Available online www.worldscientificnews.com

World Scientific News

An International Scientific Journal

WSN 211 (2026) 23-38 EISSN 2392-2192

Approximation of the Relationship between Temperature and Energy Consumption Using the Least Squares Polynomial Method

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ABSTRACT

This research analyzes the relationship between average temperature and electricity consumption per capita in Indonesia using the Least Squares Polynomial Approximation (LSPA) and the Modified Chebyshev Polynomial method. Temperature and electricity consumption data from 2009-2022 were used to build approximation models of polynomial of orders 1, 2, and 3. Model performance was evaluated based on Root Mean Square Error (RMSE) and numerical stability through the condition number. The results show that the second-order LSPA model provides the lowest RMSE, but its condition number indicates ill-conditioning characteristics. To overcome this limitation, Modified Chebyshev Polynomials were applied. This transformation significantly reduced the condition number, producing well-conditioned systems for all polynomial orders. The second-order Modified Chebyshev model achieved the best performance with the lowest RMSE and stable numerical behavior. Overall, this study demonstrates that while LSPA can approximate the temperature-electricity consumption relationship, applying orthogonal polynomial bases such as Modified Chebyshev improves model stability and accuracy.

***Keywords*:** Average Temperature, Condition Number, Electrical Energy Consumption, Least Squares Polynomial Approximation, Modified Chebyshev Polynomial, Root Mean Square Error.

(Received 11 November 2025; Accepted 17 December 2025; Date of Publication 4 January 2026)

1. INTRODUCTION

Energy consumption is one of important parameters in economy and social well-being. The increase in average global temperatures is also suspected to contribute to social impacts, such as rising crime rates. Mares & Moffett found that monthly temperature anomalies higher than historical averages were positively correlated with increases in crime rates according to UCR data in the US [1]. Various factors influence energy consumption, one of which is the change in environmental temperature. When the temperatures rise, the use of cooling devices such as fans and air conditioners (AC) also increases to maintain a comfortable body temperature. Same thing applies when temperatures drop, where heating energy consumption also increases. Although temperature variations are not significant in tropical regions such as in Indonesia, this still impacts daily electricity use, particularly for thermal comfort and the use of cooling devices.

The relationship between temperature and energy consumption has been an important topic in various previous studies. A previous study in China found that residential electricity consumption increases sharply on hot days, indicating a clear temperature-dependency of household energy demand [2]. Quayle and Diaz used the concept of Heating Degree Days as a way to calculate heating energy requirements based on daily temperatures [3]. Furthermore, Sailor and Pavlova considered air conditioning ownership and projected climate change to examine the effect of temperature on household cooling energy demand [4]. These studies demonstrated that temperature variations influence the energy demand for room temperature regulation. Other research by Auffhammer et al. found regional variations in the temperature–electricity relationship in the US, while Zhang et al. reported significant differences between northern and southern China in terms of how electricity consumption responds to temperature [5],[6].

A recent study by Liu et al. used Weighted Least Squares (WLS) to examine the effect of temperature changes on electricity consumption among a group of university students in a dormitory in China [7]. In the study, temperature was divided into several categories (bins) to observe the daily impact of temperature on electricity consumption. The results showed that when the temperature exceeded 26°C, electricity consumption increased significantly. Although Liu et al.'s method was quite accurate in identifying the effect of temperature in discrete categories using WLS, the model does not describe the relationship between temperature and energy consumption continuously [7]. Furthermore, the study focused more on user behavior in a limited context which is university students in dormitories, so the results do not fully describe energy consumption in general, especially in tropical regions like Indonesia.

To overcome these limitations, this study proposes the use of the Least Square Polynomial Approximation (LSPA) method in modeling the relationship between temperature and energy consumption continuously. This method allows the formation of a polynomial function that minimizes the squared error between observation data and model results, so that providing a more flexible and accurate approach than a simple linear model. When using the Least Squares Polynomial Approximation, problems with large condition numbers are sometimes encountered. Therefore, a more stable approach is needed using Modified Chebyshev Polynomials, which have orthogonal properties. Through this approach, the research is expected to determine the relationship between environmental temperature and electricity consumption in tropical areas and illustrate how well the Least Square Polynomial Approximation and Modified Chebyshev Polynomials method is applied. Moreover, this study will also compare polynomial models with different orders, especially orders 1, 2, and 3 to obtain the most appropriate approach in describing the relationship between temperature and electricity consumption in Indonesia.

2. MATERIAL AND METHODS

2.1. Data

The data used in this study consists of two main types, namely electricity consumption per capita in Indonesia and the average environmental temperature of Indonesia per year. Data about electricity consumption per capita in Indonesia was obtained from the official website of BPS-Statistics Indonesia, which provides the value of electricity consumption per capita from 2009 to 2022. Meanwhile, data about average annual temperature of Indonesia was obtained from the Trading Economics portal, which provides average annual temperature from 1901 to 2024. In this research, the temperature data used will be adjusted to the time range of the electricity consumption data. Both types of data are visualized in graphical form, where Figure 1 shows the trend of electricity consumption in Indonesia from 2009-2022 and Figure 2 shows the trend of average temperature in Indonesia from 2009-2022.

