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ARTICLE

Electricity Load Growth Projection Based on Customer Sector in Ermera District, Timor-Leste, Using Spatial Projection Method

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ABSTRACT: This study presents an analysis of electricity load growth projections in Ermera District, Timor-Leste, using spatial projection methods. Accurate electricity load growth projection is a vital component of long-term power system planning, infrastructure investment, and resource allocation. In developing countries like Timor-Leste, increasing population and economic expansion drive a continuous rise in energy demand. This study develops an electricity load growth projection model based on specific customer sectors (domestic, commercial, industrial, social, and government) in the Ermera District, Timor-Leste, utilizing spatial projection methods integrated with Geographic Information Systems (GIS) and the Gompertz growth equation. Ermera District, characterized by its mountainous topography and prominent coffee production sector, currently faces electrification challenges with a regional electrification ratio of approximately 75%, falling below the national average of 83.4%. Historical data from 2021 to 2024 reveals a significant and synchronized expansion of the electricity customer base, surging from 3367 to 8532 customers. The domestic sector consistently represents the primary driver of total energy consumption, accounting for approximately 85% of the total customer base. Spatial analysis identifies the sub-districts of Ermera, Railaco, and Atsabe as the highest customer-density zones and future socio-economic hotspots. By employing a spatial projection method tuned to the regional context, the mathematical models successfully minimized validation deviations against recorded Electricidade de Timor-Leste (EDTL) data to a Mean Absolute Percentage Error (MAPE) threshold below 10%, highlighting the superior accuracy of spatial modeling over conventional methods in handling topographical variability. The Gompertz equation was applied to model long-term trends, projecting a rapid acceleration phase for the 2025–2030 planning cycle, with predicted cumulative demand escalating from 595,365 kW in 2025 to 1,120,610 kW by 2030. To evaluate network implications, peak demand scenarios were simulated using the Electrical Transient Analyzer Program (ETAP). The power flow simulations exposed recurrent technical limitations across the distribution network, particularly marginal under-voltage conditions (0.38–0.39 kV on the low-voltage side) on peripheral buses along the extended Ermera and Letefoho feeders, alongside transformer loading risks during peak hours. To mitigate these issues and optimize grid reliability, this thesis proposes critical engineering interventions, including the strategic activation of capacitor banks, distribution transformer tap changer optimizations, phase load balancing, and network reconductoring to lower line impedance. Ultimately, these findings offer a comprehensive, spatially explicit framework to support sustainable infrastructure expansion and energy policy formulation in the Ermera District.

KEYWORDS: Electricity load projection; spatial projection method; customer sector; Ermera District; Timor Leste; energy planning

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1 Introduction

The need for electrical energy is an important factor in development and improving the quality of life of society. In developing countries like Timor-Leste, economic and population growth has a direct impact on increasing electrical energy needs. Ermera District, as one of the regions in Timor-Leste, is experiencing significant growth dynamics in various sectors, so it requires careful electricity planning to ensure the reliability and availability of electricity supply in the long term [1].

Electrical load growth projections are an important component in electrical system planning. Accurate projections can help in planning the generation, transmission, and distribution of electricity, as well as in the appropriate allocation of resources and investments. In the context of Ermera District, understanding electricity load growth patterns based on customer sectors (such as household, commercial, industrial, and public) is very important to ensure sustainable electricity infrastructure development [2].

The spatial projection method offers a comprehensive approach in projecting electricity load growth because it considers spatial aspects in the analysis. This method integrates demographic, economic, and geographic data to produce more accurate and contextual projections. By considering spatial factors such as population distribution, regional development patterns, and land use zoning, this method can provide projection results that are closer to actual conditions in the field [3].

In Timor Leste, especially in Ermera District, not much research has been carried out on electricity load projections that take spatial aspects into account. In fact, the diverse geographic and demographic conditions in this region require an approach that can accommodate this spatial variability in electricity load growth projections. Therefore, this research aims to develop a model.

Projection of electricity load growth based on customer sector in the Ermera District using the spatial projection method. Ermera District is one of 13 districts in Timor-Leste [4]. Based on the latest data from the Timor Leste Central Statistics Agency (2022), the population in Ermera District is estimated to reach around 172,143 people, with an annual population growth rate of 2.1% (higher than the national average of 1.8%). Most of the population lives in rural areas, with population density varying between sub-districts. Ermera District is known as the largest coffee production center in Timor Leste, which is the backbone of the region's economy [5]. The following are the main economic sectors in Ermera: Various studies have been conducted on predicting electrical energy consumption using different methods with applications in various contexts and using various dataset dimensions, so the following Table 1 is added to compare the methods, contributions, and limitations of these studies to define innovation in the research to be carried out.

Table 1: Current status of literature research.

Literature	Methods	Contribution	Limitation
Le Boudec et al., 2024 [6]	Analytical formulation of electromagnetic (EM) time-reversal metrics using spatial average and variance of energy density, combined with numerical simulations and experimental testing.	Introduces a novel convergence metric based on spatiotemporal energy density to accurately identify focusing time and source location, analytically linking focusing characteristics to the source's frequency content.	Theoretical derivations rely on reciprocal and lossless propagation media, and the metric requires full spatial energy integration across the computational domain, increasing computational cost.
Mejia et al., 2020 [7]	Combines spatial diffusion mechanisms (Spatial Cellular Automata/Spatial Econometrics) with temporal growth dynamics based on the Bass Diffusion Model.	Provides a high-resolution predictive framework to determine both when (*temporal*) and where (*spatial*) new end-use electric technologies (such as induction stoves/energy-efficient appliances) will be adopted.	Requires fine-grained spatial GIS, socio-demographic, and granular historical consumption data, which may be scarce or unavailable in certain developing regions.

