

Performance Evaluation of Monthly Electricity Demand Forecasting in Thailand Using Machine Learning and Statistical Models

Teerapong Chongwat¹, Artitayaporn Rojarath^{2*}

¹Faculty of Informatics, Mahasarakham University, Mahasarakham 44150, Thailand

²Multi-agent Intelligent Simulation Laboratory (MISL) Research Unit, Department of Information Technology, Faculty of Informatics, Mahasarakham University, Mahasarakham 44150, Thailand

*Corresponding author's email: artitayaporn.r@msu.ac.th

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ABSTRACT

This research aims to systematically evaluate and compare the performance of time series forecasting models for predicting monthly electricity consumption in Thailand. The study focuses on assessing model suitability and the impact of parameter configurations on forecasting accuracy. Three forecasting approaches are considered, including an Artificial Neural Network (ANN), a Long Short-Term Memory (LSTM) network, and an AutoRegressive Integrated Moving Average (ARIMA) model. All models are trained and evaluated using the same dataset to ensure a fair comparison. The experimental results demonstrate that the ANN model consistently achieves the best overall performance when evaluated across all electricity consumer groups. The ANN model attains a Mean Absolute Error (MAE) of 71.72, a Mean Squared Error (MSE) of 20,050.34, a Root Mean Squared Error (RMSE) of 93.06, a Mean Absolute Percentage Error (MAPE) of 9.54%, and an R^2 value of 0.45, outperforming both the LSTM and ARIMA models in most evaluation metrics. In contrast, the ARIMA model demonstrates higher prediction errors in several consumer groups, indicating challenges in capturing nonlinear patterns and demand variability. The forecasting results of the ANN model indicate that the business and industrial sector constitutes the group with the highest level of electricity consumption.

1. Introduction

At present, electricity demand in Thailand continues to rise, thereby increasing the importance and complexity of power resource planning and management. Such changes are driven by multiple factors, which contribute to temporal fluctuations in electricity consumption, including climatic and seasonal conditions, economic activities, infrastructure development, and urban expansion [1]. This uncertainty in electricity demand forecasting constitutes a major challenge for both public and private sector stakeholders in planning and managing power resources to ensure adequacy and alignment with future demand [2]. In the absence of accurate planning, multiple adverse outcomes arise, including electricity shortages during peak demand periods, which undermine both public quality of life and the operational efficiency of business and industrial sectors. Infrastructure investments that are misaligned with actual demand result in either excessive or insufficient capacity, thereby adversely affecting the efficient use of national budgets and resources and increasing unnecessary electricity generation costs.

The present research critically examines challenges reported in the existing literature on time series data analysis using deep learning techniques for electricity demand forecasting. Cui et al. [3] demonstrate that deviations from normal electricity demand patterns during the COVID-19 pandemic introduce systematic bias and

consequently reduce the accuracy of subsequent demand forecasts. To address this problem, the research proposes a deep learning framework, namely the Long Short-Term Memory Multiseasonal Net with a deseasonalized approach (LSTM-MSNet-DS), which incorporates COVID-19 adjustments for electricity demand forecasting. The framework is then integrated with a multiple linear regression model to isolate the effects of the pandemic from electricity consumption data. In [4], the research focuses on energy management challenges in large-scale environments, such as university campuses, which are characterized by substantial energy consumption. This research focuses on forecasting electricity demand for a university campus using an Artificial Neural Network (ANN) to identify the most suitable model for long-term forecasting. In addition, a key challenge in forecasting monthly electricity demand arises from the presence of both growth trends and seasonal fluctuations [5]. Su et al. [5] address this challenge by employing a hybrid HP-RNN-ARIMA framework that integrates the advantages of statistical modeling and deep learning, with the outputs of both components subsequently combined to generate the final forecast.

To address these challenges, electricity consumption forecasting requires accurate tools and techniques for analyzing and predicting future demand trends. Accordingly, this research focuses on the application of time series analysis techniques, which effectively forecast changes in data over time [6]. In [7], they investigate

electricity demand forecasting within the residential sector. The research indicates that effective energy management in buildings requires 24-hour-ahead forecasting to support the control of resources such as heat pumps, energy storage systems, and electric vehicles. The research integrates Long Short-Term Memory (LSTM), a deep learning architecture for time-series modeling, with Next Generation Reservoir Computing (NG-RC), a machine learning approach, to produce 15-minute-resolution electricity demand forecasts over a 24-hour horizon. Similarly, Ghimire et al. [8] show that daily electricity demand forecasting is significantly enhanced by a hybrid deep learning framework that integrates Intrinsic Component Mode Decomposition (ICMD) with ANN and EDLSTM, enabling the systematic modeling of the nonlinear, non-stationary, and multi-frequency characteristics of the time series.

A review of the existing literature reveals a research gap in electricity demand forecasting in Thailand, as most prior studies rely primarily on traditional statistical approaches and often evaluate model performance using only a limited set of performance metrics. In contrast, numerous studies in international literature focus on high-frequency data and large-scale datasets, which differ substantially from the context of national-level monthly data with a limited number of observations. Accordingly, this research addresses the identified research gap by conducting a comparative analysis of three statistical and deep learning models under identical experimental conditions. The investigation utilizes long-term monthly electricity consumption data from Thailand and applies consistent evaluation metrics to ensure fairness and to minimize bias in the comparison of models.

In this research, three primary forecasting techniques are presented, namely the Artificial Neural Networks (ANN), the AutoRegressive Integrated Moving Average (ARIMA) model, and the Long Short-Term Memory (LSTM) neural network. The performance of these models is evaluated using five statistical indicators: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the R^2 score (coefficient of determination), which quantify forecasting errors and model accuracy. This research aims to systematically evaluate and compare the performance of time series forecasting models in predicting monthly electricity demand in Thailand. The model with the highest predictive performance is employed to forecast Thailand's monthly electricity consumption for 2025. Accurate forecasting reduces the risk of electricity shortages during periods of high demand, while the analysis of forecasting results provides in-depth insights into Thailand's electricity consumption behavior by revealing historical patterns and trends in energy use.

Contribution. This study provides contributions to electricity demand forecasting and the application of time series-based statistical and deep learning models by conducting a comprehensive and controlled comparative analysis of ARIMA, ANN, and LSTM models using long-term monthly electricity consumption data from Thailand. The key contributions are summarized as follows:

- A systematic and methodologically consistent comparison of ANN, LSTM, and ARIMA models is conducted using identical datasets and experimental settings, enabling a fair and unbiased evaluation of monthly electricity consumption forecasting performance in Thailand.
- The empirical results demonstrate that the ANN model consistently outperforms LSTM and ARIMA across all electricity consumer groups, as measured by MAE, MSE, RMSE, MAPE, and

R^2 , and provide robust evidence to support model selection in practical electricity demand forecasting applications.

- A unified evaluation framework that integrates multiple error-based and goodness-of-fit metrics is established to assess forecasting performance across diverse electricity consumer groups, which enables a more comprehensive and reliable interpretation of model effectiveness in real-world electricity demand forecasting.
- The study focuses on conducting a comparative analysis between statistical and deep learning models using long-term monthly data from Thailand, rather than developing a new algorithm.

2. Literature Review and Theoretical Background

2.1 Literature Review

Srisurin et al. [21] developed a forecasting model for Thailand's electricity consumption by comparing four statistical methods: decomposition, Holt's Method, Winters' Method, and Box-Jenkins approach. Forecasting accuracy was evaluated using MAPE, with the dataset comprising monthly electricity consumption data from January 2006 to October 2021. The results show that Winters' method is the most appropriate model, estimating total annual electricity consumption for 2022 at 194,887.04 GWh.