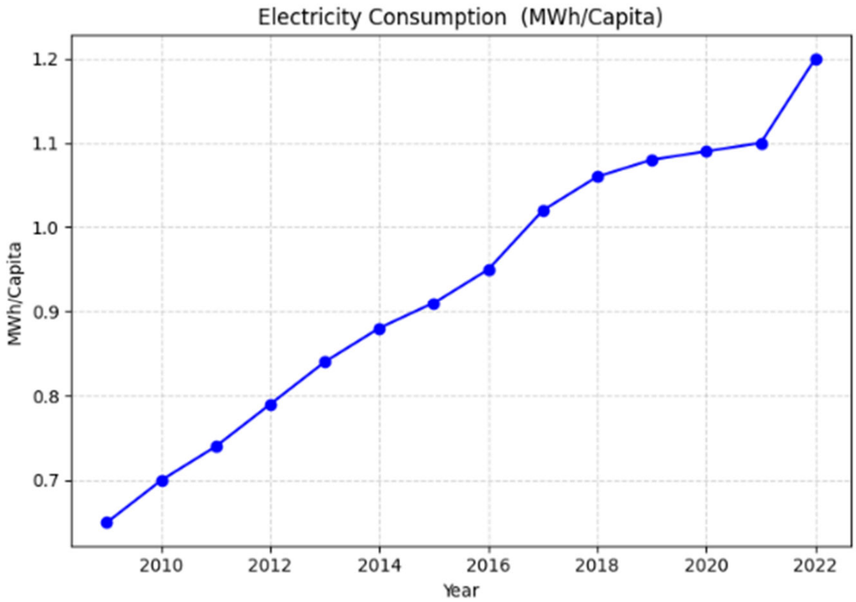

Figure 1. Electricity Consumption in Indonesia from 2009 to 2022.

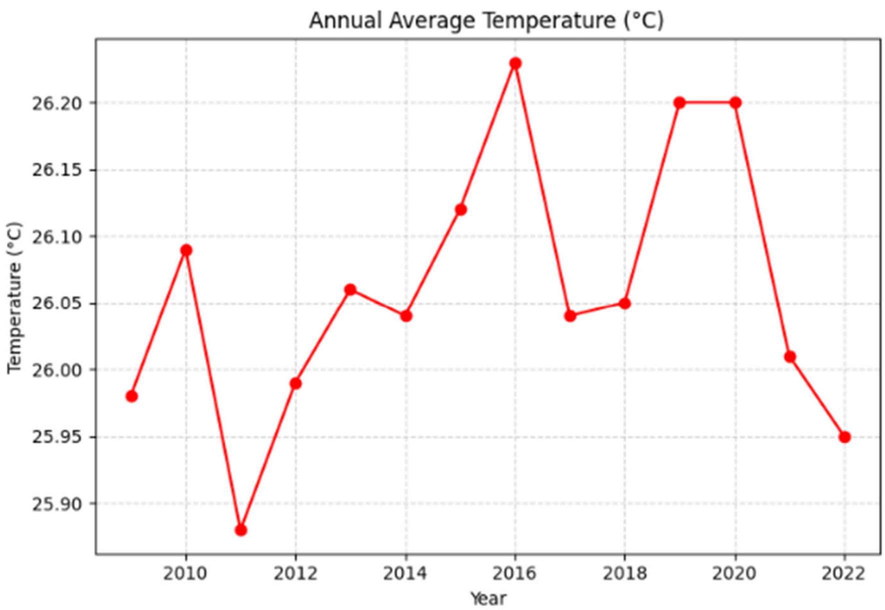

Figure 2. Average Temperature in Indonesia from 2009 to 2022.

2.2. Least Squares Polynomial Approximation (LSPA)

Before introducing LSPA, the procedure for using the y data is explained as follows:

$$y = ae^{\alpha_2\varphi_1(x)+\alpha_3\varphi_2(x)+\cdots+\alpha_n\varphi_m(x)}$$

$$\ln y = \ln a + \alpha_2\varphi_1(x) + \alpha_3\varphi_2(x) + \cdots + \alpha_n\varphi_m(x)$$

$$f(x) = \alpha_1 + \alpha_2\varphi_1(x) + \alpha_3\varphi_2(x) + \cdots + \alpha_n\varphi_m(x)$$

$$n = 2, 3, \ldots, n \qquad m = 1, 2, \ldots, m$$

Atkinson explains that LSPA method used to determine a polynomial degree n that approximate the continuous function $f(x)$ on the interval $[\alpha, \beta]$ [8]. The general form of the polynomial is written as

$$\hat{f}(x) = \alpha_1 + \alpha_2 x + \alpha_3 x^2 + \cdots + \alpha_m x^{m-1} \qquad (1)$$