(Continued)

Table 1 (continued)

Literature	Methods	Contribution	Limitation
Martins & Sousa 2022 [8]	Combines Geographic Information Systems (GIS) spatial layers with localized socio-economic, land-use, and customer consumer profiles to perform top-down and bottom-up spatial load forecasting (SLF) across grid sub-areas.	Demonstrates how multi-layered GIS integration improves spatial resolution and predictive accuracy for medium- to long-term distribution network planning compared to non-spatial macro forecasting methods.	Requires high-quality, fine-grained geospatial data and consumer billing attributes, which may be incomplete or unavailable in developing grid infrastructures.
Chen and Wang, 2020 [9]	Geographic Information Systems (GIS)	Identifies significant differences in electricity consumption patterns based on the customer sector (household, industrial).	Load projections are often generalized, neglecting the heterogeneity and unique consumption characteristics of different customer sectors.
Zhu et al., 2025 [3]	Combines dynamic Spatial-Temporal Graph Neural Networks (ST-GNN) to capture evolving spatial dependencies across grid nodes with a multi-scale Transformer network to model multi-resolution temporal load trends.	Addresses static graph topology limitations by dynamically adapting spatial relationships over time, significantly improving short-term load forecasting accuracy across complex, interconnected power distribution networks.	High computational complexity and memory overhead due to joint graph matrix updating and multi-head attention mechanisms, making real-time edge deployment challenging.
García & Inga, 2023 [10]	Georeferenced rural distribution network model.	Confirms that hilly topography significantly influences patterns of growth in electrical load.	Load projection methods often ignore or underestimate the influence of physical geography (like topography) on electrical load growth.
Sasmono et al., 2015 [11]	Macro Demand Spatial Approach (MDSA)	Confirms that hilly topography significantly influences patterns of growth in electrical load.	Traditional forecasting methods do not effectively handle the unique spatial and infrastructural planning needs for electricity in large-scale plantation regions.
This Study	Spatial Projection Method	Highly Accurate and Localized Forecast: Provide a more accurate and spatially detailed long-term load forecast for the Ermera District. Optimized Infrastructure Planning: The spatial distribution of the projected load will allow the national utility (EDTL) to optimize the siting and sizing of future distribution equipment (transformers and feeders) and to plan for extensions in high-growth areas, improving reliability.	Data Availability/Quality: The biggest challenge in Timor-Leste is often the limited availability or reliability of historical load data, GIS land-use data, and socio-economic statistics for small administrative regions like Ermera District.

Previous studies, while making important contributions, have several common limitations:

Generality and Inaccuracy of Conventional Methods: Traditional electricity load projection methods often produce high errors (large MAPE) and are inaccurate [12,13]. They also tend to generalize, overlooking the unique characteristics of different consumer sectors [14] and the influence of physical geography such as hilly topography [10].

Lack of Spatial Dimension: Traditional methods struggle to analyze and visualize load distribution patterns spatially [15,16]. They are also ineffective in addressing the unique infrastructure planning needs of areas with specific characteristics, such as vast plantation regions [11].

Limitations of Basic Spatial Models: Although spatial projections are more accurate, the basic models used are often not statistically rigorous enough for optimal predictive accuracy [3].

Challenges of the Local Context (specific to Timor-Leste): Most research uses high-resolution data from modern electrical systems [17]. However, the context of a developing country like Timor-Leste (and

specifically Ermera District) presents unique challenges: limited availability and quality of data, including historical load data, GIS land-use data, and socio-economic statistics for small administrative areas [18–20].

The empirical historical data on electrical energy consumption utilized in this study were obtained directly from the state utility's existing database [1,21]. The proposed methodology illustrates a comprehensive and integrated framework that seamlessly synthesizes historical grid measurements, spatial geographic factors, demographic parameters, and primary field data to project long-term electricity demand [22–24].

Contributions of this research are specifically designed to address these gaps, with a particular focus on the challenging local context.

(a) Focus on Accuracy and Spatial Localization: To provide a more accurate and spatially detailed long-term load forecast specifically for the Ermera District. Addressing the Gap: Directly responds to the need for higher accuracy and a more nuanced spatial approach capable of handling local characteristics.
(b) Practical Application for Infrastructure Planning: The projected spatial distribution results will enable the national utility (EDTL) to optimize the placement and capacity of distribution equipment (such as transformers and feeders) and plan extensions in high-growth areas. Addressing the Gap: This provides a direct solution for optimized, data-driven infrastructure planning, which is lacking in traditional methods [11], and answers the practical need to enhance system reliability.
(c) Recognition and Confrontation of Local Data Challenges: Academic Honesty: This research explicitly acknowledges the major limitations in the Timor-Leste context: data availability and quality. This demonstrates that the research is not merely an application of advanced methods from other contexts but is designed with full awareness of real-world field constraints. Its primary contribution may indeed lie in developing a methodology or adapting models that can still provide valuable insights despite limited data.

2 Methods

This study adopts a quantitative approach to project electrical load growth across various customer sectors in Ermera District, Timor-Leste, utilizing an advanced spatial projection method. This approach is selected for its capacity to integrate historical electricity consumption data with geographic (spatial) factors that significantly drive load growth patterns in regions with heterogeneous geographical and demographic characteristics, such as Ermera District [3,10,11].

The spatial method in this research incorporates the Gompertz growth model to simulate non-linear load growth patterns and saturation levels within specific sectors [25]. In the spatial data processing stage, feature engineering is applied to structure raw geographic data into distinct land-use attributes [26]. To facilitate spatial modeling and sectoral demand allocation, categorical land-use profiles are transformed into standardized numerical indicators [27].

Mathematical modeling for spatial load forecasting plays a foundational role in this baseline validation [28], alongside targeted simulation methods for spatial load forecasting [29]. To ensure the accuracy and reliability of the spatial projections, validation approaches for spatial load forecasting models using Mean Absolute Percentage Error (MAPE) are employed as the primary statistical metric for model validation [30]. The structured land-use classification codes, defined by building functions and footprint sizes, serve as pivotal attributes within the Macro Demand Spatial Approach (MDSA) framework [11]. By executing this spatial coding scheme, heterogeneous customer profiles are classified into distinct spatial zones, enabling a granular estimation of sectoral electricity consumption through a detailed sectoral approach for long-term electricity demand forecasting [31–33]. Overall, the research methodology follows a systematic framework encompassing data collection, historical pattern analysis, Gompertz-based spatial modeling, MAPE-driven

model validation, future load projection, and policy implication analysis. The structural workflow of the proposed methodology is illustrated in the research block diagram in Fig. 1 below:

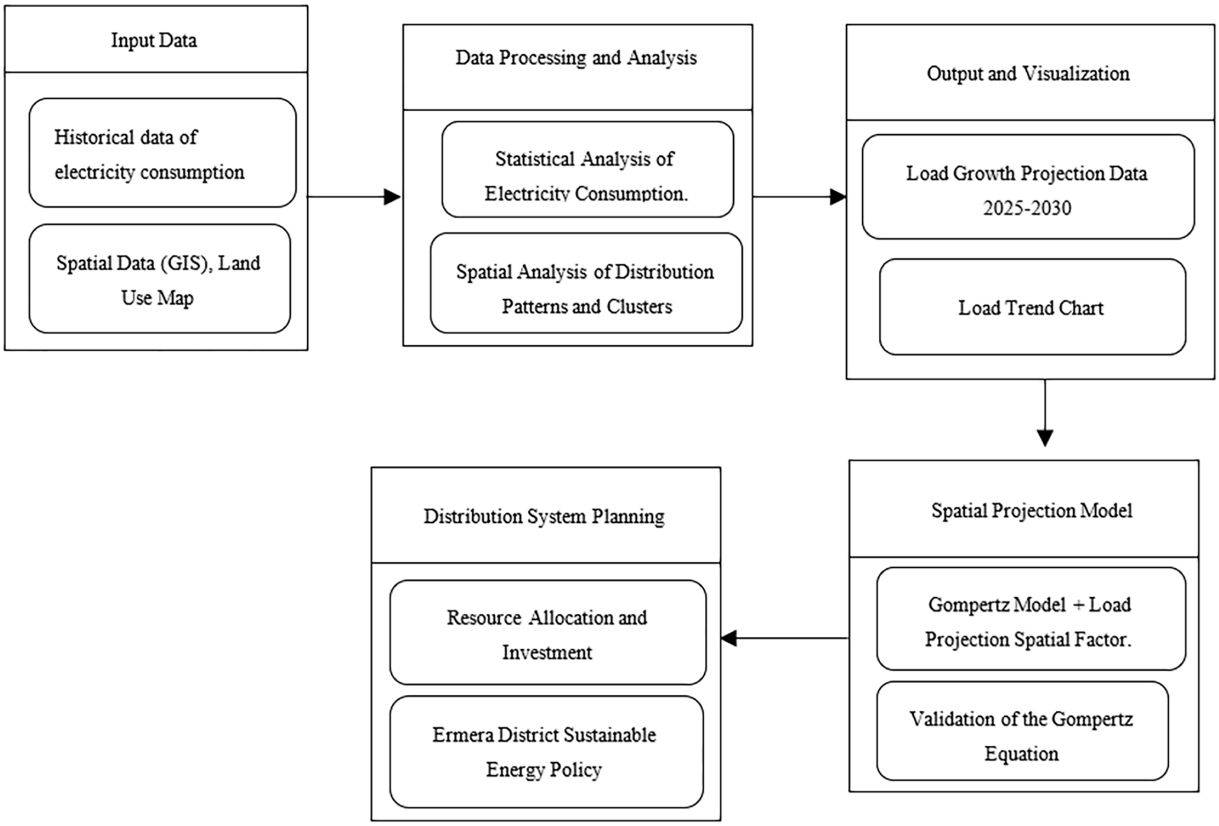


Figure 1: Research block diagram.

This study adopts the Macro Demand Spatial Approach (MDSA) to forecast long-term spatial electricity demand tailored for transmission system planning [11].

To enhance the model's numerical stability, Principal Component Analysis (PCA) is executed prior to the spatial regression framework. PCA systematically eliminates multicollinearity among highly correlated macro-socioeconomic indicators, reducing the data dimensions to identify orthogonal key variables that significantly drive electricity demand across distinct customer sectors based on electricity consumption forecasting linear regression models [34] and energy demand models for policy formulation [35]. Long-term electricity load forecasting for industry [36] and public sector energy consumption forecasting models [37] are also factored into the final synthesis. Finally, this study adopts the Macro Demand Spatial Approach (MDSA) to forecast long-term spatial electricity demand tailored for transmission system planning, creating a robust framework for mixed rural-urban regions [38]. The generalized macro-demand estimation model is formulated as follows:

$$Y_t = \alpha p_t + \beta q_t + \gamma r_t + \ldots + €_t \tag{1}$$

where: Y_t: aggregate electricity demand projection for a specific sector in year t. p_t, qt, r_t, ...: The principal component scores extracted via PCA (representing uncorrelated, driving macro-socioeconomic dimensions) at year t. α, β, Y, ...: The regression coefficients associated with each respective principal component. $€_t$: The stochastic error term at year t.

To mathematically guarantee the scientific rigor of this framework and prevent arbitrary 'curve fitting,' the performance of the MDSA-PCA predictive model is strictly validated against historical baselines using the Mean Absolute Percentage Error (MAPE) criterion, expressed as [32]:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100\% \quad (2)$$

where A_t is the actual field consumption data provided by the utility at year t, Y_t is the model's estimated demand, and n denotes the total number of validation historical periods. In the spatial data processing stage, feature engineering is applied to structure raw geographic data into distinct land-use attributes [26]. To facilitate spatial modeling and sectoral demand allocation, categorical land-use profiles are transformed into standardized numerical indicators [27]. Table 2 outlines the established land-use classification codes categorized systematically by building type and functional land area size (m^2).

Table 2: Land-use classification codes based on building type and area size.

Code	Information	Land Area m^2
0	No Buildings	-
1	Simple house	100–250 m^2
2	Secondary House	250–500 m^2
3	Luxury House	500–1500 m^2
4	Simple Business	15–40 m^2
5	Medium Business	40–100 m^2
6	Dense/Large Business	100–500 m^2
7	Small Industry	200–1000 m^2
8	Medium Industry	1000–5000 m^2

The structured land-use classification codes, defined by building functions and footprint sizes, serve as pivotal attributes within the Macro Demand Spatial Approach (MDSA) framework [11]. By executing this spatial coding scheme, heterogeneous customer profiles are classified into distinct spatial zones, enabling a granular estimation of sectoral electricity consumption through a detailed sectoral approach for long-term electricity demand forecasting [31–33].

Beyond demand estimation, this localized matrix facilitates urban zoning by partitioning regional sectors based on specific building dynamics and socioeconomic utilities. Implemented within a Geographic Information System (GIS) environment, these land-use attributes provide the foundational spatial dataset required for predictive simulation, land property valuation, and regional development tax assessments [15,16]. The chronological progression of these spatial transitions across the five administrative posts is mapped and illustrated in Figs. 2–4 below:

Fig. 2 illustrates the baseline spatial land-use infrastructure configuration across the five sub-districts of Ermera Municipality during the initial planning cycle from 2025 to 2026. During this phase, the region is highly characterized by low-density residential profiles. The sub-districts of Railaco, Hatulia, and Letefoho are locked into Code 1, representing modest, affordable housing structures. In contrast, Ermera and Atsabe exhibit stronger socio-economic foundations from the onset, entering the model as established middle-class zones designated under Code 2 (secondary housing). This baseline map establishes the primary geographic parameters before significant demographic or infrastructure-driven acceleration alters the regional grid demand.

