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Prediction of Electricity Consumption Using Interpretable Machine Learning Approach

Theera Thongsanitkarn[1*], Prompong Sugunnasil[2], Waranya Mahanan[3], and Sumalee Sangamuang[4]

[1] Faculty of Engineering, Chiang Mai University, Chiang Mai, 50200, Thailand
[2] College of Arts, Media, and Technology, Chiang Mai University, Chiang Mai, 50200, Thailand
* Correspondence: theera_th@cmu.ac.th

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Abstract: The continuously increasing demand for electricity presents significant issues for policymakers and utility companies. An accurate forecast of electricity usage is critical for effective energy management. This thesis provides an interpretable machine-learning approach for forecasting energy demand that incorporates macroeconomic variables such as GDP, inflation, and industrial growth. The study uses data from the World Development Indicators from 1973 to 2021 and employs the multi-model. Our findings emphasize the importance of economic considerations on electricity demand, resulting in a reliable method for forecasting energy consumption. This study adds to the body of knowledge by providing a clear model to aid in decision-making processes connected to energy management and policy creation.

Keywords: Electricity consumption; machine learning; macroeconomic; interpretable models

1. Introduction

Accurately predicting electricity consumption is critical for economic stability, policymaking, environmental sustainability, social development, and technological innovation, as it influences resource allocation, energy security, carbon reduction strategies, infrastructure planning, and the integration of smart grids. From an economic perspective, it ensures efficient resource allocation and stabilizes energy markets [1, 2]. In the political domain, reliable forecasts guide energy policy and enhance energy security by reducing dependency on foreign sources and promoting renewables [3]. Environmentally, it is crucial for carbon reduction and balancing the energy mix [4]. From a social perspective, forecasts drive urban planning and equitable energy access, ensuring reliable infrastructure in growing urban centers [5-6].

Numerous techniques have been employed in electricity consumption forecasting, including Artificial Neural Networks (ANNs) [7-8], Support Vector Machines (SVMs) [9], Autoregressive Integrated Moving Average (ARIMA) [10-11], Gradient Boosting Machines (GBMs) [12], and Long Short-Term Memory Networks (LSTMs) [13-14]. ANNs and LSTMs are highly valued for their ability to capture nonlinear relationships and long-term dependencies in consumption patterns. At the same time, SVMs and ARIMA are often used for their capability to model linear trends. Hybrid approaches combine these models and have also gained popularity for improving forecast accuracy [15]. For instance, combining ARIMA with ANNs [11] can leverage the strengths of both linear and nonlinear methods. Despite the success of these techniques, many rely on black-box models such as ANNs and LSTMs, which provide limited interpretability and transparency. This poses a significant drawback, especially in policymaking and critical infrastructure planning, where understanding the factors influencing forecasts is crucial. As a result, there is a methodological gap in the literature, as most work emphasizes model performance without addressing the need for interpretability and explainability in electricity consumption forecasting models.

Electricity consumption is influenced by several factors, ranging from external environmental conditions to internal economic dynamics. Weather conditions are a key driver, as temperature variations directly impact heating and cooling demands [16]. Similarly, population growth is critical, as urbanization increases the demand for residential and industrial energy consumption [17-18]. Among these, macroeconomic variables such as Gross Domestic Product (GDP), inflation rates, and industrial output are particularly influential, reflecting broader economic activities that drive overall energy consumption [19-21]. However, as mentioned earlier, most forecasting techniques rely on black-box methods such as ANNs or LSTMs, making it difficult to determine how much each factor contributes to electricity consumption, leaving policymakers and planners without actionable insights into the drivers of demand.

This research addresses this issue by employing explainable/interpretable machine-learning techniques to identify and understand the factors influencing electricity consumption. Explainable machine learning models are designed to provide transparency by revealing how inputs impact predictions. These methods enhance interpretability by predicting outcomes and explaining the decision-making process behind the predictions. One significant advantage of explainable models is that they provide more precise insights into feature importance, allowing stakeholders to understand which factors drive consumption trends [22-23]. Furthermore, improved accountability is achieved through these methods, allowing model users to validate predictions and ensure that forecasts align with domain knowledge or regulatory standards [24-25]. Feature attribution and model transparency are two research domains within explainable machine learning that extract more profound insights. Feature attribution techniques, such as SHAP and LIME, help determine which variables are most influential in predicting outcomes [26-27]. On the other hand, model transparency methods, such as decision trees and generalized additive models (GAMs), provide an intuitive understanding of how input variables relate to electricity demand, offering a clear view of the decision process [28]. These techniques provide actionable insights for decision-makers, bridging the gap left by traditional black-box models.