To measure how well the polynomial $\hat{f}(x)$ approximates the function $f(x)$, a total error function is defined by

$$G(\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_m) = \sum_{j=1}^{n}\left[(\alpha_1 + \alpha_2 x_j + \alpha_3 x_j^2 + \cdots + \alpha_m x_j^{m-1}) - y_j\right]^2 \qquad (2)$$

To determine $\alpha_1, \alpha_2, \ldots, \alpha_m$ that minimize the total error function with optimum conditions are given by

$$\frac{\partial G}{\partial \alpha_i} = 0, \quad i = 1,2, \ldots, m$$

was obtained a system of linear equations to determine the coefficients $\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_m$ as follows

$$2\sum_{j=1}^{n}\left[\left(\sum_{k=0}^{m}\alpha_k x_j^k\right) - y_j\right] x_j^i = 0$$

$$\sum_{k=0}^{m}\alpha_k\left(\sum_{j=1}^{n}x_j^{i+k}\right) = \sum_{j=1}^{n}y_j x_j^i$$

$$\sum_{k=0}^{m}\left(\sum_{j=1}^{n}x_j^{i+k}\right)\alpha_k = \sum_{j=1}^{n}y_j x_j^i, \quad i = 0,1,2,3, \ldots, m \qquad (3)$$

2.3. Root Mean Square Error (RMSE)

Root mean square error (RMSE) is a measure used to assess the difference between the values predicted by a model and the values actually observed [9]. The smaller the RMSE value, the better the model's performance [10]. RMSE always has a positive value and should be zero to obtain a perfect estimate [11]. Atkinson's RMSE formula is as follows [8]

$$E = \sqrt{\frac{1}{n}\Sigma\,[\hat{f}(x_j) - y_j]^2}$$

With:

E	: Root Mean Square Error (RMSE)
n	: Total number of observation data
$\hat{f}(x_j)$	: The value of the j-th prediction model result
y_j	: Actual value of the j-th data

2.4. Condition Number

Atkinson explains that the concept of condition number is used to measure the level sensitivity of the solution of a linear system to its error, which is defined as follows [8]

$$La = b$$

with

$$L = \begin{pmatrix} 1 & x_1 & x_1^2 & \cdots & x_1^i \\ 1 & x_2 & x_2^2 & \cdots & x_2^m \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_j & x_j^2 & \cdots & x_j^m \end{pmatrix}, \quad a = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_m \end{pmatrix}, \quad b = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_j \end{pmatrix}$$

Condition number defined by Atkinson as [8]

$$cond(L) = \|L\|\|L^{-1}\|$$

The condition number indicates whether a system is ill-conditioned or well-conditioned. More specifically, the condition number provides a bound on the relative error in the solution when there are small disturbances in the input data [12]. The condition number constraint guarantees the numerical stability and positive definiteness of the approximation form simultaneously [13].

2.5. Modified Chebyshev Polynomial

Atkinson explains that to obtain a well-conditioned system, it is necessary to choose a basis function $\{\varphi_1(x), \varphi_2(x), \ldots, \varphi_m(x)\}$ which must be independent and ideally orthogonal to the discrete product defined by the point $\{x_j\}$ [8]. Another approach often used for low-pass functions with all poles is Chebyshev, which was initially used in the study of steam engines by the Russian P. L. Chebyshev in 1899 [14]. Chebyshev polynomials with orthogonality constraints have developed into a highly effective approach for numerical analysis [15]. In addition to orthogonal functions, Chebyshev also studied the concepts of inequalities, prime numbers, probability theory, quadratic forms, integral theory, geographical maps, formulas for geometrical volumes, and mechanics, as well as problems in converting circular motion into linear motion using mechanical couplings [16]. Let the functions $f(x)$ that are represent by Atkinson given by [8]

$$f(x) = \alpha_1\varphi_1(x) + \alpha_2\varphi_2(x) + \cdots + \alpha_m\varphi_m(x) \qquad (4)$$

To measure how well the polynomial $\hat{f}(x)$ approximates the function $f(x)$, a total error function is defined by

$$G(\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_m) = \sum_{j=1}^{n} \left[(\alpha_1\varphi_1(x_j) + \alpha_2\varphi_2(x_j) + \cdots + \alpha_m\varphi_m(x_j)) - y_j\right]^2 \qquad (5)$$