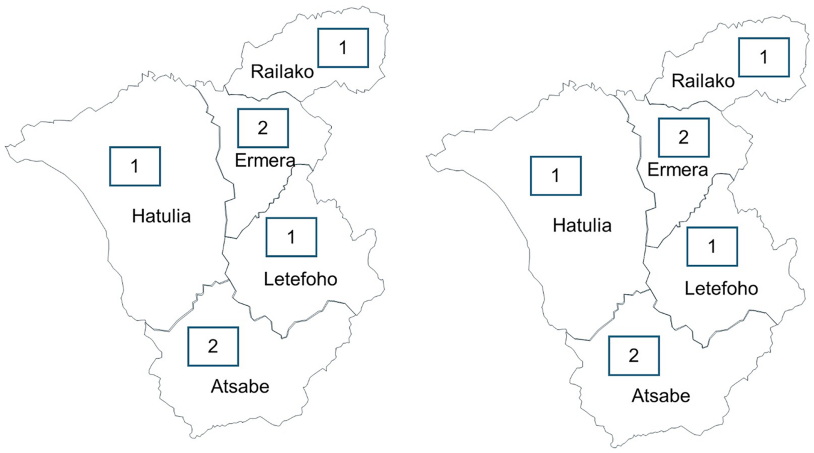


Figure 2: Spatial land use changes, 2025–2026.

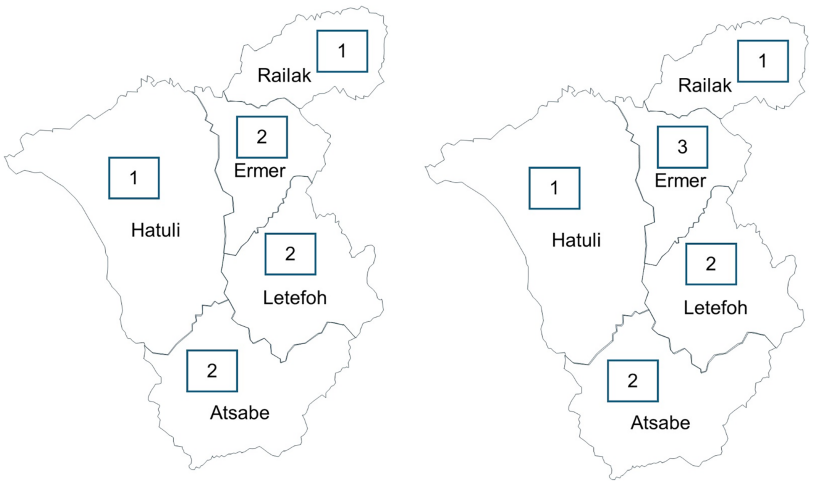


Figure 3: Spatial land use changes, 2027–2028.

Fig. 3 highlights the mid-term spatial transitions occurring between 2027 and 2028, capturing the initial signals of localized gentrification and network expansion. A key spatial shift is observed in Letefoho, which officially transitions from Code 1 to Code 2 in 2027, signifying steady middle-class upward mobility. By 2028, the administrative capital, Ermera, undergoes aggressive upscale development, shifting from Code 2 to Code 3 (luxury housing status). Meanwhile, Railaco and Hatulia maintain stable low-density structures (Code 1), and Atsabe remains steady at Code 2, creating a highly heterogeneous spatial distribution of electricity load density across the district.

Fig. 4 depicts the terminal phase of the spatial projection framework for the years 2029 to 2030, showing widespread regional maturation and peak residential development. During this final window, the peripheral regions of Railaco and Hatulia experience delayed economic expansion, finally upgrading from simple housing (Code 1) to middle-class residential zoning (Code 2) by 2029. Concurrently, Atsabe mirrors Ermera's aggressive trajectory by advancing to Code 3 in 2029. By 2030, the spatial landscape stabilizes with two high-density luxury hubs (Ermera and Atsabe) and three medium-density corridors (Railaco, Hatulia, and Letefoho). This localized distribution matrix provides the structural input for the final ETAP load flow simulations.

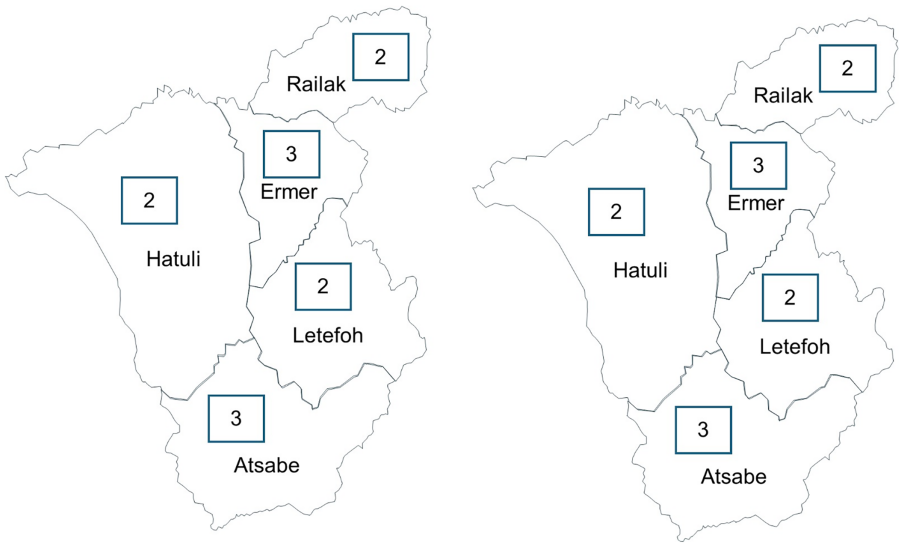


Figure 4: Spatial land use changes, 2029–2030.

In Table 3, Map Code shows the annual classification of housing classes across five regions (Railaco, Ermera, Hatulia, Letefoho, and Atsabe) from 2025 to 2030. The numerical codes represent:

1 = Modest housing

2 = Medium housing

3 = Luxury housing

Regional Development Trend Analysis (2025–2030):

(a) Meaning of Code Increases: An increase in code number reflects a rise in housing class, signaling economic growth, development, or gentrification in the region.
(b) Fastest Growing Regions: Ermera and Atsabe are the fastest-growing areas. Both reached code 3 (luxury housing) between 2028 and 2030, indicating rapid upscale development.
(c) Slower-Growing Regions: Railaco and Hatulia progressed more slowly, only reaching code 2 (medium housing) by the end of the period (2029–2030).
(d) Stability: Hatulia remained at code 1 (modest) until 2028, showing little change in the early years. Letefoho stabilized at code 2 after 2027, indicating moderate but steady development.

