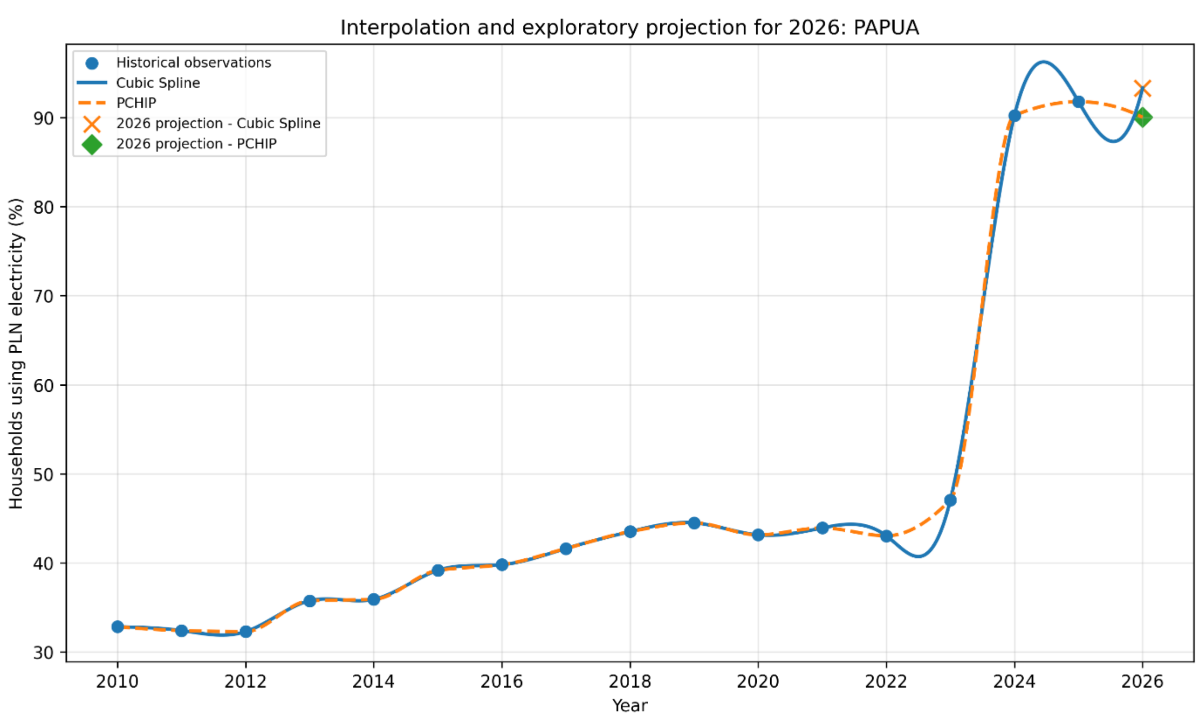
Based on Table 5, PCHIP becomes the main trajectory method in 13 provinces, Cubic Spline in 12 provinces, and 8 provinces are classified as comparable. The difference in number between PCHIP and Cubic Spline is relatively small, indicating that the results do not show absolute dominance of one method. Instead, the method selection is more strongly influenced by the historical data characteristics of each province. Cubic Spline is more suitable for provinces that produce smoother function trajectories and smaller maximum values, whereas PCHIP is more suitable for provinces with stronger local changes and trajectories that need to preserve the data shape.

Overall, this distribution confirms that both Cubic Spline and PCHIP are relevant for constructing projections of household PLN electricity access, but their application needs to be selected based on the behavior of the function in each province. The comparable category also indicates that in several provinces, the two methods produce very similar trajectories, so the difference between methods does not substantially change the projection results.