To determine $\alpha_1, \alpha_2, \ldots, \alpha_m$that minimize the total error function with optimum conditions are given by

$$\frac{\partial G}{\partial \alpha_i} = 0, \;\; i = 1,2, \ldots, m$$

The coefficients $\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_m$ determined by the linear system

$$\sum_{k=1}^{m} \alpha_k \left[\sum_{j=1}^{n} \varphi_k(x_j)\varphi_i(x_j)\right] = \sum_{j=1}^{n} y_j\varphi_i(x_j) \qquad (6)$$

Modified Chebyshev polynomials on the interval $[\alpha, \beta]$ with the general formula written by Atkinson as follows [8]

$$\varphi_k(x) = T_{k-1}\left(\frac{2x - \alpha - \beta}{\beta - \alpha}\right)$$

3. RESULT AND DISCUSSION

3.1. Data Overview

Table 1. Electricity Consumption and Average Temperature Period 2009-2022 in Indonesia.

Year	Electricity Consumption per Capita (MWH/capita)	Average Temperature (°C)
2009	0.65	25.98
2010	0.70	26.09
2011	0.74	25.88
2012	0.79	25.99
2013	0.84	26.06
2014	0.88	26.04
2015	0.91	26.12
2016	0.95	26.23
2017	1.02	26.04
2018	1.06	26.05
2019	1.08	26.20
2020	1.09	26.20
2021	1.10	26.01
2022	1.20	25.95

Table 1 shows the development of electricity consumption and temperature conditions in Indonesia over the past 14 years, from 2009 to 2022. In general, electricity consumption per capita shows an increasing trend from 0.65 MWh/capita in 2009 to 1.20 MWh/capita in 2022. Meanwhile, the average annual temperature is relatively stable, with a range of $25.88°\text{C} - 26.23°\text{C}$, which reflects the character of Indonesia's tropical climate.

3.2. Least Squares Polynomial Approximation Results of Order 1, 2, and 3

Based on the method explained in section 2.2, the system of equations from the LSPA for polynomials of orders 1, 2, and 3 as follows:

a. First-Order LSPA

Based on (1), a polynomial model of order 1 has general form

$$\hat{f}(x) = \alpha_1 + \alpha_2 x \qquad (7)$$

Thus, from (3) a system of equations is obtained.

$$n\alpha_1 + \left(\sum x_j\right)\alpha_2 = \sum y_j$$

$$\left(\sum x_j\right)\alpha_1 + \left(\sum x_j^2\right)\alpha_2 = \sum x_j y_j$$

Based on Table 1, the system of equations becomes

$$14\alpha_1 + 364.84\alpha_2 = 13.01$$

$$364.84\alpha_1 + 9{,}507.86\alpha_2 = 339.11$$

By using Python, obtained α_1 and α_2 coefficients as follows:

$$\alpha_1 = -13.025683; \quad \alpha_2 = 0.535494$$

Substitute the α_1 and α_2 into (7) so the equation model obtained is

$$\hat{f}(x_i) = -13.025683 + 0.535494x$$

b. Second-Order LSPA

Based on (1), a polynomial model of order 2 has general form

$$\hat{f}(x) = \alpha_1 + \alpha_2 x + \alpha_3 x^2 \quad (8)$$

Thus, from (3) a system of equation is obtained.

$$n\alpha_1 + \left(\sum x_j\right)\alpha_2 + \left(\sum x_j^2\right)\alpha_3 = \sum y_j$$
$$\left(\sum x_j\right)\alpha_1 + \left(\sum x_j^2\right)\alpha_2 + \left(\sum x_j^3\right)\alpha_3 = \sum x_j y_j$$
$$\left(\sum x_j^2\right)\alpha_1 + \left(\sum x_j^3\right)\alpha_2 + \left(\sum x_j^4\right)\alpha_3 = \sum x_j^2 y_j$$

Based on Table 1, the system of equations becomes

$$14\alpha_1 + 364.84\alpha_2 + 9{,}507.86\alpha_3 = 13.01$$
$$364.84\alpha_1 + 9{,}507.86\alpha_2 + 247{,}781.76\alpha_3 = 339.11$$
$$9{,}507.86\alpha_1 + 247{,}781.76\alpha_2 + 6{,}457{,}461.41\alpha_3 = 8{,}838.90$$

By using Python, obtained α_1, α_2, and α_3 coefficients as follows:

$$\alpha_1 = 12.732761; \quad \alpha_2 = -1.393053; \quad \alpha_3 = 0.036075$$

Substitute the α_1, α_2, and α_3 into (8) so the equation model obtained

$$\hat{f}(x_i) = 12.732761 - 1.393053x + 0.036075x^2$$

c. Third-Order LSPA

Based on (1), a polynomial model of order 3 has general form

$$\hat{f}(x) = \alpha_1 + \alpha_2 x + \alpha_3 x^2 + \alpha_4 x^3 \qquad (9)$$

Thus, from (3) a system of equations is obtained.