Meftah and Adel [22] investigated wind speed forecasting, which is crucial for clean energy production and power grid integration, by comparing the performance of effective time series forecasting models. The study employed ANN, RNN, and LSTM (a specialized variant of RNN) and compared their performance with the conventional ARIMA model. Model performance was evaluated using the RMSE metric. The results indicate that LSTM achieved higher predictive accuracy than ARIMA, with lower error rates and superior capability in forecasting future values, particularly for large-scale datasets.

Srisurin et al. [23] conducted a comparative study of forecasting models for Thailand's electricity demand using monthly data from the Energy Policy and Planning Office's Energy Statistics Report. Four statistical methods were compared: decomposition, simple seasonal exponential smoothing, Winters' method, and Box-Jenkins approach, with model accuracy evaluated using MAPE. The results show that the decomposition method is the most appropriate forecasting approach for Thailand's electricity demand.

Furthermore, prior research addresses time series forecasting for regional population estimation. Promnuchanont et al. [24] analyzed forecasting performance for tourist arrivals in Chiang Mai Province through a comparative evaluation of five models: ARIMA, LSTM, Prophet, XGBoost, and Random Forest, using monthly data from January 2020 to December 2023. Based on MAE, RMSE, and MAPE, the ARIMA model achieved the highest predictive accuracy with the lowest error values (MAE = 8,325.33, RMSE = 11,462.63, and MAPE = 10.16%). The findings show ARIMA is most appropriate for time series data with clear patterns and low volatility, consistent with tourist arrival data that display relatively stable trends and seasonal components. Another population-related study by Anekoonwut [25] conducted a comparative analysis of forecasting performance for international tourist arrivals from 13 countries visiting Thailand, using monthly data from January 2013 to October 2019.

Lastly, Tarmanini et al. [26] investigated electricity demand forecasting through a comparative evaluation of ARIMA and ANN models using daily consumption data from 709 Irish households over 18 months. Based on MAPE evaluation, ANN outperformed

ARIMA in handling nonlinear load data due to its ability to capture complex relational patterns among different consumer categories.

The selection of the ARIMA, ANN, and LSTM models in this study is based on a synthesis of the existing literature and the specific characteristics of monthly electricity consumption data. ARIMA represents a traditional statistical approach that is well suited for modeling trends and seasonal structures. In contrast, ANN demonstrates the ability to learn complex nonlinear relationships within the data. Meanwhile, LSTM is specifically designed to handle sequential data and to effectively capture long-term dependencies in time series. The comparative evaluation of the three model categories under the same dataset and experimental conditions reflects a systematic analysis of traditional statistical approaches in relation to contemporary machine learning and deep learning methods. This design enables a comprehensive assessment of the suitability of each approach for forecasting monthly electricity demand in Thailand.

2.2 Theoretical Background

This section presents the theories and concepts relevant to this study, with emphasis on analytical tools and methodologies for electricity consumption forecasting.

2.2.1 Time Series Data

Time series analysis is applied because this type of data reflects the behavior of a system or phenomenon that changes continuously over time. One of the most fundamental characteristics of time series data is temporal ordering, which causes individual observations to be interdependent rather than independent of one another [9]. Consequently, the sequence of the data directly affects its meaning and the validity of analytical interpretation. Time series data possess temporal dependency, whereby observations at the current time are correlated with those from previous time periods [10]. These characteristic forms a fundamental basis for the development of both statistical and machine learning models, such as autoregressive models and recurrent neural networks, which utilize historical information to explain patterns or to forecast future values [11].

In general, time series data are classified into two main forms.

(1) Additive model

$$Y = T + S + C + I \quad (1)$$

(2) Multiplicative model

$$Y = T \times S \times C \times I \quad (2)$$

where

Y = a time series

T = the influence of the long-term trend component

S = the seasonal effect

C = the cyclical component

I = the irregular or random component

A commonly observed characteristic of time series data is the trend component, which reflects long-term changes in the data, including increasing, decreasing, or stable patterns over time. Such trends may arise from structural changes within the system or from external factors that affect the process under investigation, in addition to the underlying trend component. Time series data often exhibit seasonality, which refers to recurring patterns that

occur at regular and fixed time intervals, such as daily, monthly, or yearly cycles. This characteristic is particularly important for analyzing and forecasting data in information systems related to energy, economics, or industrial operations [12].

2.2.2 Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) constitute statistical and computational approaches that are fundamentally inspired by the structure and functioning of the human nervous system. An ANN consists of layers of nodes, or artificial neurons, in which each node is interconnected through adjustable weights that are modified during the learning process [13]. ANN are particularly well suited for modeling complex and nonlinear data structures, such as those commonly encountered in time series forecasting tasks. From a structural perspective, an ANN consists of fundamental processing units known as artificial neurons, which are organized into layers [14]. These layers typically include an input layer, one or more hidden layers, and an output layer [15].

Each neuron receives input signals from neurons in the preceding layer, computes a weighted sum combined with a bias term, and subsequently applies an activation function to generate an output that is propagated to the subsequent layer. The operation of a single artificial neuron is described by the following fundamental equation.

$$Z = \sum_{i=1}^n w_i x_i + b \quad (3)$$

where

x_i = The value of the input variable at index i

w_i = The weight that connects the input data to the neuron

b = bias

Z = linear combination

The resulting value is subsequently processed through an activation function $f(\cdot)$ to generate the output of the neuron, as expressed below.

$$y = f(z) \quad (4)$$

2.2.3 AutoRegressive Integrated Moving Average (ARIMA)

The ARIMA model constitutes a fundamental statistical approach for the analysis and forecasting of time series data, which comprise observations that evolve continuously over time and demonstrate dependence on historical patterns. Time series data commonly exhibit structural patterns such as trends, seasonality, and temporal variability [16]. The ARIMA model integrates three fundamental components, namely Autoregressive (AR), Integrated (I), and Moving Average (MA), which jointly form a flexible modeling framework that is well suited for analyzing data characterized by statistical non-stationarity [17].

The ARIMA model is expressed in the form $ARIMA(p, d, q)$

where

p = the order of the autoregressive (AR) component

d = the number of differencing operations applied to achieve stationarity (Differencing)

