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Long-Term Electricity Demand Forecasting for Thailand's Small Business Sector: An LSTM-Based Approach

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Abstract: Accurate electricity demand forecasting is essential for Thailand's energy system planning, particularly for the small business sector, whose consumption exhibits high variability (coefficient of variation: 26.34%). This study develops a Long Short-Term Memory (LSTM) model to forecast monthly electricity consumption of Thailand's small business sector over a 12-month horizon from September 2025 to August 2026. The analysis is based on 284 months of historical consumption data (January 2002–August 2025) obtained from official national statistics. The forecasting framework employs Min–Max normalization and a supervised learning formulation with a 12-month lookback window. The dataset is chronologically divided into training (80%) and testing (20%) subsets, and model performance is evaluated using Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). The optimized LSTM model achieves strong forecasting accuracy, with a training RMSE of 93.93 and MAPE of 5.45%, and a testing RMSE of 143.68 and MAPE of 6.25%. These results meet the criterion for highly accurate forecasting (MAPE < 10%), demonstrating the model's ability to capture long-term trends and seasonal patterns while generalizing well to unseen data. The findings highlight the suitability of LSTM-based models for long-term electricity demand forecasting in high-volatility small-business sectors and underscore their practical relevance for energy planning and policy development in Thailand.

Keywords: Electricity Consumption, Demand Forecasting, Long Short-Term Memory, Mean Absolute Percentage Error, Small Business Sector.

1 INTRODUCTION

Accurate electricity consumption forecasting is a fundamental requirement for the stability, efficiency, and long-term sustainability of Thailand's power system. Reliable demand projections support national energy management by informing the Power Development Plan (PDP) and generation planning, ensuring adequate reserve margins to meet peak demand while maintaining system reliability. Moreover, precise forecasting enables cost-efficient power plant dispatch and facilitates the integration of variable renewable energy resources, thereby supporting Thailand's energy transition and long-term policy objectives [1].

Advances in deep learning have significantly improved time-series forecasting for complex and nonlinear systems. Among these approaches, the LSTM model, a specialized form of recurrent neural networks (RNNs), has demonstrated strong capability in learning long-range temporal dependencies [2]. Compared with classical time-series models such as decomposition-based Holt–Winters and ARIMA, LSTM can effectively capture nonlinear dynamics, model seasonal patterns, and retain relevant historical information over extended forecasting horizons [3]. Moreover, LSTM has achieved higher accuracy in ecological footprint forecasting compared with classical and hybrid models [4]. LSTM adapts better to complex, non-stationary time series than ARIMA [5]. These characteristics make LSTM particularly suitable for electricity demand forecasting, where consumption behavior is influenced by interacting economic, operational, and environmental factors.

Previous studies have applied LSTM-based models to electricity demand forecasting in Thailand and reported superior predictive performance over conventional statistical approaches, particularly in capturing nonlinear demand behavior and seasonal variability [6]–[9]. However, most existing research has focused on aggregated demand or short-term forecasting horizons, while long-term monthly forecasting for specific business segments with high demand volatility remains relatively underexplored. This study addresses this gap by focusing on the small-business sector, one of the most volatile segments of electricity consumption in Thailand. Using 284 months of monthly electricity consumption data from January 2002 to August 2025 obtained from the National Statistical Office, Ministry of Digital Economy and Society [10], descriptive statistical analysis shows that small businesses exhibit the highest relative variability, with a coefficient of variation (CV) of 26.34%, compared with medium and large enterprises, as shown in Table 1. Monthly electricity consumption increases substantially with business size, ranging from a mean of 1,454 GWh for small businesses to 5,298 GWh for large businesses.

This pronounced volatility presents a significant forecasting challenge and motivates the development of robust long-term prediction models. Accordingly, this study develops an LSTM-based forecasting framework to predict monthly electricity consumption of Thailand's small business sector over a 12-month horizon. By targeting a high-volatility segment and a long-term forecasting task, the study provides empirical evidence on the effectiveness of LSTM models for strategic electricity demand forecasting and generates insights relevant to energy planning and policy development in Thailand.