$$n\alpha_1 + \left(\sum x_j\right)\alpha_2 + \left(\sum x_j^2\right)\alpha_3 + \left(\sum x_j^3\right)\alpha_4 = \sum y_j$$

$$\left(\sum x_j\right)\alpha_1 + \left(\sum x_j^2\right)\alpha_2 + \left(\sum x_j^3\right)\alpha_3 + \left(\sum x_j^4\right)\alpha_4 = \sum x_j y_j$$

$$\left(\sum x_j^2\right)\alpha_1 + \left(\sum x_j^3\right)\alpha_2 + \left(\sum x_j^4\right)\alpha_3 + \left(\sum x_j^5\right)\alpha_4 = \sum x_j^2 y_j$$

$$\left(\sum x_j^3\right)\alpha_1 + \left(\sum x_j^4\right)\alpha_2 + \left(\sum x_j^5\right)\alpha_3 + \left(\sum x_j^6\right)\alpha_4 = \sum x_j^3 y_j$$

Based on Table 1, the system of equations becomes

$$14\alpha_1 + 364.84\alpha_2 + 9{,}507.86\alpha_3 + 247{,}781.76\,\alpha_4 = 13.01$$

$$364.84\alpha_1 + 9{,}507.86\alpha_2 + 247{,}781.76\alpha_3 + 6{,}457{,}461.41\,\alpha_4 = 339{,}11$$

$$9{,}507.86\alpha_1 + 247{,}781.76\alpha_2 + 6{,}457{,}461.41\alpha_3 + 168{,}290{,}785.13\,\alpha_4 = 8{,}838.90$$

$$247{,}781.76\alpha_1 + 6{,}457{,}461.41\alpha_2 + 168{,}290{,}785.13\alpha_3 + 4{,}385{,}963{,}256.29\,\alpha_4 = 230{,}392.20$$

By using Python, obtained $\alpha_1, \alpha_2, \alpha_3$, and $\alpha_4$coefficients as follows

$$\alpha_1 = 11.243291; \quad \alpha_2 = -1.365160; \quad \alpha_3 = 0.040565; \quad \alpha_4 = -0.000129$$

Substitute the $\alpha_1, \alpha_2, \alpha_3$, and α_4 into (9) so the equation model obtained

$$\hat{f}(x_i) = 11.243291 - 1.365160x + 0.040565x^2 - 0.000129x^3$$

3.3. Least Squares Polynomial Approximation Analysis

The first, second, and third-order Least Squares Polynomial Approximation models were analyzed to determine the accuracy of the model in approximating the data and the numerical stability for each polynomial order. The analysis was accomplished by using two methods: that is, Root Mean Square Error (RMSE) to evaluate the level of accuracy of approximation results and condition number to evaluate the numerical stability of the model.

Table 2. Comparison of LSPA Results Based on RMSE and Condition Number.

Polynomial Order	RMSE	Cond(L)
1	1.616647	49,970,135.694
2	1.616080	330,124,372,991.976
3	1.625162	15,281,745,855,404.016

Based on Table 2, RMSE values from the three models show relatively small differences. The lowest RMSE value was obtained using the second-order polynomial model. Meanwhile, the condition number values of the three polynomial orders in Table 2 are large, indicating that the model is ill-conditioned. Therefore, the second-order polynomial model is considered the most balanced model because it provides high accuracy with an acceptable level of numerical stability. Thus, the second-order polynomial model is the best representation to describe the relationship between average temperature and per capita electricity consumption in Indonesia.

3.4. Modified Chebyshev Polynomial Results

In section Least Squares Polynomial Approximation Analysis, the condition number was obtained with a large value indicating ill-conditioned characteristics. To improve the stability of the Least Square Polynomial Approximation, improvements were made using the Modified Chebyshev Polynomial. Based on Table 3.1.1, the average minimum temperature (x_{min}) was obtained as 25.88 and the average maximum temperature (x_{max}) was obtained as 26.23 so that for interval $[\alpha, \beta] = [25.88, 26.23]$ obtained

$$\varphi_k(x) = T_{k-1}\left(\frac{2x - 52.11}{0.35}\right)$$

$$\varphi_1(x) = T_0\left(\frac{2x-52.11}{0.35}\right) = 1$$

$$\varphi_2(x) = T_1\left(\frac{2x-52.11}{0.35}\right) = \left(\frac{2x-52.11}{0.35}\right)$$

$$\varphi_3(x) = T_2\left(\frac{2x-52.11}{0.35}\right) = 2\left(\frac{2x-52.11}{0.35}\right)^2 - 1$$

$$\varphi_4(x) = T_3\left(\frac{2x-52.11}{0.35}\right) = 4\left(\frac{2x-52.11}{0.35}\right)^3 - 3\left(\frac{2x-52.11}{0.35}\right)$$

Thus, the Chebyshev transformation obtained is shown in the following Table 3

Table 3. Chebyshev Transformation Data.