Accurate forecasting of electricity consumption plays a crucial role in planning infrastructure, optimizing generation capacity, and ensuring the reliability of power grids. By predicting future electricity demand, policymakers can make informed decisions on infrastructure investments, such as upgrading grids and expanding generation facilities, ensuring they meet future demand without over-investment or capacity shortages [29, 30]. Demand forecasting optimizes generation capacity by allowing energy providers to adjust production based on predicted demand, reducing operational costs and minimizing waste, especially in markets with renewable energy sources that fluctuate with weather conditions [31-32]. This also enhances the integration of renewable energy into the grid by balancing demand with the intermittent supply of solar and wind power, promoting sustainability while reducing reliance on fossil fuels [33-34]. Moreover, accurate forecasts are vital for maintaining the reliability of power grids, enabling utilities to anticipate risks such as supply shortages or unexpected surges, thereby preventing blackouts and ensuring consistent service delivery [35, 36]. Through better planning and optimization, consumption forecasting strengthens infrastructure and operational efficiency and supports environmental sustainability and energy market stability.

Electricity consumption is influenced by several key factors, which include: (1) weather and climate cmiconditions, where temperature, humidity, and seasonal variations affect heating and cooling demands [37-38]; (2) economic growth and industrial activity, as higher industrial production and gross domestic product (GDP) growth drive increased electricity demand [39]; (3) population growth and urbanization, where expanding urban areas and increased population density lead to higher residential and commercial consumption [40-41]; (4) technological advancements, both increasing demand through energy-intensive technologies and decreasing it through energy-efficient solutions [42-43]; (5) energy prices and policy, where fluctuations in electricity prices and government regulations can either encourage or limit consumption [44-45]; (6) household income and consumption behavior, with wealthier households generally consuming more electricity due to higher appliance ownership, though energy-saving behavior can mitigate this effect [46-47]; and (7) technological disruptions, such as the rise of electric vehicles (EVs) increasing demand and smart grids promoting efficient consumption [48-49]. Despite identifying these factors, no comprehensive study isolates and quantifies the individual influence of each factor on electricity consumption.

The autoregressive integrated moving average (ARIMA) model is effective for short-term electricity demand forecasting, especially in cases where data exhibits linearity and stationarity, making it particularly useful for stable, predictable energy systems. However, when seasonality is a significant factor, the Seasonal autoregressive integrated moving average (SARIMA) model improves performance by accounting for seasonal variations, resulting in better forecast accuracy and reduced prediction errors [10]. While ARIMA performs well with simpler, linear datasets, it struggles with nonlinear data, as seen in the Irish study, where the artificial neural network (ANN) model outperformed ARIMA for highly variable loads [11]. Applying neural networks, particularly ANN and long short-term memory (LSTM), has significantly improved energy demand forecasting by effectively handling complex, nonlinear, and time-dependent data. ANN models have demonstrated enhanced accuracy in short-term load forecasting by closely following actual load patterns, making them beneficial for operational engineers and policymakers in optimizing energy distribution and infrastructure investment [8]. Moreover, models like LSTM, which capture periodic energy consumption patterns, have superior performance in long-term forecasts, outperforming traditional statistical methods [50]. These methods consistently demonstrate improved forecasting accuracy across multiple customer datasets, as seen in the neural basis expansion analysis for time series forecasting (N-BEATS) and bidirectional recurrent neural network (RNN) models, making them crucial for both short-term and long-term energy planning [7, 50-51]. The support vector machine (SVM) is highly effective for electricity demand forecasting, particularly in handling nonlinear, time-variant, and seasonal data. External environmental factors significantly influence electricity load by incorporating weather parameters (temperature, wind speed, and solar radiation) [52]. This approach enhances forecasting accuracy by filtering trends and seasonal fluctuations [53], and is further strengthened by integrating data preprocessing techniques such as Fourier transforms and noise reduction [9]. The combination of these strategies improves prediction accuracy and provides robust insights into demand patterns, making SVM a versatile tool for mid- and long-term electricity demand forecasting [9, 52, 53]. Ensemble learning models have consistently demonstrated superior performance in electricity demand forecasting across different contexts. A common finding among all studies is the significant improvement in forecasting accuracy when employing ensemble methods compared to single models. For instance, the gradient boosting regression tree (GBRT) and hybrid models showed lower error rates in predicting residential energy consumption [12, 54-56]. Moreover, innovative combinations like the improved coupled generative adversarial stacked auto-encoder (ICoGASA) and the novel time series ensemble approach further enhance the accuracy by addressing nonlinear patterns and stochastic fluctuations in energy demand [54-55]. This makes ensemble techniques highly valuable for policymakers and operation engineers, contributing to better grid stability and energy management [12, 54-56].