Table 1. Descriptive statistics of monthly electricity consumption by business size (GWh)

Business Size	N	Mean	Median	SD	Minimum	Maximum	CV (%)
Small	284	1,454	1,511	383.0	693	2,274	26.34
Medium	284	2,205	2,227	405.0	1,406	3,103	18.37
Large	284	5,298	5,648	1,035.0	2,797	6,836	19.54

Note: Processed from National Statistical Office, Ministry of Digital Economy and Society (2025)

This study aims to develop and apply an LSTM model to forecast monthly electricity consumption for Thailand's small business sector from September 2025 to August 2026. Unlike previous studies that primarily focused on aggregated national demand or short-term forecasting horizons, this study emphasizes long-term monthly forecasting for a high-variability sector-specific consumption dataset.

The main contributions of this study are as follows. First, a sector-specific long-term electricity demand forecasting framework is developed using a 23-year historical dataset representing Thailand's small business electricity consumption. Second, the proposed LSTM-based forecasting model is evaluated against a classical SARIMA baseline to assess its effectiveness in capturing nonlinear temporal patterns and seasonal variations. Third, the study provides a 12-month-ahead forecasting analysis that supports strategic electricity demand planning for high-variability consumption sectors. Finally, the results demonstrate the suitability of deep learning approaches for long-term sector-level electricity demand forecasting using extended historical datasets.

2 RESEARCH METHODOLOGY

The overall architecture and procedural steps of the forecasting framework developed in this study are illustrated in Fig. 1. The workflow encompasses data collection, normalization, a sliding-window transformation for supervised learning, and subsequent model training and evaluation. To address the identified research gap, this study adopts a systematic LSTM-based modelling framework for long-term electricity demand forecasting in Thailand's small business sector. The following section describes the data, model architecture, training procedure, and evaluation methodology in detail.

2.1. Data Collection and Description

The dataset used in this study consists of 284 monthly observations of electricity consumption from Thailand's small business sector, obtained from the National Statistical Office, Ministry of Digital Economy and Society [10]. Each observation represents aggregated monthly electricity usage measured in gigawatt-hours (GWh). The dataset spans 23 years and 8 months, from January 2002 to August 2025, providing sufficient temporal coverage for long-term time-series analysis and forecasting. The dataset's extended time horizon enables the model to capture structural trends, seasonal patterns, and long-term variability inherent in small-business electricity consumption. Such temporal depth is particularly important for deep learning–based forecasting models, which require substantial historical data to effectively learn complex temporal dependencies [11]-[12].

2.2. Data Preprocessing

Prior to model development, the electricity consumption time series was preprocessed to improve numerical stability and ensure suitability for LSTM-based learning [13]. The raw data were rescaled using Min–Max normalization to map values into the [0,1] range, which is commonly applied to facilitate stable and efficient neural network training. To preserve temporal integrity, the dataset was partitioned chronologically into training and testing subsets, with 80% of the observations (229 months) used for model training and the remaining 20% (55 months) reserved for performance evaluation. This chronological split was adopted to prevent information leakage across time. Subsequently, the normalized time series was transformed into a supervised-learning representation using a sliding-window approach [14]. A 12-month lookback window was used as the input sequence, with the corresponding target output being electricity consumption in the subsequent month. In this study, the input features consist of a single univariate time series (GWh). Thus, the data were transformed into a three-dimensional tensor with shape [Samples, 12, 1], where 12 denotes the number of timesteps (lookback period), and 1 denotes the number of features. This specific tensor format is required by the LSTM architecture to effectively process sequential dependencies.

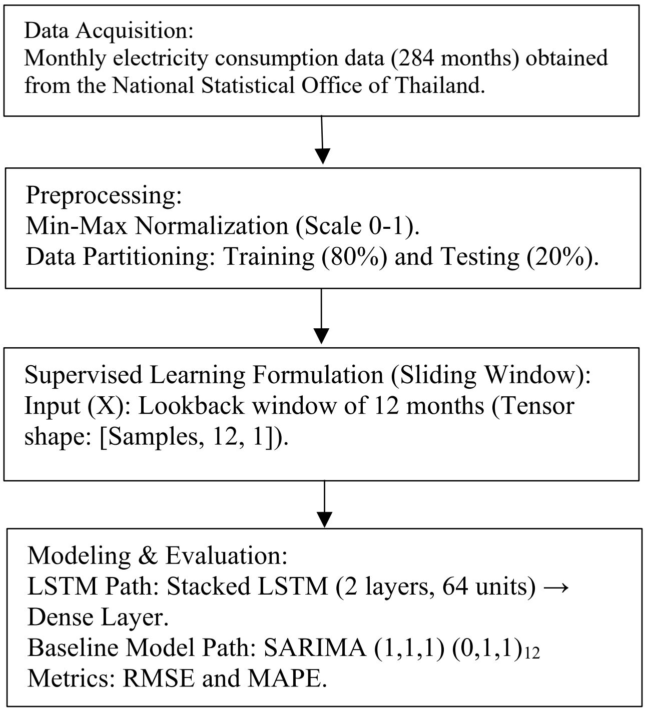

Fig. 1. The systematic workflow of the proposed electricity demand forecasting framework, illustrating the stages of data acquisition, preprocessing through Min-Max normalization, the sliding window transformation for supervised learning, and the comparative modeling approach using LSTM and SARIMA architectures.