Year	Electricity Consumption per Capita (MWH/Capita)	φ_1	φ_2	φ_3	φ_4
2009	0.65	1	-0.429	-0633	0.971
2010	0.70	1	0.200	-0.920	-0.568
2011	0.74	1	-1.000	1.000	-1.000
2012	0.79	1	-0.371	-0.724	0.909
2013	0.84	1	0.029	-0.998	-0.086
2014	0.88	1	-0.086	-0.985	0.255
2015	0.91	1	0.371	-0.724	-0.909
2016	0.95	1	1.000	1.000	1.000

2017	1.02	1	-0.086	-0.985	0.255
2018	1.06	1	-0.029	-0.998	0.086
2019	1.08	1	0.829	0.373	-0.210
2020	1.09	1	0.829	0.373	-0.210
2021	1.10	1	-0.257	-0.868	0.703
2022	1.20	1	-0.600	-0.280	0.936

a. *Modified Chebyshev Polynomial* Order 1

Based on (4), a Chebyshev polynomial model of order 1 has general form

$$f(x) = \alpha_1\varphi_1(x) + \alpha_2\varphi_2(x) \qquad (10)$$

Based on (6), a system of equations is obtained

$$n\alpha_1 + \alpha_2 \sum \varphi_2(x) = \sum y_j$$

$$\alpha_1 \sum \varphi_2(x) + \alpha_2 \sum \varphi_2(x)^2 = \sum y_j\varphi_2(x)$$

So that, the system of equations becomes

$$14\alpha_1 + 0.4\alpha_2 = 13.01$$

$$0.4\alpha_1 + 4.315\alpha_2 = 0.742$$

By using Python, obtain α_1 and α_2 coefficients as follows

$$\alpha_1 = 0.926827; \quad \alpha_2 = 0.086041$$

Based on *Chebyshev Polynomial* order one, the equation model obtained

$$f(x) = 0.926827 + 0.086041x$$

b. *Modified Chebyshev Polynomial* Order 2

Based on (4), a Chebyshev polynomial model of order 1 has general form

$$f(x) = \alpha_1\varphi_1(x) + \alpha_2\varphi_2(x) + \alpha_3\varphi_3(x) \qquad (11)$$

Based on (6), a system of equations is obtained

$$n\alpha_1 + \alpha_2 \sum \varphi_2(x) + \alpha_3 \sum \varphi_3(x) = \sum y_j$$

$$\alpha_1 \sum \varphi_2(x) + \alpha_2 \sum \varphi_2(x)^2 + \alpha_3 \sum \varphi_2(x)\varphi_3(x) = \sum y_j\varphi_2(x)$$

$$\alpha_1 \sum \varphi_3(x) + \alpha_2 \sum \varphi_2(x)\varphi_3(x) + \alpha_3 \sum \varphi_3(x)^2 = \sum y_j\varphi_3(x)$$

So that, the system of equations becomes

$$14\alpha_1 + 0.4\alpha_2 - 5.370\alpha_3 = 13.01$$
$$0.4 + 4.315\alpha_2 + 1.265\alpha_3 = 0.742$$
$$-5.370\alpha_1 + 1.265\alpha_2 + 9.340\alpha_3 = -4.846$$

By using Python, obtained α_1, α_2, and α_3 coefficients as follows:

$$\alpha_1 = 0.928109; \quad \alpha_2 = 0.084966; \quad \alpha_3 = 0.003262$$

Based on *Chebyshev Polynomial* of order two, the equation model obtained:

$$f(x) = 0.928109 - 0.084966x + 0.003262x^2$$

c. *Modified Chebyshev Polynomial Order 3*

Based on (4), a Chebyshev polynomial model of order 1 has general form

$$f(x) = \alpha_1\varphi_1(x) + \alpha_2\varphi_2(x) + \alpha_3\varphi_3(x) + \alpha_4\varphi_4(x) \qquad (12)$$

Based on (6), a system of equations is obtained

$$n\alpha_1 + \alpha_2\sum\varphi_2(x) + \alpha_3\sum\varphi_3(x) + \alpha_4\sum\varphi_4(x) = \sum y_j$$
$$\alpha_1\sum\varphi_2(x) + \alpha_2\sum\varphi_2(x)^2 + \alpha_3\sum\varphi_2(x)\varphi_3(x) + \alpha_4\sum\varphi_2(x)\varphi_4(x) = \sum y_j\varphi_2(x)$$
$$\alpha_1\sum\varphi_3(x) + \alpha_2\sum\varphi_2(x)\varphi_3(x) + \alpha_3\sum\varphi_3(x)^2 + \alpha_4\sum\varphi_3(x)\varphi_4(x) = \sum y_j\varphi_3(x)$$
$$\alpha_1\sum\varphi_4(x) + \alpha_2\sum\varphi_2(x)\varphi_4(x) + \alpha_3\sum\varphi_3(x)\varphi_4(x) + \alpha_4\sum\varphi_4(x)^2 = \sum y_j\varphi_4(x)$$