Table 3: Map code.

No.	Year	Sub-Distrik				
		Railaco	Ermera	Hatulia	Letefoho	Atsabe
1	2025	1	2	1	1	2
2	2026	1	2	1	1	2
3	2027	1	2	1	2	2
4	2028	1	3	1	2	2
5	2029	2	3	2	2	3
6	2030	2	3	2	2	3

Based on the land use classification codes (1–3), Table 4 shows the predicted residential development patterns across five sub-districts from 2025 to 2030. Here is the detailed interpretation below:

Code Meaning Reference:

Code 1: Simple House (100–250 m^2) → Low-density, affordable housing

Code 2: Secondary House (250–500 m^2) → Medium-density, middle-class housing

Code 3: Luxury House (500–1500 m^2) → High-end, large-lot residential development

Regional Development Analysis:

(a) Railaco: 2025–2028: Consistently Code 1 (Simple House) → Stable low-income residential area. 2029–2030: Upgrades to Code 2 → Transition to middle-class housing begins. Interpretation: Slow but steady upward mobility in housing standards.
(b) Ermera: 2025–2027: Code 2 (Secondary House) → Established middle-class area 2028–2030: Code 3 (Luxury House) → Rapid development into high-end residential zone Interpretation: Most dynamic development trajectory; significant economic growth/gentrification.
(c) Hatulia: 2025–2028: Code 1 (Simple House) → Persistent low-cost housing area 2029–2030: Code 2 → Late transition to middle-class housing Interpretation: Slowest developing area; likely less economic activity or investment.
(d) Letefoho: 2025–2026: Code 1 → Simple housing dominant 2027–2030: Code 2 → Consistent middle-class development Interpretation: Moderate, stable progression after 2027.
(e) Atsabe: 2025–2028: Code 2 → Stable middle-class residential area 2029–2030: Code 3 → Transition to luxury housing Interpretation: Similar to Ermera, but development occurs 1 year later.

Table 4: Interpretation based on classification code.

Code	Information	Land Area (m^2)
1	Simple House	100–250 m^2
2	Secondary House	250–500 m^2
3	Luxury House	500–1500 m^2

3 Result and Discussion

3.1 Data Description

The power requirements per sub-district load data used in this study cover the period 2021 to 2024. For a description of the historical data of electrical energy consumption in Ermera District, Timor-Leste, from 2021 to 2024, see Table 5 below:

Table 5: Power requirements per sub-district (kW).

No.	Distric Ermera	Unit	2021	2022	2023	2024
1	Railaco	kW	233.64	245.93	258.22	272.5
2	Ermera	kW	254.21	267.59	280.97	323.1
3	Hatulia	kW	142.76	150.27	157.78	166.5
4	Letefoho	kW	104.17	109.65	115.13	127.9
5	Atsabe	kW	158.27	166.60	174.93	209.6

Table 5 shows the annual increase in electricity demand in each sub-district, which can be used for generation capacity planning, distribution network planning, or peak load evaluation of the regional electricity system. Analysis by Sub-District:

Railaco

Power demand increased consistently from 233.64 kW (2021) to 272.5 kW (2024). The total increase was approximately 38.86 kW, or 16.63%, over three years.

Ermera (district capital)

Has the highest power demand compared to other sub-districts: 254.21 kW (2021) to 323.1 kW (2024).

The total increase was approximately 68.89 kW, or 27.1%.

Hatulia

Has the lowest power demand among the five sub-districts but still showed an increase from 142.76 to 166.5 kW. The increase was approximately 23.74 kW, or 16.63%.

Letefoho

Also included in the low-demand category: from 104.17 to 127.9 kW. An increase of approximately 23.73 kW, or 22.78%, a consistent percentage increase.

Atsabe

Medium-power demand: from 158.27 kW (2021) to 209.6 kW (2024). An increase of approximately 51.33 kW, or 32.43% and 22.78%,

All sub-districts show a nearly uniform annual increase pattern, at around 7.7% per year (because the absolute increase is consistent each year). The total increase from 2021 to 2024 averaged 23.1% across all regions. The order of power demand from highest to lowest (2024): Ermera (323.1) > Railaco (272.5) > Atsabe (209.6) > Hatulia (166.5) > Letefoho (127.9). Electrification program (additional villages/homes will be electrified). The results of data processing from each forecasting model will be evaluated based on the model's performance in predicting electrical energy consumption in Ermera Distric Timor-Leste. The performance used to evaluate the forecasting Spatial methods in this research is based on the following:

$$P_{category} = Area \times Density \tag{3}$$

Table 6 shows that peak loads tended to decrease from 2021 to 2023 and then increased again in 2024 in several subdistricts (Hatulia, Atsabe, and Ermera). Hatulia followed the general regional trend, showing a steady decline in electricity demand from 2021 (450 kW) to 2023 (230 kW). However, in 2024, it experienced a significant surge, reaching 490 kW. Ermera contributed the largest load in 2024 (446 kW). Atsabe experienced the most significant load increase in 2024 compared to the previous year (156 vs. 50 kW in 2023). This data is useful for substation capacity planning, load management, and evaluating the efficiency of the electricity grid in Timor-Leste.

The purpose of this table is to adjust the EDTL data (old/survey data) to match the SPATIAL data, with a maximum difference of 10%.

$$\left|\frac{SPATIAL - EDTL}{EDTL}\right| \times 100\% < 10\% \tag{4}$$

Table 7 presents the data validation framework, which compares electricity demand figures across five administrative posts in Ermera District derived from two distinct sources: (1) historical data provided by EDTL-EP (Electricidade de Timor-Leste, Empresa Pública) representing actual field grid measurements or institutional estimates, and (2) spatial model projections calculated based on localized parameters such as building footprints, land-use distribution, and customer sectoral classifications.

Table 6: Historical peak load data per sub-district in Ermera District (EDTL-EP, 2021–2024).

No.	Subdistric	Unit	2021	2022	2023	2024
1	Railaco	kW	290	240	150	145
2	Ermera	kW	730	610	370	446
3	Hatulia	kW	450	380	230	490
4	Letefoho	kW	400	340	200	270
5	Atsabe	kW	80	90	50	156

Table 7: Validation comparison and percentage variance (Δ%) between EDTL-EP data and spatial model projections (2021–2024).