2.3. Model Architecture

The forecasting model employs LSTM layers to capture temporal dependencies in monthly electricity consumption data [15]. Stacked LSTM layers are used to enhance the model's ability to learn both short-term dynamics and long-term temporal patterns. The optimized architecture consists of two stacked LSTM layers with 64 units each, selected to balance model expressiveness and computational efficiency. Dropout regularization is applied between LSTM layers during training to reduce overfitting and improve the model's generalization capability. A fully connected dense layer is employed as the final layer of the network to generate the forecasted electricity consumption value. Rectified Linear Unit (ReLU) activation functions are used in the dense hidden layer to support nonlinear feature learning, while the LSTM layers internally use sigmoid and tanh activation functions. A linear activation function is applied in the output layer to accommodate continuous-valued regression.

2.4. Model Training

The model was trained using Mean Squared Error (MSE) as the loss function to measure the discrepancy between predicted and observed electricity consumption values. The Adam optimizer was used with a learning rate of 0.001 and a batch size of 16, and training was run for up to 100 epochs. These hyperparameters were determined empirically to ensure effective convergence and computational efficiency. To prevent overfitting and enhance generalization performance, an early stopping mechanism was implemented by monitoring validation loss during training. The training process was automatically terminated if no significant improvement was observed over 10 consecutive epochs (patience = 10), ensuring that the model remained well-generalized to unseen data.

2.5. Model Evaluation

Model performance is assessed using RMSE and MAPE, which are widely used evaluation metrics for time-series forecasting models [16]. RMSE reflects the magnitude of forecasting errors and is sensitive to large deviations, while MAPE expresses prediction accuracy as a percentage relative to actual observations. Forecasting accuracy is assessed against commonly referenced MAPE thresholds: an MAPE below 10% indicates highly accurate forecasting; values between 10% and 20% represent good forecasting performance; values between 20% and 50% correspond to reasonable accuracy; and values exceeding 50% are considered inaccurate. Model performance is further examined through visual comparison of predicted and observed electricity consumption using line plots, together with residual analysis to assess error distribution and potential model bias.

2.6. Baseline Statistical Model: SARIMA

To demonstrate the effectiveness of the proposed LSTM model, a Seasonal Autoregressive Integrated Moving Average (SARIMA) model was employed as a classical statistical baseline [17]. The development of the SARIMA model followed the Box–Jenkins iterative methodology. The presence of temporal dependencies was first assessed using the Autocorrelation function, Partial autocorrelation function, and the Ljung–Box Q-test. To achieve stationarity, first-order non-seasonal differencing ($d = 1$) and seasonal differencing ($D = 1$) were applied to remove trends and annual cycles. The optimal orders for (p, d, q) and $(P, D, Q)_{12}$ were identified by analyzing significant lags in the ACF and PACF plots, and a grid search was conducted to compare multiple candidate models. The final model, SARIMA$(1,1,1)(0,1,1)_{12}$, was selected based on the minimum Akaike Information Criterion (AIC) value, which balances model goodness-of-fit and parsimony. The residuals of the selected model were tested using the Ljung–Box test to confirm that they behaved as white noise (p-value > 0.05), indicating that the model successfully captured all systematic patterns in the data.

2.7. Implementation Tools

All model development and experimentation were implemented using Python, which provides a flexible and widely adopted environment for scientific computing and machine learning applications. The LSTM model was developed using TensorFlow/Keras for deep learning implementation. Data preprocessing and numerical operations were performed using NumPy and Pandas, which offer efficient data manipulation and analytical capabilities. Additionally, the SARIMA baseline model was implemented using the statsmodels library in Python 3.9 for comparative performance analysis.