q = the order of the moving average (MA) component

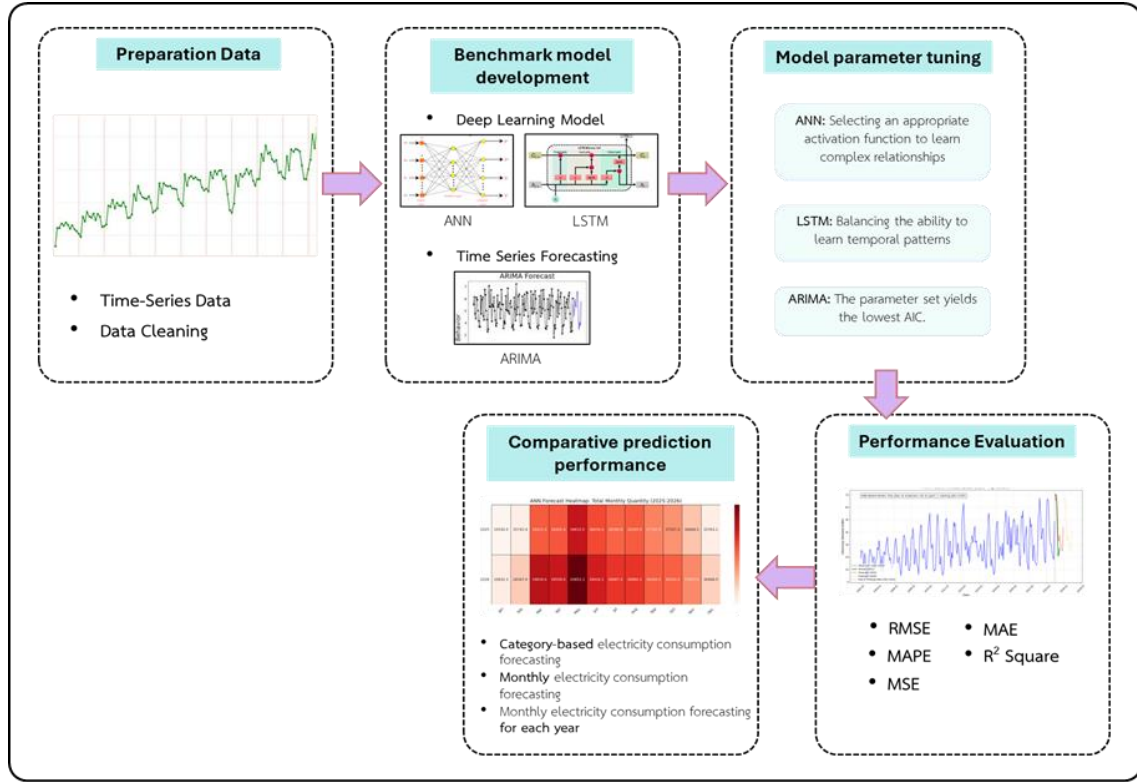


Fig. 1 Framework overview for Electricity Consumption Forecasting.

After the data undergo differencing d times, the ARIMA equation is expressed in the following general form.

$$y_t = c + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (5)$$

where

- y_t = The differenced time series value at time t
- c = constant term
- ϕ_i = The parameters of the autoregressive component
- θ_j = The parameters of the moving average component
- ε_t = The random error term (white noise) at time t

The application of the ARIMA model enhances the understanding of underlying temporal patterns and supports accurate forecasting of future values. Furthermore, the model provides a high degree of flexibility, allowing effective adaptation to time series data with diverse patterns and structural characteristics [18].

2.2.4 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks represent a specialized architecture of Recurrent Neural Networks (RNNs) that are developed to address key limitations of traditional RNNs, particularly the vanishing gradient and exploding gradient problems, which hinder the learning of long-term dependencies [19], and this limitation contributes to gradient degradation during the learning process through backpropagation through time.

Within an LSTM unit, the architecture comprises a cell state c_t and a hidden state h_t , which are responsible for retaining and transmitting information across successive time steps. The operation of an LSTM at time step t is described through the equations of its three gating mechanisms, as follows [20].

(1) Forget Gate determines the proportion of information from the previous memory state that is retained

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (6)$$

(2) Input Gate determines the new information that is written into the memory cell

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (7)$$

$$\tilde{c}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (8)$$

(3) Output Gate and Hidden State determine the output values produced by the LSTM unit

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (9)$$

$$h_t = o_t \odot \tanh(c_t) \quad (10)$$

where

- x_t = The input data at time t
- h_{t-1} = The hidden state from the previous time
- W_* and b_* = The weight matrices and bias terms
- $\sigma(\cdot)$ = sigmoid function
- $\tanh(\cdot)$ = hyperbolic tangent function
- $\odot$ = Element-wise multiplication

3. Materials and Methods

The overall research methodology is illustrated in Fig. 1, which presents the proposed electricity consumption forecasting framework and encompasses a 21-year data collection period. The research methodology is structured into five principal stages: (1) data preparation and management to ensure the accuracy and analytical suitability of the dataset; (2) benchmark model development to establish reference models for comparison; (3) parameter tuning to optimize forecasting performance; (4) model performance evaluation to assess the predictive capability of the proposed models or methods; and (5) comparative forecasting analysis to systematically examine the results and synthesize the performance of each model. The details of each stage are described in the subsequent sections.

3.1 Preparation Data

3.1.1 Thailand Monthly Electricity Consumption (TMEC) Dataset

This research employs monthly electricity consumption data for Thailand obtained from the Energy Policy and Planning Office (EPPO) under the Ministry of Energy. The dataset covers a 23-year period from 2002 to 2024 and comprises a total of 3,506 records. In this study, the data are organized into two levels of analysis. The raw dataset comprises 3,506 records, whereas the aggregated national-level time series employed for model training consists of 276 observations. For the user-segment analysis, monthly electricity consumption data are disaggregated by tariff category, with each category containing an equal number of 276 observations, thereby ensuring methodological consistency across groups. The dataset consists of five main attributes: year, month, electricity consumer category (tariff), electricity consumption (quantity), and unit of measurement (GWh). Electricity consumers are classified into 13 categories, ranging from small residential users to large-scale industrial and commercial entities.

3.1.2 Data Cleaning

In this study, the original TMEC dataset is systematically cleaned and restructured to ensure data quality and suitability for subsequent analysis. The process begins with screening and removing variables that do not contribute to the analysis, particularly the UNIT column, which contains a uniform measurement unit of gigawatt-hours (GWh) across all records. This procedure reduces the dimensionality of the data and minimizes redundancy among variables. Subsequently, a new temporal variable is generated by integrating the Year and Month columns to create a Date column in a structured time format (YYYY-MM-01), with the data type converted to datetime to facilitate time series analysis.

Furthermore, electricity consumers are categorized into six main groups: Residential, Business and Industry, Public and Social, Agriculture, Special Rate, and Special Others. The TMEC dataset is divided into two subsets: a training set comprising 80% of the data, which spans the period from 2002 to 2019 (216 months, 18 years), and a test set comprising the remaining 20%, which covers the period from 2020 to 2024 (60 months, 5 years). The 80/20 split ratio is employed to ensure that the model has sufficient long-term observations to learn the underlying trend and seasonal components embedded in the 23-year monthly electricity data. Concurrently, the most recent five years of data (60 months) are reserved as the test set to facilitate an evaluation of forecasting performance under a realistic out-of-sample setting, thereby ensuring temporal consistency and methodological validity in the assessment process.

In this study, cross-validation techniques are not employed because time series data exhibit inherent temporal dependencies, as discussed in Section 2.2.1. Random data partitioning through cross-validation poses the risk of information leakage and disrupts the time-series data splitting order of observations, potentially leading to overly optimistic performance estimates.

3.1.3 Analysis of Electricity Consumption Trends Across Consumer Categories

As part of the preliminary analysis, electricity consumption trend plots are constructed for each consumer category to provide an overall perspective and to facilitate an understanding of the distinct consumption patterns of each group over the observed period. The purpose of constructing these plots is to observe variations in electricity consumption, identify long-term trends, and examine

differences in consumption behavior, thereby providing essential insights into preliminary usage patterns and informing the development of forecasting models in subsequent stages. In the analysis of electricity consumption trends, monthly electricity usage is ranked by consumer category. This approach describes the ranking of total electricity consumption according to grouped tariff categories for each month and year. This analysis aims to identify the primary consumer groups with the highest electricity consumption in each month and to examine fluctuations in the rankings among the major consumer categories.

3.2 Model Parameter Tuning

The models are categorized into two groups: (1) neural network models (ANN and LSTM) and (2) the ARIMA statistical model.

3.2.1 The ANN and LSTM models are both neural network-based approaches and therefore employ identical parameter configurations. The look-back window used as model input is defined as 6-, 12-, 18- and 24-time steps. The number of hidden units is specified as 32, 64, and 128, while the network depth is set to 1, 2, and 3 layers. In addition, the learning rate of the Adam optimizer is tuned to 0.01, 0.001, and 0.0001 to identify the configuration that yields optimal performance, in conjunction with the mean squared error (MSE) loss function. To mitigate overfitting, the number of training epochs is fixed at 15, and the batch size is set to 32.