So that, the system of equations becomes

$$14\alpha_1 + 0.4\alpha_2 - 5.370\alpha_3 + 2.131\alpha_4 = 13.01$$
$$0.4\alpha_1 + 4.315\alpha_2 + 1.265\alpha_3 - 0.345\alpha_4 = 0.742$$
$$-5.370\alpha_1 + 1.265\alpha_2 + 9.340\alpha_3 - 1.623\,\alpha_4 = -4.846$$
$$2.131\alpha_1 - 0.345\alpha_2 - 1.623\alpha_3 + 6.523\alpha_4 = 2.277$$

By using Python, obtained $\alpha_1, \alpha_2, \alpha_3$, and α_4 coefficients as follows:

$$\alpha_1 = 0.921747; \quad \alpha_2 = 0.088352; \quad \alpha_3 = 0.008663; \quad \alpha_4 = 0.054775$$

Based on Chebyshev Polynomial of order three, the equation model obtained is:

$$f(x) = 0.921747 + 0.088352x + 0.008663x^2 + 0.054775x^3$$

3.5. Modified Chebyshev Polynomial Analysis

The first, second, and third-order of Modified Chebyshev Polynomial models were analyzed to determine the accuracy of the model in approximating the data and the numerical stability for each polynomial order. The analysis was accomplished by using two methods, that is Root Mean Square Error (RMSE) to evaluate the level of accuracy of approximation results and condition number to evaluate the numerical stability of the model.

Table 4. Comparison of Modified Chebyshev Polynomial Results Based on RMSE and Condition Number.

Order	RMSE	Cond(L)
1	22.857584	7.009712
2	1.611161	4.336898
3	∞	3.566448

Based on Table 4, the RMSE values of the three models show quite a difference, especially at order 1 where the RMSE value is large, indicating a very poor fit. However, at order 2, the RMSE value is very small, indicating it fits the data best in terms of error. In contrast to the condition number results in the least square polynomial approximation, the condition number values of the three orders of the modified Chebyshev polynomial in Table 3 are small, indicating that the model is well-conditioned, meaning that small changes in the data only result in small changes in the solution. Therefore, the second-order polynomial model is considered the most optimal model because it provides the lowest error rate and does not cause ill-conditioned problems. Thus, the second-order polynomial model is the best representation to describe the relationship between average temperature and electricity consumption per capita in Indonesia.

3.6. Visualization

To facilitate the interpretation of the results, data visualization was performed with the relationship between average temperature (x) and electricity consumption per capita (y) based on the results of the first, second, and third order Least Squares Polynomial Approximation (LSPA) models.

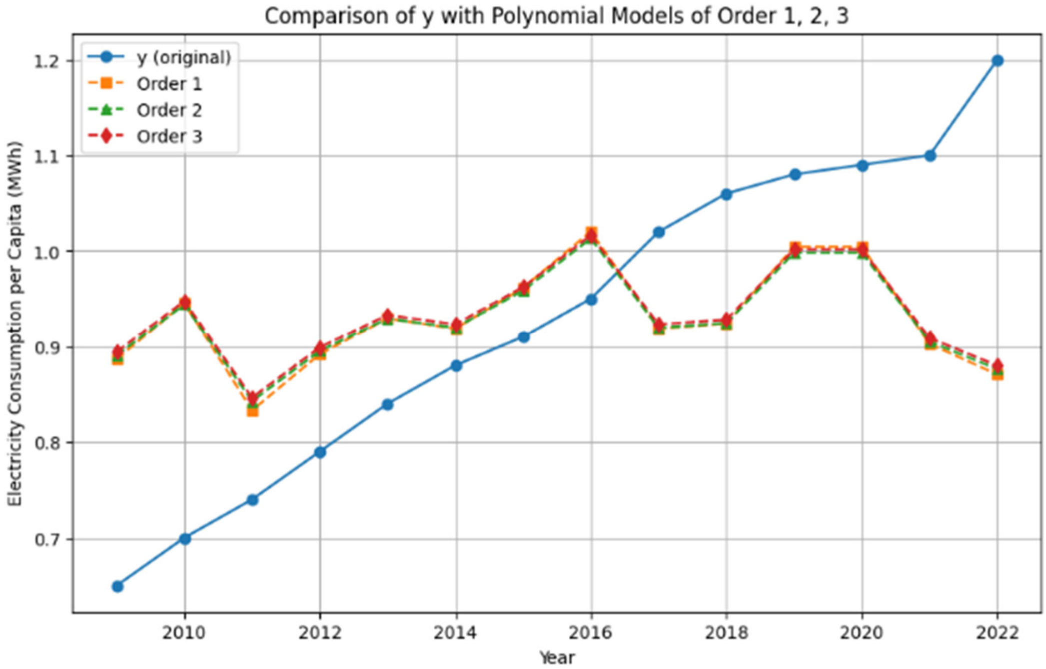

Figure 3. Results of LSPA order 1,2, and 3.