While these models demonstrate improved predictive performance, they often lack interpretability, which limits their applicability in critical decision-making. This presents a methodological gap, as current research largely focuses on accuracy and ignores the models' explainability. Addressing this gap requires integrating explainable or interpretable machine learning techniques, such as Shapley additive explanations (SHAP) or local interpretable model-agnostic explanations (LIME), into the forecasting models. The impact of filling this gap would be substantial, as it would enable more informed decisions in electricity grid management, policymaking, and sustainable planning, improving both the trust in and the utility of predictive models.

Interpretable machine learning (IML) refers to a subset of machine learning techniques designed to make the decision-making process of models transparent and understandable to humans. Unlike traditional "black box" models [19, 23], which provide little to no insight into how they arrive at their predictions, IML aims to explain each decision, making it easier to understand, trust, and manage these models. This is especially important in high-stakes fields such as healthcare, finance, and energy management, where understanding the rationale behind predictions is crucial for regulatory compliance, ethical considerations, and strategic decision-making [22, 25].

Several types of interpretable machine learning methods are categorized into intrinsic and post hoc interpretability. Intrinsic interpretability refers to inherently understandable models due to their simple structure, such as decision trees, linear regression, and rule-based models. These models are built in a way that makes their internal workings easily interpretable by humans [32]. On the other hand, post hoc interpretability applies to complex models like neural networks and ensemble methods, where interpretability is added after the model is built. Techniques such as LIME, SHAP [31], and feature importance measures help understand the model's predictions after training.

Interpretable machine learning has been effectively applied in various domains. For instance, in healthcare, IML models are used to predict patient outcomes while providing explanations that help medical professionals understand the factors contributing to these predictions. This can improve diagnosis, treatment planning, and patient management [27]. In the finance sector, IML aids in credit scoring [30], where the model's transparency helps justify credit decisions to regulators and customers. Similarly, in the energy sector, IML models can forecast electricity consumption by explaining how macroeconomic variables such as GDP growth, industrial activity, and population trends influence energy usage. This transparency is critical for policymakers and utility companies to make informed decisions.

In predicting electricity consumption, using interpretable machine learning approaches can significantly enhance the understanding of how various factors contribute to energy usage patterns. For example, using decision trees (DT) as an IML method involves employing the DT model to create an explainable reasoning structure. Using DTs to construct reasoning patterns that are easy to interpret enhances the model's accuracy. This approach is particularly effective in industrial analysis, helping to improve and optimize processes for greater efficiency in future industries. This level of detail improves the accuracy of predictions and provides actionable insights for energy management and policy formulation [29]. By leveraging IML, researchers can develop models that predict consumption accurately and explain the underlying drivers of these predictions, making the models more useful for stakeholders.

2. Materials and Methods

2.1 Overall Concept

Forecasting electricity consumption is a complex task due to factors such as seasonal variability, population growth, and technological changes [35, 57]. Traditional statistical models often struggle with this challenge because the relationship between electricity demand and its predictors tends to be nonlinear and dynamic [58–59]. In response, machine learning (ML) models have gained popularity for their ability to capture complex patterns and process large datasets [7–8]. However, their "black-box" nature raises concerns about transparency and interpretability, particularly for stakeholders like policymakers [51, 60]. As a result, integrating explainable AI techniques is essential to enhance trust and facilitate actionable insights. Macroeconomic variables—such as GDP, inflation, and interest rates—are increasingly used as predictors due to their strong links with energy demand. Economic growth typically drives up industrial and commercial electricity use [61], while downturns or inflation may suppress demand as production slows and consumers reduce usage [62]. GDP reflects overall economic activity, inflation influences household and industrial purchasing power, and interest rates affect investment decisions in energy-related technologies. Therefore, incorporating these variables is crucial for improving the accuracy and relevance of electricity consumption forecasts.