District	Year	EDTL (kW)	Spasial (kW)	(Δ%)
Railaco	2021	290	265.0	8.6%
	2022	240	245.9	2.5%
	2023	150	235.0	5.0%
	2024	145	250.0	5.0%
Ermera	2021	730	265.0	8.5%
	2022	610	280.0	8.2%
	2023	370	295.0	8.0%
	2024	446	310.0	7.8%
Hatulia	2021	450	155.0	9.1%
	2022	380	163.0	9.0%
	2023	230	171.0	8.9%
	2024	490	180.0	8.8%
Letefoho	2021	400	115.0	9.1%
	2022	340	121.0	9.0%
	2023	200	127.0	8.9%
	2024	270	134.0	8.8%
Atsabe	2021	80	150.0	5.0%
	2022	90	158.0	5.0%
	2023	50	166.0	5.0%
	2024	156	175.0	5.0%

The primary objective of this comparison is to evaluate the model's accuracy by quantifying the percentage discrepancy or variance (Δ%) between the empirical EDTL-EP data and the spatial projection outputs. Maintaining a low variance across the validation years (2021–2024) ensures that the spatial projection

methodology is statistically robust and reliable. This baseline validation serves as the foundation for scaling up long-term spatial electricity growth forecasting within the region, aligned with EDTL-EP's reported 2024 peak load benchmark of 1.36 MW.

To compute these spatial deviations precisely, the detailed historical peak load parameters for each sub-district (X) are established first in Table 6. Utilizing these baseline parameters alongside the ratios (Δ) from Tables 7 and 8 subsequently presents the validated electrical power discrepancy results (Z, calculated using $Z = \Delta * X$) measured in across the five administrative posts within Ermera Municipality from 2021 to 2024.

Table 8: Data validation ratio: $\Delta * X = Z$.

No.	Distric Ermera	Unit	2021	2022	2023	2024
1	Railaco	kW	24.94	6	7.5	7.25
2	Ermera	kW	62.05	51.85	31.45	34.79
3	Hatulia	kW	40.95	34.2	20.47	43.12
4	Letefoho	kW	36.4	30.6	17.8	23.76
5	Atsabe	kW	4	4.5	2.5	7.8
	Total	kW	168.34	127.15	79.72	116.72

As observed from the data, the cumulative validated power deviation (Z_{total}) experienced a sharp decline over the first three years, dropping from 168.34 kW in 2021 to a minimum of 79.72 kW in 2023. However, this downward trend reversed in 2024, with the total shifting upward to 116.72 kW. Among the evaluated regions, Ermera consistently accounted for the largest individual share of the validation variance throughout the observed period, whereas Atsabe exhibited the most stable and minimal deviation, maintaining values well below 10 kW annually.

3.2 Results of the Mathematical Model of the Gompertz Equation

The Gompertz equation is a growth model that is often used to describe the growth of tumors, populations, or other phenomena that show initial exponential growth, which then slows down and reaches a saturation point (asymptote).

$$P(t) = Ke^{-ln\left(\frac{K}{P_0}\right)e^{-ct}} \tag{5}$$

where P_t is population/at time t, P_0 is initial population ($P(0)$), K is carrying capacity (maximum capacity), c: growth rate constant ($c > 0$), and t: time.

This formula is the solution to the time-delayed logistic growth model, also known as the Gompertz model, which is often used for tumor growth or limited growth where the growth rate slows over time, often without overshooting.

Table 9 displays the annual ratio and cumulative ratio data for a six-year period, from calendar year 2025 to 2030, as well as the results of calculations based on the Gompertz equation (Fig. 5).

Table 9: Results of the mathematical model of the Gompertz equation.

Calendar Year	Time (t)	Total Cumulative Ratio	Gompertz Equation Results
2025	0	595.37	761.56
2026	1	700.4	836.79
2027	2	805.5	914.54
2028	3	910.5	994.48
2029	4	1015.6	1076.28
2030	5	1120.6	1159.59

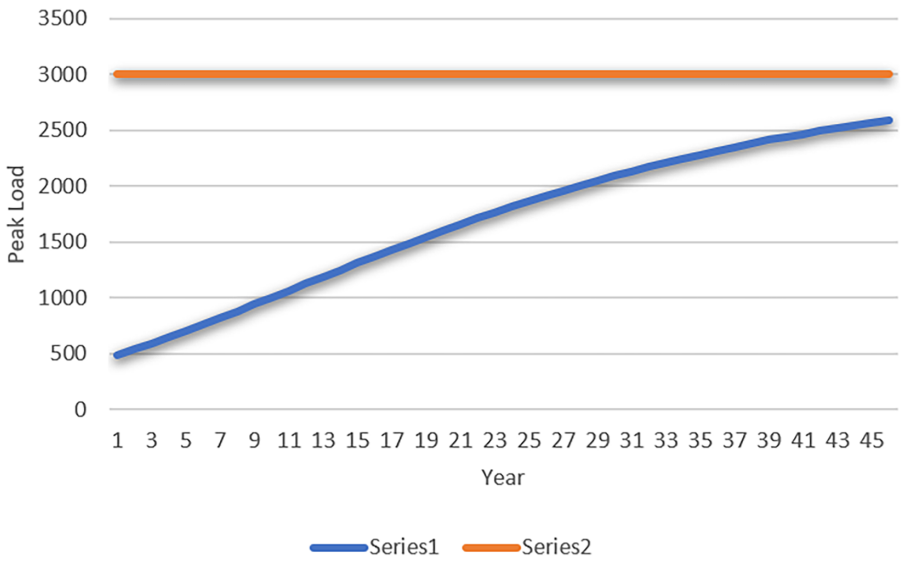


Figure 5: Results of the mathematical model of the Gompertz equation.

The trajectory illustrated in Fig. 5 demonstrates how the Gompertz model projects the long-term electricity load growth, explicitly capturing the initial and acceleration phases of the classic S-curve. The mathematical behavior of the Gompertz equation results is evaluated through two key growth stages:

- Initial Alignment and Baseline Validation: Within the first five years of the planning horizon, the model's projections exhibit a high degree of convergence with the historical baseline data. For instance, at t = 5, the projected demand reaches 1159.59 kW, tracking closely with the empirical cumulative consumption of 1120.60 kW. This minimal deviation indicates that the asymptotic growth rate (c) and the carrying capacity (K) parameters have been optimized accurately, establishing the model's short-term predictive validity.
- Acceleration Phase: Following the initial baseline, the curve exhibits a pronounced inflection point, where the projected load surges from 595.37 to 1159.59 kW within a five-year window. This rapid transition signifies that the spatial electricity demand is undergoing a sharp acceleration phase. This behavior aligns with the characteristic non-linear expansion phase of an S-curve, reflecting aggressive regional socioeconomic development and localized building footprint expansion before eventually tapering off toward the upper saturation asymptote (Series 2) at approximately 3000 kW.