3.2.2 The ARIMA Model is a statistical forecasting method defined by three core parameters: p , d , and q . Parameter optimization is conducted using a grid search procedure, in which p , representing the autoregressive (AR) order, is evaluated over the range of 0 to 2; d , denoting the order of differencing, is examined within the same range; and q , corresponding to the Moving Average (MA) order, is likewise varied from 0 to 2. Model selection is based on the Akaike Information Criterion (AIC), with the model configuration yielding the lowest AIC value selected as the optimal model.

3.3 Model Performance Evaluation

The predictive performance of the models is systematically evaluated using a set of error-based and goodness-of-fit metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The mathematical formulations of these evaluation metrics are presented as follows.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (11)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (12)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (13)$$

$$MAPE = \left(\frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \right) \times 100 \quad (14)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (15)$$

where y_i denotes the actual observed value, $\hat{y}_i$ represents the predicted value, $\bar{y}$ refers to the mean of the actual values, and n indicates the total number of observations.

Lower MAE, MSE, RMSE, and MAPE values indicate smaller deviations between predicted and actual values, indicating higher predictive accuracy. In contrast, higher R^2 values indicate stronger goodness of fit and an improved ability to capture the overall data patterns.

4. Experimental Setup and Results

4.1 Data Trend Analysis

Figure 2 illustrates the trend in monthly electricity consumption in Thailand over the period from 2002 to 2024. Based on a comprehensive analysis of Thailand's monthly electricity consumption data spanning a 23-year period and comprising 276 observations, this study examines the relationship between the time variable (t) and electricity consumption (Y_t). From the time series plot, electricity consumption exhibits a steady increase over time. This pattern clearly indicates an upward trend in national electricity demand, which is attributed to factors such as economic expansion, population growth, the expansion of the industrial sector, and the continuous increase in the use of electrical technologies and appliances in both the residential and service sectors. The presence of this trend indicates that the data exhibit non-stationary behavior over time, a critical factor that must be carefully considered in the selection and development of suitable models for electricity consumption analysis and forecasting.

4.2 Ranking of Electricity Consumer Groups Based on Electricity Consumption

The analysis considers data from the most recent five-year period (2020–2024) to provide a comprehensive representation of the structural characteristics of electricity consumption across different consumer groups. A five-year period is sufficient to mitigate the influence of short-term fluctuations and to clearly reveal the sustained electricity consumption trends of each consumer group. This ranking provides clear evidence of the diverse structure of national electricity consumption across different consumer groups. The business and industrial sector constitutes the primary contributor to overall electricity demand, whereas the residential sector demonstrates a continuous increase in electricity consumption.

This contrast clearly illustrates the differentiated structure of electricity use across consumer groups, as shown in Table 1. Such findings are critical for understanding electricity demand dynamics and for informing effective national energy planning.

Table 1 presents the ranking of electricity consumption by consumer group over the past five years (2020–2024). The findings demonstrate that the Business and Industry sector accounts for the highest level of electricity consumption, totaling 30,819.73 GWh, thereby underscoring the pivotal role of economic activities in driving national electricity demand.

The residential sector ranks second, with a total electricity consumption of 24,071.74 GWh, indicating a continuous increase in household electricity use associated with urban expansion and changes in lifestyle patterns. The Special Others consumer group, which includes temporary electricity usage and electricity supplied free of charge, records a total electricity consumption of 2,202.41 GWh. Meanwhile, the Special Rate group, which operates under specific electricity load management conditions, records an electricity consumption of 1,371.39 GWh. The Public and Social group, comprising government agencies and non-profit organizations, consumes 91.63 GWh, whereas the Agriculture sector exhibits the lowest level of electricity consumption at 43.546 GWh, as electricity use in this sector is primarily activity-specific and seasonal in nature.

Table 1 Summary of Five-Year Trends in Electricity Consumption Rankings Across Consumer Groups.

No.	Grouped Tariff	GWh
1	Business and Industry	30819.73
2	Residential	24071.74
3	Special Others (Temporary, Free of Charge)	2202.41
4	Special Rate (Stand by Rate, Interruptible Rate, Direct Customer)	1371.39
5	Public and Social (Government & Nonprofit)	91.63
6	Agriculture	43.546

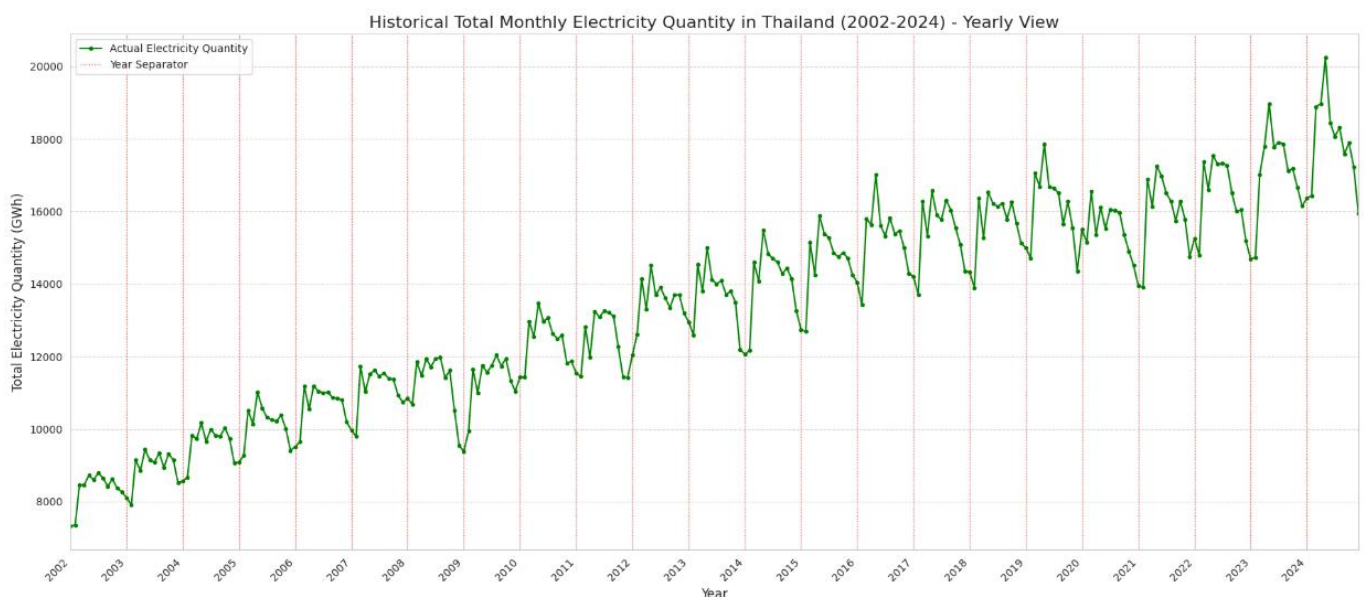
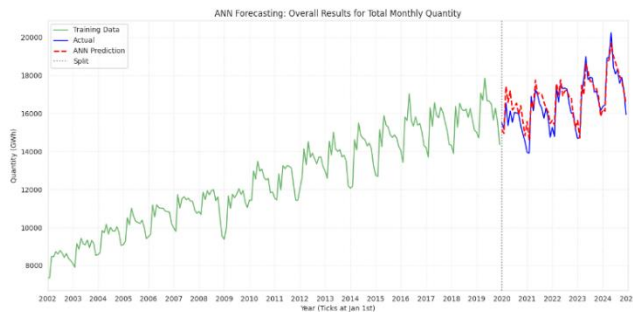


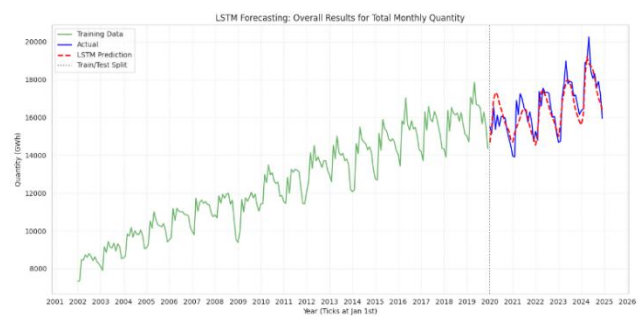
Fig. 2 Monthly Electricity Consumption in Thailand, 2002–2024.