2.8. Experimental Configuration

The hyperparameters of the LSTM model were selected through empirical experimentation to ensure stable convergence and generalization performance. Multiple candidate configurations were evaluated by varying the number of LSTM layers, hidden units, and learning rates. The final configuration, consisting of two stacked LSTM layers with 64 units each and a learning rate of 0.001, provided the best balance between forecasting accuracy and computational efficiency. Early stopping based on validation loss was applied to prevent overfitting and improve model robustness.

3 RESULTS AND DISCUSSION

The optimal LSTM model was trained using 229 months of electricity consumption data and evaluated on the remaining 55 months. Model performance was assessed using RMSE and MAPE, which are widely recognized metrics for measuring forecasting accuracy in time-series analysis [11]–[12]. During the training phase, the model achieved an RMSE of 93.93 and a MAPE of 5.45%, indicating a relatively low level of prediction error. These results suggest that the LSTM model effectively captured the temporal patterns present in the electricity consumption data.

In the testing phase, the RMSE increased to 143.68 and the MAPE to 6.25%. Although the error values were higher than those observed during training, the MAPE remained below 10%, a threshold commonly regarded as acceptable for forecasting applications. This indicates that the model generalizes reasonably well to unseen data and maintains forecasting accuracy within practical limits. Overall, the LSTM model demonstrates strong predictive capability, characterized by low training error and moderate testing error. The observed increase in RMSE and MAPE during testing reflects the expected generalization gap between training and unseen data; however, the error levels remain within acceptable forecasting standards. These findings confirm that LSTM is an effective approach for modeling long-term electricity consumption patterns in the small business sector. Regarding the SARIMA baseline model, the Ljung–Box Q-test was applied to the historical data to statistically confirm the presence of temporal dependencies. The results for both 12-month and 24-month lags yielded p-values of 0.000 ($p < 0.001$), indicating strong autocorrelation and seasonal patterns, thereby rejecting the null hypothesis of white noise.

Table 2. Forecasting errors of the optimal LSTM model vs. the SARIMA baseline

Dataset	Number of Months	RMSE	MAPE (%)
LSTM			
Training	229	93.93	5.45
Testing	55	143.68	6.25
SARIMA$(1,1,1)(0,1,1)_{12}$			
Training	229	118.42	5.82

This statistical analysis justifies the use of the LSTM network, which is specifically designed to capture long-term dependencies and cyclical trends. The optimal orders for the SARIMA model were identified using the Box–Jenkins approach. First, non-seasonal differencing (d = 1) and seasonal differencing (D = 1) were applied to stabilize the mean and remove seasonality. The orders p = 1 and q = 1 were identified through the partial autocorrelation function and Autocorrelation Function plots, respectively. The seasonal moving average term Q = 1 was selected based on the significant spike at the 12th lag in the ACF. The final configuration, SARIMA(1,1,1)(0,1,1)$_{12}$, was validated as the best-fitting model by achieving the minimum Akaike Information Criterion (AIC) value and passing the Ljung–Box test for residual independence, as shown in Table 2.

A comparative analysis in Table 2 shows that during the training period, the proposed LSTM model achieved a lower MAPE (5.45%) compared to the SARIMA baseline (5.82%). This superior performance suggests that the LSTM's memory cells are more effective at capturing the nonlinear complexities of Thailand's small business electricity consumption than traditional linear statistical models. The predicted values closely follow the observed electricity consumption trends, particularly during the training period, and remain reasonably aligned with actual values throughout the testing phase. This visual agreement is consistent with the quantitative results reported in Table 2, where the model achieved relatively low RMSE and MAPE values. Although the SARIMA model provides a reasonable statistical benchmark, the LSTM model's overall forecasting performance demonstrates a stronger ability to capture nonlinear temporal patterns and seasonal variations in the electricity consumption data. As illustrated in Fig. 2, the LSTM model effectively captures both the underlying trend and seasonal variations in electricity consumption, supporting its suitability for long-term forecasting. The forecasted electricity consumption for the period from September 2025 to August 2026 is presented in Table 3.