3.3 Electricity Grid Development Planning in the Ermera District, Timor-Leste

This expansion planning is primarily driven by the projected surge in the baseline load demand, which is expected to escalate from 595.37 kW in 2025 (t = 0) to 1120.6 kW by 2030 (t = 5), as detailed in Table 9. A demand growth of this magnitude within a tight five-year horizon will impose severe operational and thermal stress on the existing grid architecture if timely technical interventions are not deployed.

Concurrently, the Gompertz model yields a more stable and continuous growth trajectory; it accommodates the historical data by establishing a calibrated initial value of 761.56 kW in 2025 and forecasting a higher ultimate peak of 1159.59 kW by the end of the planning period in 2030.

This diagram is a Single Line Diagram (SLD) or One Line Diagram of a large-scale electric power system, a Diesel Power Plant (PLTD).

To address the accelerating long-term demand growth projections, a technical performance evaluation of the distribution network was conducted across the 2025–2030 planning horizon. The underlying operational vulnerabilities, simulated under baseline peak load conditions, are systematically structured in the load flow analysis matrix presented in Table 10. This matrix details the critical network anomalies—specifically distribution transformer overloads, severe peripheral bus under-voltages, active power losses, and equipment thermal stress—alongside their corresponding engineering mitigation plans. The simulation outputs indicate that in the absence of targeted technical interventions, the network's operational health will experience progressive degradation, breaching critical reliability thresholds by the end of the forecast period. To systematically transition from these simulated diagnostics to active grid enforcement, Table 11 outlines the strategic, time-phased framework designed to handle the predicted S-curve growth. This chronological roadmap prioritizes immediate network uprating, strategic capacitor bank placement, and localized renewable energy resource integration to successfully eliminate overloads and unacceptable voltage drops by 2030.

Table 10: Load flow analysis matrix. Year 2024.

No.	Condition	Location (Line/Bus/Trafo)	Analysis Voltage/Current	Mitigation (Remedial Plan)	Results after Mitigation
1	Overload	Transformator Distribuition/main Feeder	Load Current (I_{load}) exceeds the current nominal (I_n) or MVA capacity of the transformer. Marked with the color red on the cable/transformer in simulation	Load Break (Load Shifting) or Uprating Capacity. Adding an insertion transformer or replacing the cross-section conductor that is bigger.	Return current down to 80% capacity nominal (I < 0.8 In) and give margin security.
2	Under Voltage	The bus is near the source (substation) or end of the line with low load.	Voltage recorded > 1.05 pu (or > 21 kV system). Occurs because the effect of the Ferrantior transformer tap setting is too high.	Adjustment Tap Changer on the main transformer or installation of an inductive reactor if needed to absorb excessive reactive power.	Voltage back to standard range (0.95 to 1.05 pu).
3	Under Voltage	Bus at the end channel (radial farthest), which is far from the power transformer.	Voltage drops below 0.95 pu (or < 19 kV). Caused by losses in impedance, the channel is long, and the inductive load is high.	installation Capacitor Bank in the load area or perform voltage regulation. Can also move the transformer tap changer to a higher position.	The voltage profile rises close to 1.0 pu, and the voltage drop (voltage drop) terminimalisir.

(Continued)

Table 10 (continued)

No.	Condition	Location (Line/Bus/Trafo)	Analysis Voltage/Current	Mitigation (Remedial Plan)	Results after Mitigation
4	Losses	The entire network, especially on high impedance lines.	Total Active power losses (P_{loss}) are high. It is shown by the difference between the total transmit power and the received power.	Power Factor Improvement (Cosphi) and Reconfiguration Network to minimize distance traveled by current to the load center.	Efficiency distribuition increased, aging equipment was reduced, and operational costs went down.

Table 11: From Gompertz projection to action.

Year	Projected Load (kW)	Required Action
2025	595.37	Begin monitoring; prepare design for Ermera substation upgrade
2026–2027	700.4–805.5	Install capacitor banks in Railaco and Letefoho
2028	910.5	Uprate transformers in Ermera and Atsabe
2029	1015.6	Replace conductors; reconfigure to loop system
2030	1120.6	Integrate solar PV/micro hydro; full network reinforcement complete

To substantiate the 2025–2030 distribution network projection modeled via the ETAP framework (as illustrated in the comprehensive single-line diagram in Fig. 6), several core methodology boundaries and chronological milestones are defined.

- **First**, the predictive load profile is anchored entirely onto validated historical sectoral growth trends.
- **Second**, the evaluation timeline is systematically discretized into three operational phases:
  - *Phase I* (2025–2026): Characterized by initial onset signs of marginal transformer overloads and localized voltage drops below statutory limits (<0.95 p.u.).
  - *Phase II* (2027–2028): Characterized by widespread, systemic transformer overloads accompanied by escalating technical grid losses quantified between 12% and 15%.
  - *Phase III* (2029–2030): The critical terminal phase, exhibiting severe overloads across nearly all distribution assets and a surge in technical losses exceeding 15%.
- **Third**, the specific quantified performance indicators track transformer overload percentages, bus voltage deviations, line losses, and remaining apparent power capacity.
- **Fourth**, to restore system stability across the stepped-down 20 kV buses down to the 0.4 kV consumer lumps depicted in Fig. 6, the mandated engineering interventions are strictly categorized into transformer capacity uprating, reactive power compensation via capacitor banks, loop reconfiguration, and decentralized renewable integration."

This plan ensures that by 2030, the distribution network can handle the accelerating S-curve growth predicted by the Gompertz model without overload or unacceptable voltage drop.