Table 2 Comparative Performance Evaluation of the ANN and LSTM Model Across Electricity Consumer Categories.

No.	Tariff	MAE		MSE		RMSE		MAPE		R ²		Optimal Parameter (Timestep, Neuron, Layer, Learning Rate)
		ANN	LSTM	ANN	LSTM	ANN	LSTM	ANN	LSTM	ANN	LSTM	
1	Agriculture	7.34	8.96	91.01	125.89	9.54	11.22	25.1	28.29	0.63	0.48	{24, 128, 3, 0.001}
2	Business and Industry	171.96	224.52	55483.92	94743.84	235.55	307.8	2.83	3.65	0.57	0.27	{18, 128, 2, 0.001}
3	Public and Social	1.89	2.08	5.05	6.65	2.25	2.57	10.3	12.54	-0.14	0.51	{24, 128, 3, 0.001}
4	Residential	200.17	346.36	62875.19	217123.9	250.75	465.96	4.34	7.28	0.85	0.5	{24, 128, 3, 0.001}
5	Special Others	21.4	23.3	698.26	878.16	26.42	29.63	4.63	5.18	0.47	0.34	{18, 64, 3, 0.001}
6	Special Rate	27.61	28.83	1148.58	1381.77	33.89	37.17	10.08	10.33	0.32	0.18	{18, 64, 2, 0.001}



(a) the ANN forecasting



(b) the LSTM forecasting

Fig. 3 Forecasting Results of Monthly Electricity Consumption Using (a) the ANN Model and (b) the LSTM model.

4.3 Experimental setup

This research develops electricity consumption forecasting models using time series analysis to predict future demand from historical data. Three techniques are applied: the ANN, the ARIMA, and the LSTM, comparing statistical and machine learning approaches.

Grid Search is employed to identify optimal parameters for each electricity tariff category. Model performance is evaluated using statistical metrics, and the best-performing models are used to forecast Thailand's monthly electricity consumption for 2025–2026. Parameter configurations are categorized by model type as described below.

4.3.1 Configuration of ANN and LSTM

(1) Comparative evaluation of the ANN model across consumer groups shows the Public and Social group achieved the lowest MAE of 1.89, MSE of 5.05, and RMSE of 2.25, which indicate high forecasting accuracy and stability. The Business and Industry group recorded the lowest MAPE at 2.83%, which demonstrates strong proportional accuracy for high-consumption groups. The Residential group attained the highest R² of 0.85, which shows the model best explains variability in household electricity consumption. The optimal parameter configuration consists of 24-time steps, 128 neurons, 3 layers, and a learning rate of 0.001, as presented in Table 2.

Fig. 3 (a) illustrates the monthly electricity consumption forecasts, showing that during the period 2020–2024, which corresponds to the test data, the forecasted values generated by the ANN model (represented by the red dashed line) closely align with the observed data. However, discrepancies are observed during certain periods, particularly at peaks and troughs in electricity consumption, where the model slightly overestimates or underestimates the actual values.

(2) The LSTM model achieved best overall performance for the Public and Social group, with the lowest error values: MAE of 2.08, MSE of 6.65, and RMSE of 2.57. The R² value of 0.51, the highest among all groups, shows the model explains approximately 51% of data variance. Despite a MAPE of 12.54%, the low MAE and RMSE values indicate strong predictive accuracy. This performance used the optimal configuration of 24-time steps, 64 neurons, 1 layer, and a learning rate of 0.01. On the other hand, the Special Rate group showed the weakest performance with the lowest R² of 0.18. Although MAE of 28.83 and RMSE of 37.17 were moderate, the MAPE of 10.33% combined with low R² reveals model difficulty to capture volatile and irregular consumption patterns in this group. The results confirm that the optimized LSTM model provides accurate and reliable forecasts for the Public and Social electricity user group, as shown in Table 2.

Fig. 3 (b) presents monthly electricity consumption forecasts from the LSTM model. The training data show a steadily increasing trend with pronounced seasonal fluctuations. In the testing phase, predicted values closely align with observed data, but minor discrepancies appear at peak and valley points that indicate short-term variability. The LSTM model maintains stable performance in preserving both long-term trends and seasonal patterns of electricity consumption.

4.3.2 Configuration of the ARIMA Model

Based on the experimental results, appropriately tuning the ARIMA model parameters (p, d, q) to match the characteristics of each electricity consumer category is essential. Table 3 indicates that the Public and Social category attains the lowest MAE value of 1.10, demonstrating that the model achieves the highest level of accuracy, as reflected by the minimal average magnitude of quantitative prediction error for this group.

Table 3 Comparative evaluation of the performance of the ARIMA model across different electricity consumers.

No.	Tariff	MAE	MSE	RMSE	MAPE	R ²	Optimal Parameter
1	Agriculture	9.06	128.32	11.32	29.25	0.47	(2, 0, 0)
2	Business and Industry	237.14	96963.73	311.39	3.87	0.25	(2, 1, 2)
3	Public and Social	1.1	3.11	1.76	6.53	0.29	(1, 1, 0)
4	Residential	292.99	147397.8	383.92	6.24	0.66	(2, 1, 2)
5	Special Others	15.96	431.3	20.76	3.52	0.67	(0, 1, 1)
6	Special Rate	25.79	1133.51	33.66	9.48	0.32	(1, 1, 0)

The Public and Social category also demonstrates the best performance in terms of MSE and RMSE, with an MSE of 3.11 and an RMSE of 1.76. In terms of MAPE, the Special Others category records the lowest value at 3.52%, followed by the Business and Industry category at 3.87%, indicating that the model achieves high accuracy when evaluated on a relative basis of electricity consumption. This result suggests that the model is particularly suitable for consumer groups with substantially different scales of electricity usage. Regarding the R² metric, the Special Others category attains the highest coefficient of determination at 0.67, followed by the Residential category with an R² value of 0.66.

Regarding parameter suitability, the ARIMA (0,1,1) configuration is identified as the most appropriate overall model. In contrast, the ARIMA (2,1,2) specification is more suitable for the TMEC dataset, which is characterized by high electricity consumption levels and pronounced trends, particularly in the Business and Industry and Residential categories.

Figure 4 The graph illustrating the monthly electricity consumption forecasts generated using the ARIMA model shows discrepancies in certain periods, particularly around the peak and trough points of the data, which correspond to intervals characterized by relatively high short-term fluctuations. The model tends to underestimate or overestimate the actual values in certain periods, reflecting the limitations of the ARIMA approach in capturing rapidly changing fluctuation patterns. Consequently, forecast errors arise in specific intervals, which is consistent with the statistical metrics that indicate both the accuracy and the inherent limitations of the model across different electricity consumer groups.