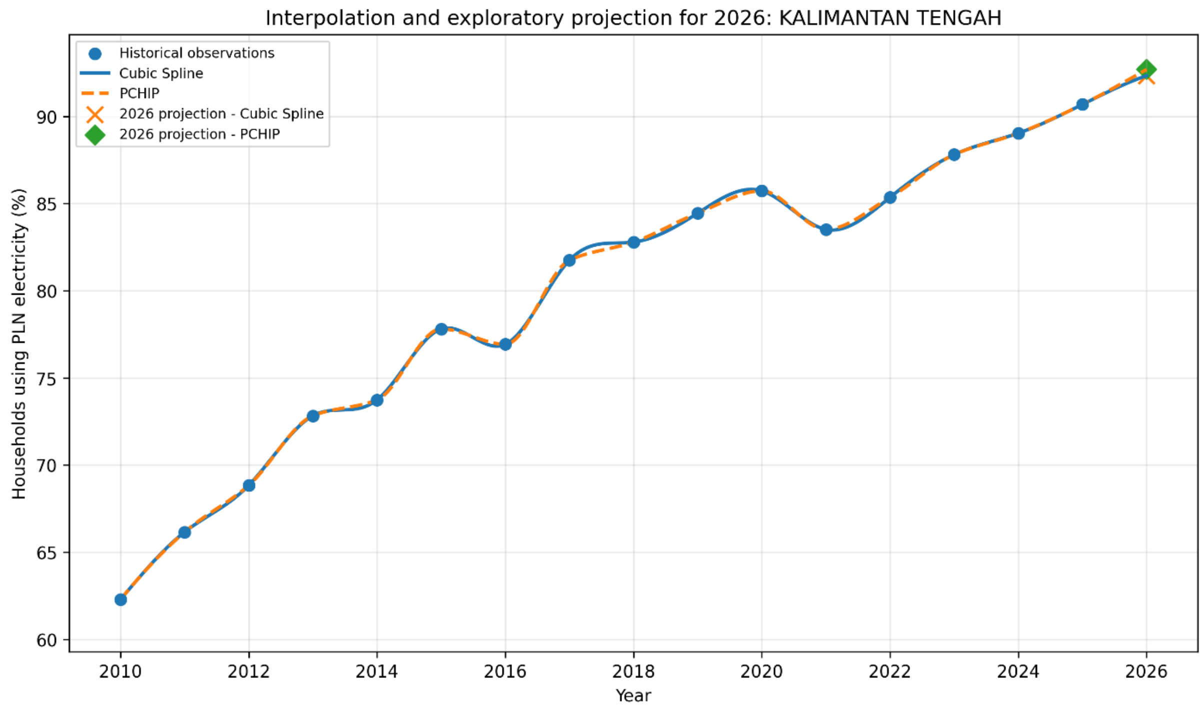
Several trajectories of provinces with relatively low projections are presented in Figure 8.