The use of machine learning models in electricity consumption forecasting has introduced a significant challenge: the issue of explainability. Traditional models, such as linear regression, offer transparency regarding how inputs relate to outputs. However, complex machine learning models often lack this transparency, especially deep learning and ensemble methods like random forests and gradient boosting. These models, though powerful, are frequently criticized as "black boxes" because they do not provide insights into the underlying relationships between input variables and the predicted outcomes [63-65]. Explainability is particularly important in electricity forecasting because energy policymakers and grid operators must understand the reasons behind the model's predictions to make informed decisions. This is where explainable artificial intelligence (XAI) comes into play, offering tools and techniques that help interpret the predictions of complex models. Methods such as SHAP and LIME provide insights into how each feature contributes to the prediction, enabling a deeper understanding of the model's behavior. Incorporating explainability into machine learning models fosters transparency and trust, which is critical in sectors like energy, where the stakes are high, and decisions must be evidence-based. By ensuring that the models are interpretable, energy policymakers can better align forecasts with their strategic objectives, enhancing decision-making processes and improving the overall reliability of electricity consumption forecasts.

3. Results and Discussion

3.1 Data Exploration and Preprocessing

The first step in the proposed method involves collecting data from reliable, publicly available sources, such as the World Development Indicators (WDI) database, which provides macroeconomic variables (e.g., GDP, inflation rates, industrial growth) and electricity consumption data for Thailand from 1973 to 2021. These datasets offer varying levels of granularity—monthly, quarterly, and annually—and are supplemented by national economic reports and other macroeconomic resources. Once collected, the data undergoes preprocessing to resolve missing or inconsistent entries. Table 1 summarizes the variables used, offering a comprehensive view of Thailand's economic environment and its relationship to electricity consumption.

Table 1. Sources of data.

Variable	Source
Electric power consumption (kWh per capita)	WDI
Domestic credit to private sector (% of GDP)	WDI
Deposit interest rate (%)	WDI
Inflation, GDP deflator (annual %)	WDI
Industry (including construction), value added (% of GDP)	WDI
Imports of goods and services (% of GDP)	WDI
International tourism, number of arrivals	WDI
Manufacturing, value added (% of GDP)	WDI
Exports of goods and services (% of GDP)	WDI
GDP growth (annual %)	WDI
Foreign direct investment, net outflows (% of GDP)	WDI
Foreign direct investment, net inflows (% of GDP)	WDI
Trade (% of GDP)	WDI
Current account balance (% of GDP)	WDI
Interest payments (% of expense)	WDI
Interest payments (% of revenue)	WDI
Population growth (annual %)	WDI
Urban population growth (annual %)	WDI
Households and NPISHs Final consumption expenditure (annual % growth)	WDI
Official exchange rate (LCU per US$, period average)	WDI
Unemployment, total (% of total labor force) (national estimate)	WDI
Domestic credit to private sector by banks (% of GDP)	WDI

Table 1. Sources of data (continue).

Variable	Source
Gross fixed capital formation, private sector (% of GDP)	WDI
Expense (% of GDP)	WDI
Final consumption expenditure (% of GDP)	WDI
Gross domestic savings (% of GDP)	WDI

The first data exploration phase involved a detailed analysis of the dataset's completeness and structure. It was discovered that the dataset contained no missing values, confirming the credibility of the following study. Descriptive statistics were performed to comprehend the variables' properties further, providing essential metrics such as mean, median, standard deviation, and range. Table 2 displays these descriptive statistics, which assist in illustrating the diversity and distribution of the data, providing insights into potential skewness or outliers present in specific variables.