4.4 Comparative Performance Evaluation of Models for Time Series Forecasting

The comparative performance analysis of the Artificial Neural Networks the ANN, the LSTM, and the ARIMA models shows that the ANN model achieves the best overall performance, exhibiting the lowest average MAE, MSE, RMSE, and MAPE values, together with the highest average R² value, as presented in Table 4. Although the ARIMA model produces satisfactory results for certain electricity consumer groups characterized by linear data structures, its overall performance remains inferior to that of the ANN model. In contrast, the LSTM model exhibits the lowest performance in this study, reflecting the limitations of deep learning approaches when applied to monthly time series data with a limited number of observations. From a theoretical perspective, LSTM architectures are better suited to large-scale data environments, where sufficient sample size supports the stable and reliable estimation of a high-dimensional parameter space. Within the context of monthly data with a limited number of observations, the relatively less complex architecture of ANN, which contains fewer parameters, demonstrates greater adaptability and achieves superior forecasting performance compared to LSTM in this experiment. Based on Table 4, a comparison of the average performance across the three forecasting models shows that the ANN approach achieves the best overall performance, as evaluated using the average values across all electricity consumption categories. Specifically, the ANN model records an average MAE of 71.72, an average MSE of 20,050.34, an average RMSE of 93.06, an average MAPE of 9.54, and an average R² of 0.45.

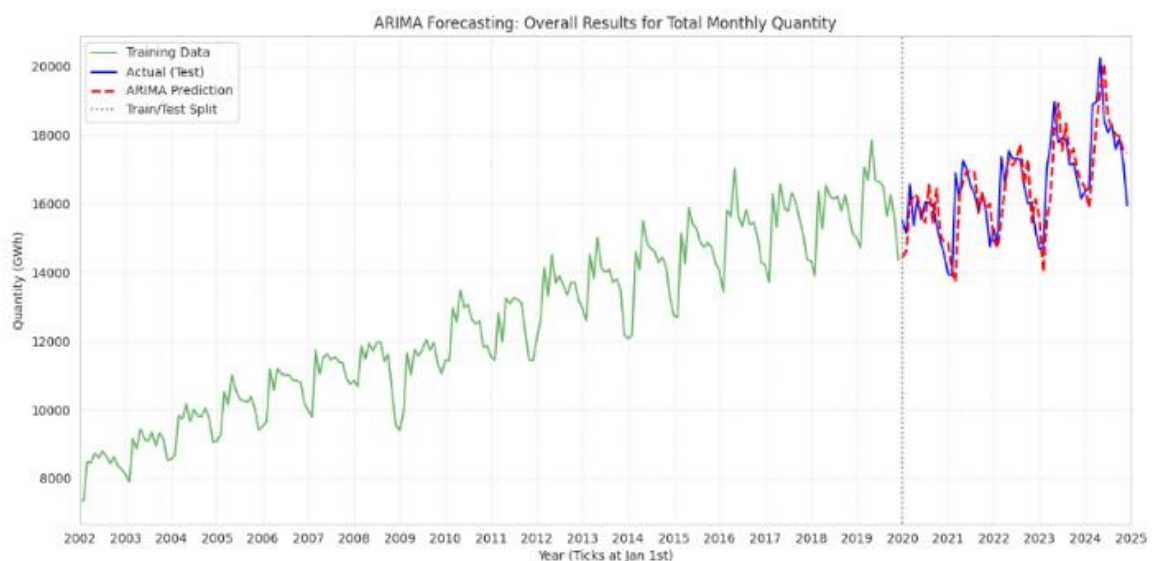


Fig. 4 Monthly electricity consumption forecasting results obtained using the ARIMA model.

Table 4 Performance comparison of forecasting models by electricity user group.

Tariff	MAE			MSE			RMSE			MAPE			R ²		
	ANN	LSTM	ARIMA	ANN	LSTM	ARIMA	ANN	LSTM	ARIMA	ANN	LSTM	ARIMA	ANN	LSTM	ARIMA
Agriculture	7.34	8.96	9.06	91.01	125.89	128.32	9.54	11.22	11.32	25.1	28.29	29.25	0.63	0.48	0.47
Business and Industry	171.96	224.52	237.14	55483.92	94743.84	96963.73	235.55	307.8	311.39	2.83	3.65	3.87	0.57	0.27	0.25
Public and Social	1.89	2.08	1.1	5.05	6.65	3.11	2.25	2.57	1.76	10.3	12.54	6.53	-0.14	-0.51	0.29
Residential	200.17	346.36	292.99	62875.19	217123.9	147397.8	250.75	465.96	383.92	4.34	7.28	6.24	0.85	0.5	0.66
Special Others	21.4	23.3	15.96	698.26	878.16	431.3	26.42	29.63	20.76	4.63	5.18	3.52	0.47	0.34	0.67
Special Rate	27.61	28.83	25.79	1148.58	1381.77	1133.51	33.89	37.17	33.66	10.08	10.33	9.48	0.32	0.18	0.32
Average	71.72	105.67	97	20050.34	52376.7	41009.63	93.06	142.39	127.13	9.54	11.21	9.81	0.45	0.21	0.44

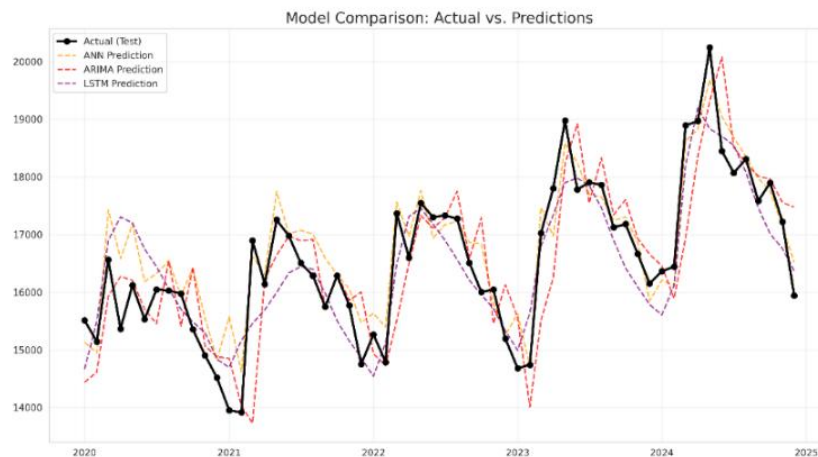


Fig.5 Comparative results of electricity consumption forecasting models based on over the past 5 years.

Table 4 presents a comparison of the performance of the ANN, the LSTM, and the ARIMA models across different electricity consumer groups. A detailed examination of the results reveals that the ANN model achieves superior overall predictive performance across multiple electricity consumer groups. These findings suggest that the ANN architecture provides sufficient flexibility to capture nonlinear relationships and seasonal components inherent in monthly data. At the same time, the model complexity remains appropriate for the dataset size (276 observations), thereby supporting stable parameter estimation. With regard to electricity consumer groups in Thailand, the results presented in the table indicate that the Business and Industry category consistently exhibits higher error metrics than the other groups across all evaluated models.

This observation suggests that the Business and Industry segment exhibits greater variability and a more complex underlying data structure than the other categories. Electricity demand in the business and industrial sectors is closely associated with economic activities, production cycles, and external factors that are not incorporated into the model. Consequently, the data exhibit irregular fluctuations and non-stationary patterns, which pose difficulties for linear learning mechanisms in ARIMA and even for the sequential structures of LSTM to effectively capture.

The ARIMA model demonstrates relatively strong performance in certain categories where the trend and seasonal patterns remain stable and consistent. Within the context of monthly data with a limited number of observations, the LSTM model, characterized by a relatively large number of parameters, does not fully capture complex patterns to maximum capacity. Consequently, the overall predictive performance of the LSTM model remains inferior to that of the ANN in this experiment.