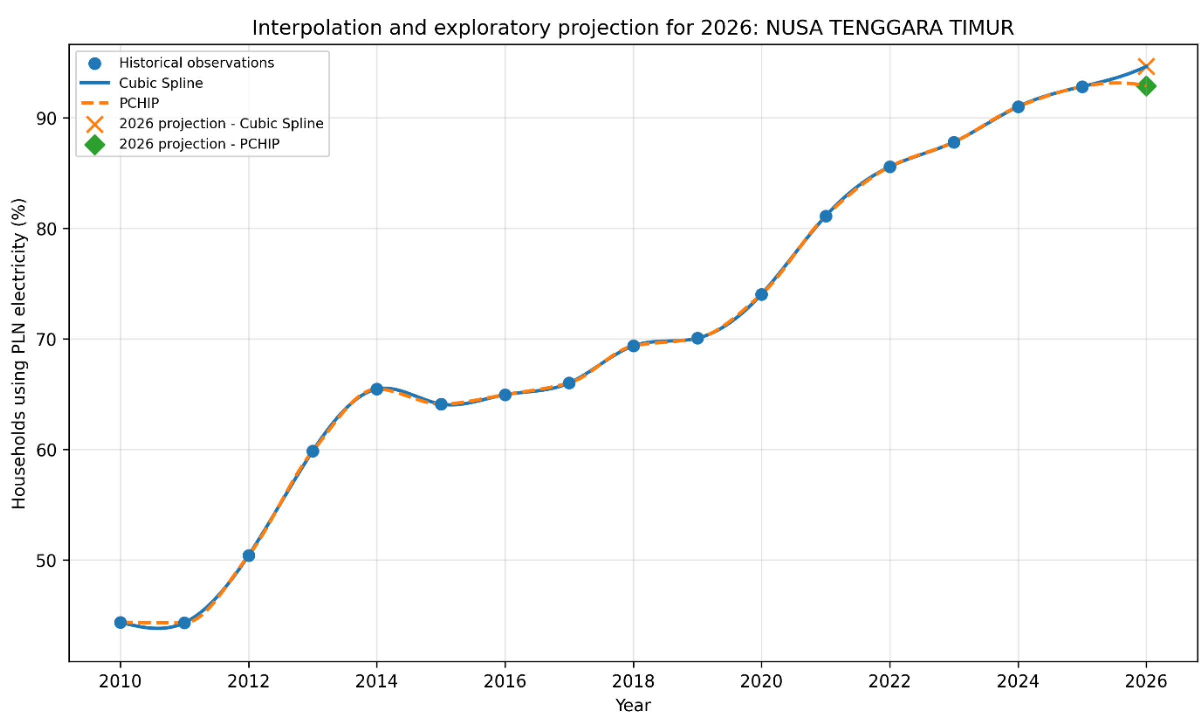
(a) West Papua



(b) Papua



(c) Central Kalimantan



(d) East Nusa Tenggara

Figure 8. Trajectories of Provinces With Relatively Low Projections.

Figure 8 shows that provinces with relatively low projections still have increasing trajectories toward 2026. West Papua has a main projection of 86.01% with Cubic Spline as the main trajectory method. Papua has a main projection of 90.03% with PCHIP as the main method. Central Kalimantan has a main projection of 92.34% with Cubic Spline. East Nusa Tenggara has a main projection of 92.89% with PCHIP, while West Kalimantan has a main projection of 94.37% with PCHIP.

This group of provinces shows that PLN electricity access continues to increase, but their positions remain lower than those of most other provinces. This is important because the projection results not only show provinces that have approached full access, but also identify regions that still require greater attention in achieving more equitable household electricity access.

4. CONCLUSION

This study compared Cubic Spline and PCHIP in constructing the trajectory of the percentage of households using PLN electricity by province in Indonesia based on historical data from 2010 to 2025. The results show that household PLN electricity access experienced a clear increase, as indicated by the rise in the mean value from 77.92% in 2010 to 97.60% in 2025, the increase in the minimum value from 32.83% to 84.16%, and the decrease in the standard deviation from 17.01 to 3.44. These findings address the research objective by showing that historical PLN electricity access data can be represented through interpolation approaches to examine development patterns and produce an exploratory projection for 2026. The projection results indicate that most provinces have reached a high level of access, whereas West Papua, Papua, Central Kalimantan, East Nusa Tenggara, and West Kalimantan remain in the group with relatively lower projected values.

Based on the Chebyshev norm evaluation over the 2025-2026 interval, PCHIP becomes the main trajectory method in 13 provinces, Cubic Spline in 12 provinces, and 8 provinces are classified as comparable. These results answer the research problem by showing that no single method is absolutely superior for all provinces because method selection is influenced by the historical pattern and trajectory characteristics of each region. Cubic Spline is more suitable for certain provinces where it produces smaller maximum function values, whereas PCHIP is more suitable for other provinces with stronger local changes. Thus, the use of the Chebyshev norm provides a clear comparative basis for determining the main trajectory and makes the projection results useful as an initial quantitative overview for examining the equity of household PLN electricity access across provinces in Indonesia. Future research can develop this study by comparing other numerical interpolation models, such as Akima interpolation, Makima interpolation, B spline, or smoothing spline, and by applying constrained interpolation so that projected percentage values remain within the realistic interval of 0% to 100%.

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