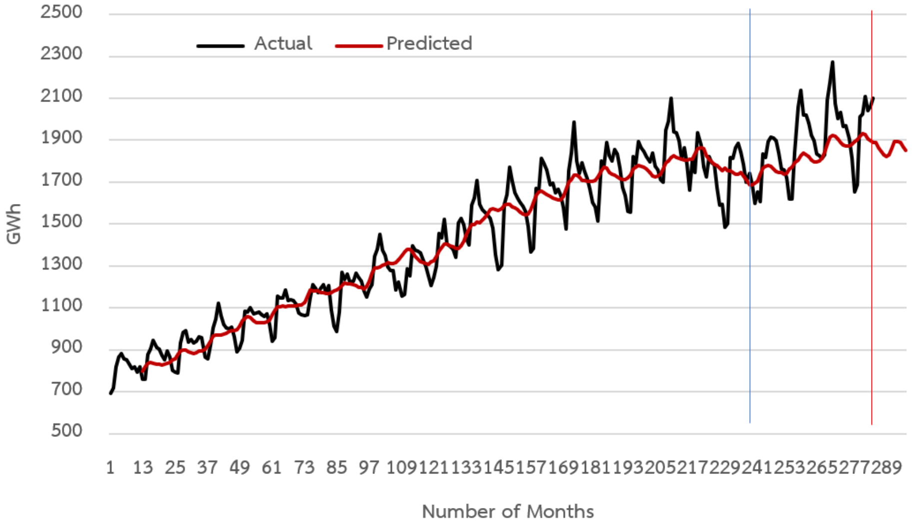

Fig. 2. Actual versus predicted electricity consumption during the training period, testing period, and 12-month forecasting horizon

Table 3. The predicted small business electricity consumption

Year	**Month**	**Electricity Consumption (GWh)**
2025	September	1,888.24
	October	1,863.47
	November	1,845.71
	December	1,829.03
2026	January	1,821.90
	February	1,829.40
	March	1,860.74
	April	1,894.93
	May	1,894.42
	June	1,889.26
	July	1,869.10
	August	1,851.11
Total		**22,337.29**

Note: Values represent the 12-month-ahead electricity consumption forecast generated by the LSTM model.

The forecasting accuracy achieved by the proposed LSTM model, as reflected by a testing RMSE of 143.68 and a MAPE of 6.25%, is comparable to or exceeds the performance reported in related studies. Guimarães da Silva and Meneses [18] reported MAPE values ranging from 6% to 10% for daily electricity consumption forecasting using LSTM and bidirectional LSTM architectures. Likewise, Alden et al. [19] reported RMSE values between 100 and 150 kWh for smart-home electricity consumption forecasting, which closely correspond to the magnitude of prediction errors observed in this study. Taken together, these comparative results provide evidence that the LSTM model developed in this study delivers robust and reliable forecasting performance, effectively capturing both long-term demand trends and seasonal consumption patterns within the small business sector.

4 CONCLUSION

This study developed and evaluated an LSTM model to forecast monthly electricity consumption for Thailand's small business sector, using 284 months of historical data spanning January 2002 to August 2025. The optimal model, trained on 229 months and tested on 55 months of data, achieved a training RMSE of 93.93 with a MAPE of 5.45%, and a testing RMSE of 143.68 with a MAPE of 6.25%. These results indicate that the LSTM model effectively captures long-term trends and seasonal variations in electricity consumption, producing forecasts with high accuracy (MAPE < 10%). The visual comparison between observed and predicted electricity consumption further supports the model's ability to generalize to unseen data, confirming its suitability for long-term forecasting in small-business energy management. Overall, the findings demonstrate the robustness of LSTM models in learning nonlinear temporal dependencies and highlight their practical relevance for electricity demand forecasting and energy planning in Thailand. While the present study confirms the effectiveness of the LSTM-based approach, several directions remain open for future research:

- Hybrid and Comparative Models: Future studies may integrate LSTM with other deep learning architectures (e.g., GRU, CNN–LSTM) or conduct systematic comparisons with classical statistical models (e.g., ARIMA, Holt–Winters) to further assess relative strengths and limitations.
- Incorporation of Exogenous Variables: Including external factors such as temperature, economic indicators, or business activity levels may improve forecasting accuracy by capturing broader drivers of electricity demand.
- Higher-frequency Data: Extending the analysis to daily or hourly electricity consumption would allow evaluation of the scalability and adaptability of LSTM models to finer temporal resolutions.
- Cross-sectoral Applications: Applying similar forecasting frameworks to other sectors, including medium and large businesses as well as residential and industrial consumption, could provide a more comprehensive perspective on national electricity demand.
- Integration with Smart Grid Systems: Embedding LSTM-based forecasts into demand-side management strategies and smart grid operations may enhance real-time decision-making and support Thailand's energy transition.

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ETHICS STATEMENT

This study did not involve human or animal participants and therefore did not require ethical approval.

STATEMENT OF CONFLICT OF INTERESTS

The authors declare no conflicts of interest related to this study.

LICENSING

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