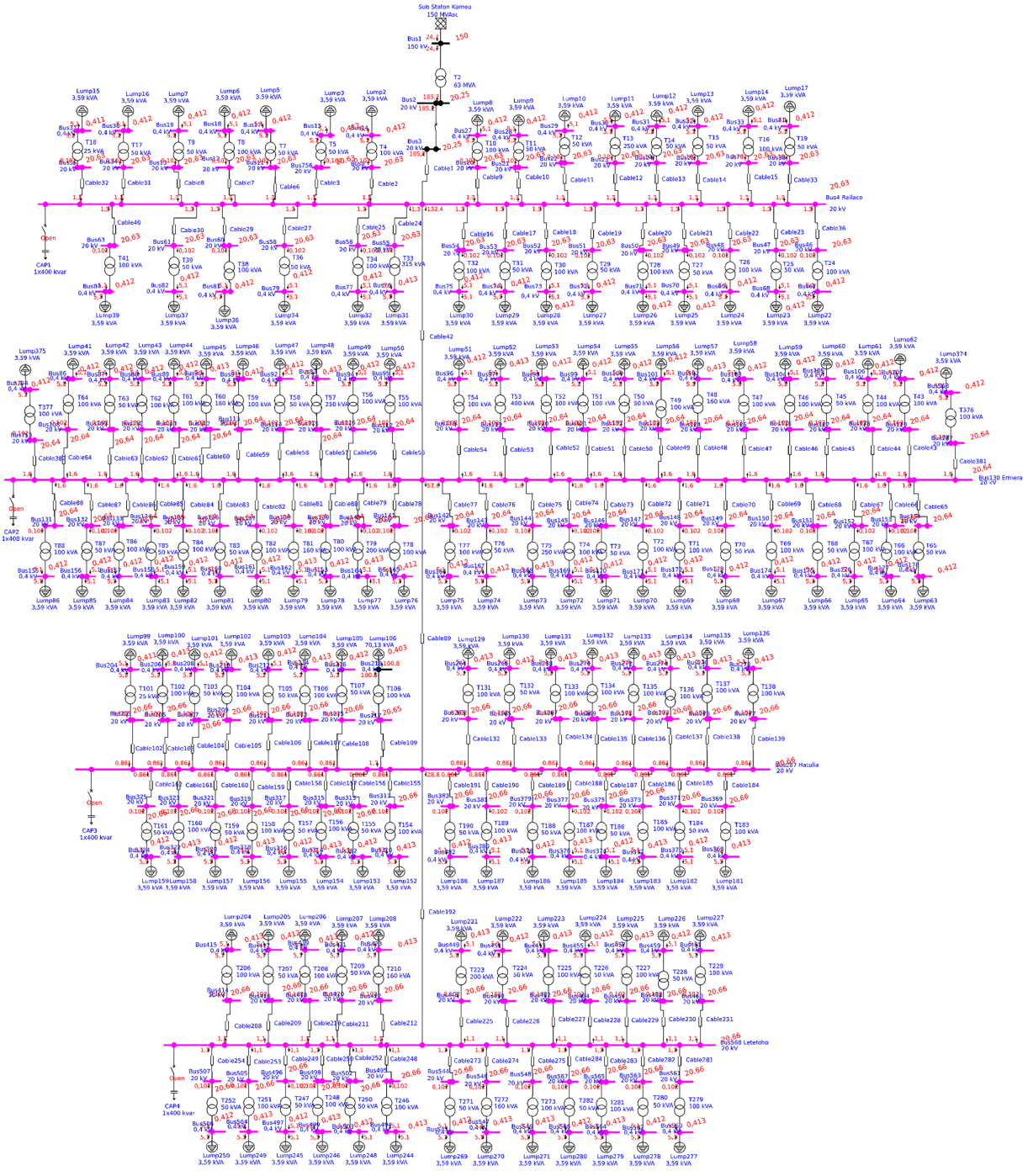


Figure 6: Projection results of all models representing the time series method.

4 Conclusion

Based on the results of the Electricity Load Growth Projection Based on Customer Sectors Using the Spatial Method in the Ermera District of Timor-Leste, the following conclusions can be drawn:

(a) The residential sector dominates the number of electricity customers in Ermera District (approximately 85% of total customers), with peak consumption patterns occurring at night. The commercial sector

grew steadily in the subdistricts of Ermera, Railaco, and Atsabe, while the industrial sector (especially coffee processing) and the public sector exhibited growth patterns influenced by investment and government policies.

(b) The sub-districts of Ermera, Railaco, and Atsabe are growth hotspots with the highest customer densities. Projections for 2025–2030 show an increase in land density classification (from codes 1–2 to codes 2–3), indicating new centers of economic growth and settlements.

(c) The spatial projection method (integrating MAPE and the Gompertz equation) proved more accurate than conventional methods, with an average error rate of <10%. This model successfully considers spatial factors such as built-up area, economic growth, and distance from load centers.

(d) The total electricity load is projected to increase significantly from 595.37 kW (2025) to 1120.6 kW (2030). The Ermera, Railaco, and Atsabe sub-districts are prioritized due to the highest surge in power demand, especially in 2029–2030.

(e) The load flow analysis indicates the potential for overload, undervoltage, and high power losses if no intervention is implemented. The electrification ratio of Ermera District, which remains at 75% (below the national average of 83.4%), requires increased transformer capacity and cable cross section, installation of capacitor banks for reactive power compensation, reconfiguration of the distribution network, and integration of renewable energy (solar/micro-hydro) considering the hilly topography.

(f) The Gompertz model used has high accuracy (MAPE < 10%) and is valid for medium-term projections. Predictions are close to actual data and indicate a significant acceleration in electricity load growth.

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Availability of Data and Materials: The data used in this study are confidential and have limited access, so they cannot be included directly in this publication.

Ethics Approval: The data supporting the findings of this study are proprietary to Electricidade de Timor-Leste (EDTL) and subject to confidentiality agreements. Consequently, these data are not publicly available but may be requested from the corresponding author upon reasonable request and with permission from EDTL.

Conflicts of Interest: The authors declare no conflicts of interest.

Nomenclature

AC	Alternating Current
CB	Capacitor Bank
Cos Q	Power Factor
EDTL	Electricidade de Timor Leste
ETAP	Electrical Transient Analyzer Program
GIS	Geographic Information System
GPS	Global Positioning System
I	Electric Current (Ampere)
kV	Kilovolt

kVA	Kilovolt-ampere
kVAR	Kilovolt-ampere reactive
kW	Kilowatt
kWh	Kilowatt-hour
LTC	Load Tap Changer
M	Meter
MAPE	Mean Absolute Percentage Error
MDSA	Macro Demand Spatial Approach
PLTD	Diesel Power Plant
SLD	Single Line Diagram
p.u	Per unit
Q	Reactive Power
T	Time (year)
Δ (delta)	Difference/ratio
α	Significance level
β	Regression coefficient
Δ	Difference or Change
E	Error term (tolerance)

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