Accordingly, the ANN approach is identified as the most effective method for forecasting future electricity consumption trends.

Figure 5 illustrates five-year retrospective forecasts of electricity consumption from 2020 to 2024 for each model compared with observed values. All three models exhibit clear upward trends and pronounced seasonal variability. The ANN model shows the closest alignment with observed values across nearly all periods, effectively capturing both expansion and contraction phases of electricity consumption. This is particularly evident at peak and valley points, which reflects the model's capability to learn complex non-linear relationships. The results are consistent with statistical analyses that indicate the ANN model yields lower forecasting errors and better explains data variance.

In contrast, the ARIMA model adequately captures the underlying trend during stable periods with gradually evolving consumption patterns.

However, during sudden structural changes or high volatility, particularly at peaks or post-trough recovery phases, the model generates forecasts that deviate substantially from observed values. For the LSTM model, despite being a deep learning approach designed for time series data, the forecasted curves appear relatively smooth and lag behind observed values across multiple periods. This limitation is evident during rapid consumption changes, which increases errors in the capture of peak and valley points. Such behavior reflects LSTM constraints when applied to monthly time series data with limited observations and pronounced seasonal patterns.

Therefore, in this study, the ANN model is selected as the primary approach for forecasting Thailand's monthly electricity consumption for the 2025–2026 period.

4.5 Forecasting Results of Monthly Electricity Consumption for the 2025–2026 Period

The monthly electricity consumption for the 2025–2026 period is forecast using the ANN technique, which exhibits superior performance in terms of quantitative error metrics. The ANN model achieves the lowest average MAE and RMSE values compared with the other models, indicating that the resulting forecasts exhibit the closest alignment with the observed values. The average MAPE of the ANN model remains low, reflecting strong percentage-based forecasting accuracy, particularly for large electricity consumer groups such as Business and Industry and Residential. This forecasting analysis employs monthly electricity consumption data covering the period from January 2002 to July 2025 for model estimation and prediction.

Figure 6 presents the national electricity consumption forecasts, indicating that total annual electricity consumption in 2025 is projected to reach approximately 12,021.13 GWh, representing a decline relative to 2024, the most recent year included in the analysis, during which total electricity consumption amounts to 14,710.61 GWh. However, the trend in the subsequent year indicates that total electricity consumption is expected to increase again, with the projected level for 2026 rising to approximately 14,176.50 GWh. A detailed examination of the forecasting results by electricity tariff categories reveals that the industrial sector consistently records the highest electricity consumption across all months and constitutes the largest proportion of total national electricity usage when compared with other consumer groups. In 2025, the industrial sector records a total electricity consumption of 163,892.47 GWh, reflecting the significant role of the industrial sector in shaping the overall structure of national electricity demand.

A trend analysis of electricity consumption during the 2025–2026 period demonstrates that consumption levels in both years remain below those recorded in 2024, which serves as the baseline year for comparative evaluation. The forecasting results indicate that maintaining electricity generation capacity and reserve margins at levels comparable to those observed in 2024 is sufficient to accommodate short- to medium-term electricity demand over the next 1–2 years. These findings serve as supporting evidence for

effective planning and management of electricity resources while avoiding unnecessary short-term infrastructure investments.

4.6 Forecasting Trends of Electricity Consumption by Category for the 2025–2026 Period

The forecasting of electricity consumption trends by category is conducted to analyze the direction and patterns of future changes in electricity demand, with separate consideration given to each consumer group, as illustrated in Fig. 7.

The electricity consumption forecasting results for each consumer group clearly reflect distinct patterns of electricity usage. The Agriculture group exhibits pronounced seasonal variability, with electricity consumption declining during the mid-year period and rising again in early 2026, a pattern consistent with agricultural activity cycles and prevailing climatic conditions.

In contrast, the Business and Industry group sustains high electricity consumption levels and displays the greatest degree of variability among all consumer categories. Electricity consumption exhibits continuous fluctuations from late 2025 through 2026, reflecting sensitivity to economic conditions and production activities. Nevertheless, this sector remains a principal contributor to national electricity demand. The Public and Social consumer-group exhibits a gradual upward trend with low variability, indicating a relatively stable pattern of electricity consumption associated with government operations and public services. The observed variations are driven primarily by changes in service provision structures rather than seasonal factors.

The Residential consumer group demonstrates a high level of electricity consumption with pronounced seasonal variability, increasing during the early and mid-year periods due to climatic influences and household electricity usage behaviors. In contrast, the Special Others group demonstrates moderate variability with a slight long-term upward trend, reflecting an irregular yet steadily growing pattern of electricity consumption. The Special Rate consumer group demonstrates a sustained upward trend in electricity consumption with high stability, reflecting the planned and systematic nature of electricity usage within this category.

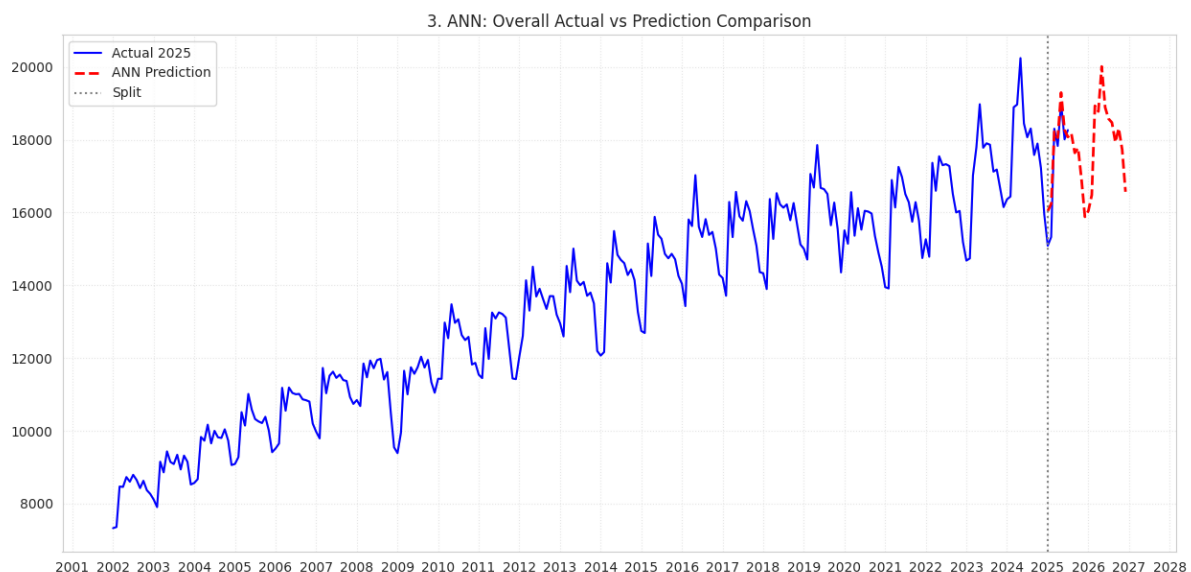


Fig. 6 Electricity consumption forecasts for 2025–2026 based on the ANN model (The red dashed line).



Fig. 7 Electricity consumption trend forecasts by category for the 2025–2026 period: (a) Agriculture, (b) Business and Industry, (c) Public and Social, (d) Residential, (e) Special Others, and (f) Special Rate.