Figure 3 shows a comparison between actual electricity consumption data and the estimated values generated by the first-, second-, and third-order polynomial approximation models. The graphical results show that all three models are able to capture the general upward trend in electricity consumption as the average temperature increases, and the differences between the curves are visually negligible. These graphical results are consistent with the numerical results using RMSE, which show minimal differences across polynomial orders. Furthermore, visualization was also carried out on the results of the modified Chebyshev polynomial models of order one, two, and three as follows.

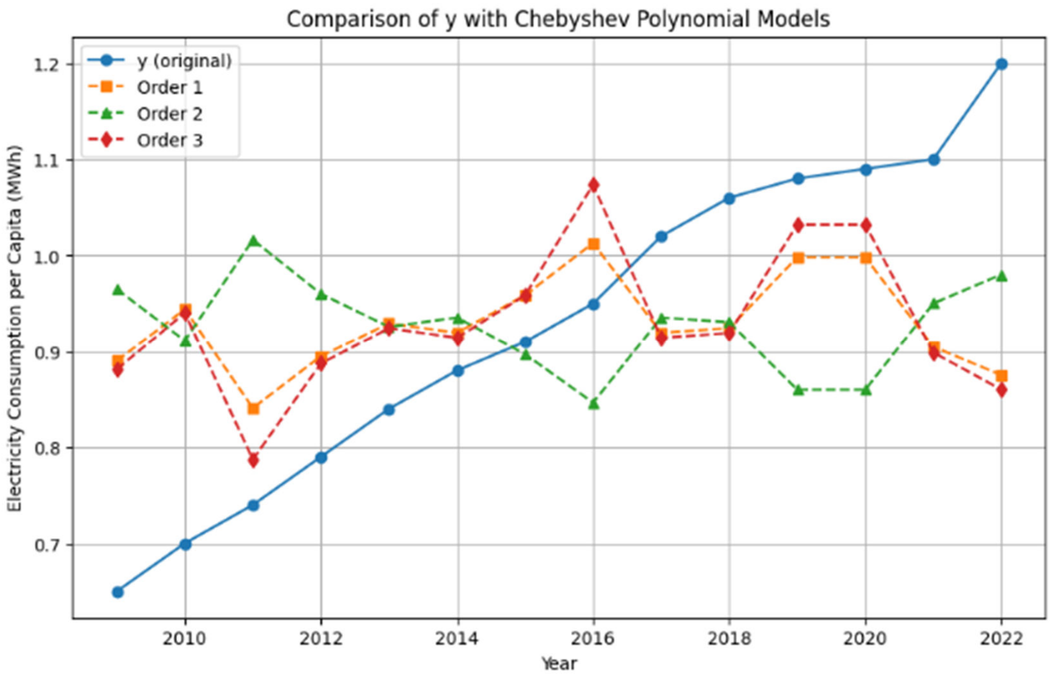

Figure 4. Results of Modified Chebyshev Polynomial order 1,2, and 3.

Based on Figure 4, the first-order and third-order model displays a general increasing trend; meanwhile, the second-order model appears to deviate from the first and third order models. This occurs because the polynomial $T_2(x)$ is symmetric and forces the equation to be quadratic. When the actual data pattern is not perfectly quadratic, the second-order model can produce a curve that actually increases, even though the first- and third-order models show a decrease. These results indicate that the Chebyshev-based polynomial approximation to the transformed temperature variable $t \in [-1,1]$ produces a stable and accurate numerical model, with the second-order model provide a more accurate representation of the data.

4. CONCLUSION

This research proves that the Least Squares Polynomial Approximation method can effectively model the relationship between average temperature and per capita electricity consumption in Indonesia. Based on the RMSE and condition number analysis, the second-order polynomial model provides the most optimal results. However, the large condition number in the least squares polynomial approximation model indicates room for improvement using the modified Chebyshev polynomial.

Based on the RMSE and condition number analysis of the modified Chebyshev polynomial, the second-order polynomial model provides the most optimal results. The RMSE value for the modified Chebyshev polynomial in this case cannot show that the higher the order of the polynomial, the lower the RMSE value. This model is able to illustrate the increasing trend in electricity consumption as average temperature increases, reflecting the behavior of electricity consumption in tropical regions. It is hoped that further research can expand the scope of research data by considering other factors such as population growth, use of energy-saving technology, urbanization levels, and considering the use of other, more stable numerical approaches.

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