5. Discussion

5.1 Overall Trends in the One-Year-Ahead Forecast of Electricity Consumption

Figure 8 presents the one-year-ahead electricity consumption forecast. The ANN model effectively captures the overall trend and temporal variation, with forecasts for 2025 closely aligning with observed values. The results indicate a strong ability to learn nonlinear patterns, particularly during periods of rapid early-year growth and sustained mid-year demand. The experimental results indicate that ANN achieves a lower average error than LSTM and attains a higher average R^2 across several electricity consumer groups. The obtained results demonstrate that ANN effectively captures nonlinear patterns and seasonality in monthly time series data, particularly under conditions of limited observations. The observed performance trends suggest important implications for model selection in time series forecasting, highlighting that greater architectural complexity does not necessarily translate into improved generalization capability. The pattern becomes increasingly evident in long-horizon monthly time series forecasting settings, in which neural models of lower architectural complexity often demonstrate generalization performance comparable to, or superior to, that exhibited by more complex recurrent architectures.

In the context of electricity demand forecasting for 2026, there is a significant likelihood of peak demand periods exceeding average consumption levels. This consideration is critical for power

system planning, as such peak conditions necessitate adequate reserve generation capacity and effective load management strategies. Accordingly, the forecasting results provide a robust basis for planning reserve generation capacity, optimizing renewable energy integration, and deploying energy storage systems to reduce the risk of electricity shortages during periods of elevated demand.

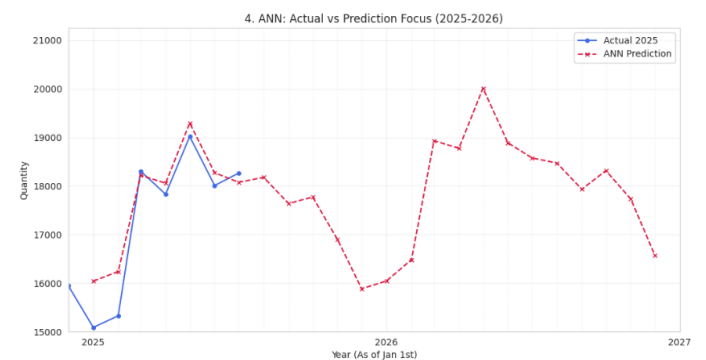


Fig. 8 One-Year-Ahead Forecast of Electricity Consumption Trends for 2025–2026.

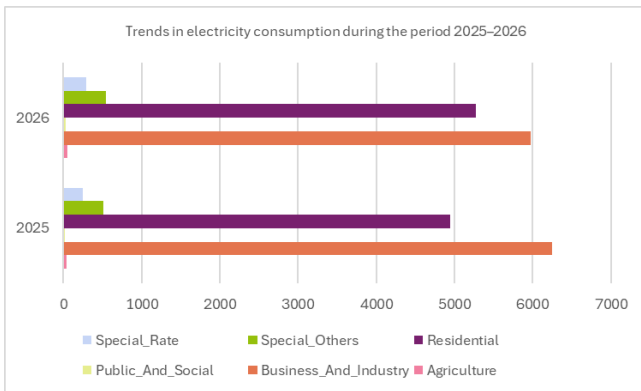


Fig. 9 Electricity Consumption Trends by Consumer Category during 2025–2026.

Figure 9 illustrates the overall annual distribution of electricity demand. The Business and Industry group records the highest consumption in both 2025 and 2026, which emphasizes the significant role of manufacturing and economic activities in national electricity demand. This group shows a slight decline in 2026 compared with 2025, which indicates stable or moderately slowing energy consumption. The Residential group, the second-largest category, shows an increasing trend in 2026 compared with 2025. This pattern represents sustained growth in household electricity demand and may be associated with urban expansion and population growth.

The findings provide strong empirical evidence that the ANN-based forecasts substantially reduce forecasting errors across multiple statistical evaluation metrics while consistently capturing the structural characteristics of major national electricity consumer groups.

5.2 A Comparative Analysis of Performance between Two Model Categories

In this research, the evaluated models comprise the ANN and the LSTM as representatives of neural network approaches, and ARIMA as a representative of the statistical modeling framework. Based on experimental results evaluated using statistical performance metrics, including MAE, MSE, RMSE, MAPE, and R^2 , the neural network models demonstrate higher overall forecasting accuracy. In particular, the ANN achieves the most notable performance across multiple electricity consumer groups, indicating a strong capability to learn complex data relationships and to effectively capture both long-term trends and seasonal variability.

From a technical perspective, neural network models offer a key advantage through their ability to capture non-linear relationships and accommodate the inherent complexity of time series data. This capability aligns well with the characteristics of electricity consumption data, which are typically influenced by multiple factors and exhibit distinct temporal variation patterns. The experimental results indicate that the ANN model yields lower average error values and higher R^2 scores in several cases compared with the LSTM and the ARIMA models. The ANN architecture is particularly well suited to monthly data with a limited number of observations and facilitates effective learning of seasonal patterns through appropriate time-step configuration. Although the LSTM model is explicitly designed for sequential data, within the context of monthly data with a relatively limited number of observations, the model requires a larger dataset to fully learn and represent long-term relationships effectively.

Consistent with the model complexity–data size tradeoff principle, models exhibiting greater structural complexity demand substantially larger datasets to ensure stable and reliable parameter estimation. By comparison, ANN, defined by a relatively simple architectural structure and an inductive bias aligned with nonlinear regression tasks, demonstrates greater adaptability in small-scale data settings.

For the statistical ARIMA model, the experimental results indicate higher overall error and deviation levels compared with the neural network models. This outcome reflects limitations in handling non-linear patterns and irregular fluctuations, which hinder comprehensive capture of the underlying data structure and consequently lead to higher forecast errors, as observed in the results.

5.3 Limitations

The first limitation of this research pertains to the reliance on monthly electricity data. The monthly level of temporal resolution does not fully capture short-term fluctuations in electricity consumption.

Another limitation, the exclusive reliance on historical electricity consumption as a single predictor, without incorporating exogenous variables such as weather conditions, temperature, rainfall, or economic indicators, which may influence fluctuations in electricity demand.

5.4 Future Work

Future research will integrate spatio-temporal graph neural networks [27] with quantile-based transformers to jointly model spatial dependencies and probabilistic uncertainty [28], to achieve robust electricity demand forecasting under dynamic load patterns and extreme events.

6. Conclusion

This study compares 3 time series forecasting models, including ANN, LSTM, and ARIMA, for electricity consumption prediction. The ANN model demonstrates superior overall performance, achieving an average MAE of 71.72, MSE of 20,050.34, RMSE of 93.06, MAPE of 9.54, and an R^2 of 0.45 on the TMEC dataset, indicating lower forecasting errors and improved ability to explain data variability. The optimal ANN configuration for the TMEC dataset consists of 24 time steps, 128 neurons, 3 layers, and a learning rate of 0.001.

Across consumer groups, the ANN model showed strong performance: the Public and Social group achieved the lowest MAE at 1.89, the Business and Industry group recorded the lowest MAPE at 2.83%, and the Residential group attained the highest R^2 at 0.85. Therefore, the ANN model was selected for forecasting Thailand's monthly electricity consumption during 2025–2026 to support electricity system planning and resource management. The results demonstrate that the ANN model effectively captures complex relationships in data with trend and seasonal components, outperforming traditional statistical models.

Highly accurate monthly forecasting results generated by the ANN model serve as valuable inputs for electricity generation planning, reserve margin planning, and short-term grid stability management. Furthermore, the analysis of consumption trends and usage structures across different electricity consumer categories supports infrastructure investment planning by aligning strategic decisions with evolving patterns of electricity demand.

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Declaration of AI Use

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Author Contributions:

Teerapong Chongwat: Conceptualization, Methodology, Data Curation, Software, Validation, Visualization, Writing – original draft.

Artitayaporn Rojarath: Conceptualization, Methodology, Validation, Investigation, Formal Analysis, Writing – original draft, Writing – review & editing, Supervision, Funding Acquisition.

Declaration of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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