Table 2. Statistical description of the data.

	count	mean	std	min	25%	50%	75%	max
Electric power consumption (kWh per capita)	49	1.36E+03	9.24E+02	1.67E+02	4.17E+02	1.36E+03	2.08E+03	2.90E+03
Domestic credit to private sector (% of GDP)	49	9.65E+01	4.34E+01	2.25E+01	5.69E+01	9.69E+01	1.39E+02	1.67E+02
Deposit interest rate (%)	49	5.70E+00	4.76E+00	0.00E+00	1.30E+00	3.29E+00	9.75E+00	1.37E+01
Inflation, GDP deflator (annual %)	49	4.48E+00	4.19E+00	-2.58E+00	1.78E+00	4.08E+00	5.75E+00	2.03E+01
Industry (including construction), value added (% of GDP)	49	3.47E+01	3.84E+00	2.58E+01	3.20E+01	3.63E+01	3.73E+01	3.99E+01
Imports of goods and services (% of GDP)	49	4.49E+01	1.54E+01	2.01E+01	2.93E+01	4.53E+01	5.70E+01	6.95E+01
International tourism, number of arrivals	49	1.05E+07	1.06E+07	4.28E+05	2.35E+06	6.95E+06	1.42E+07	3.99E+07
Manufacturing, value added (% of GDP)	49	2.58E+01	3.45E+00	1.87E+01	2.29E+01	2.68E+01	2.82E+01	3.09E+01
Exports of goods and services (% of GDP)	49	4.61E+01	1.96E+01	1.84E+01	2.41E+01	4.82E+01	6.60E+01	7.14E+01
GDP growth (annual %)	49	5.19E+00	4.09E+00	-7.63E+00	3.44E+00	5.37E+00	8.00E+00	1.33E+01
Foreign direct investment, net outflows (% of GDP)	49	8.38E-01	1.21E+00	-1.82E-02	9.37E-03	2.73E-01	1.24E+00	3.79E+00
Foreign direct investment, net inflows (% of GDP)	49	1.96E+00	1.50E+00	-9.89E-01	7.18E-01	1.79E+00	2.90E+00	6.44E+00
Trade (% of GDP)	49	9.10E+01	3.46E+01	3.87E+01	5.40E+01	9.51E+01	1.21E+02	1.40E+02

Table 2. Statistical description of the data.

	count	mean	std	min	25%	50%	75%	max
Electric power consumption (kWh per capita)	49	1.36E+03	9.24E+02	1.67E+02	4.17E+02	1.36E+03	2.08E+03	2.90E+03
Domestic credit to private sector (% of GDP)	49	9.65E+01	4.34E+01	2.25E+01	5.69E+01	9.69E+01	1.39E+02	1.67E+02
Deposit interest rate (%)	49	5.70E+00	4.76E+00	0.00E+00	1.30E+00	3.29E+00	9.75E+00	1.37E+01
Inflation, GDP deflator (annual %)	49	4.48E+00	4.19E+00	-2.58E+00	1.78E+00	4.08E+00	5.75E+00	2.03E+01
Industry (including construction), value added (% of GDP)	49	3.47E+01	3.84E+00	2.58E+01	3.20E+01	3.63E+01	3.73E+01	3.99E+01
Imports of goods and services (% of GDP)	49	4.49E+01	1.54E+01	2.01E+01	2.93E+01	4.53E+01	5.70E+01	6.95E+01
International tourism, number of arrivals	49	1.05E+07	1.06E+07	4.28E+05	2.35E+06	6.95E+06	1.42E+07	3.99E+07
Manufacturing, value added (% of GDP)	49	2.58E+01	3.45E+00	1.87E+01	2.29E+01	2.68E+01	2.82E+01	3.09E+01
Exports of goods and services (% of GDP)	49	4.61E+01	1.96E+01	1.84E+01	2.41E+01	4.82E+01	6.60E+01	7.14E+01
GDP growth (annual %)	49	5.19E+00	4.09E+00	-7.63E+00	3.44E+00	5.37E+00	8.00E+00	1.33E+01
Foreign direct investment, net outflows (% of GDP)	49	8.38E-01	1.21E+00	-1.82E-02	9.37E-03	2.73E-01	1.24E+00	3.79E+00
Foreign direct investment, net inflows (% of GDP)	49	1.96E+00	1.50E+00	-9.89E-01	7.18E-01	1.79E+00	2.90E+00	6.44E+00
Trade (% of GDP)	49	9.10E+01	3.46E+01	3.87E+01	5.40E+01	9.51E+01	1.21E+02	1.40E+02
Manufacturing, value added (% of GDP)	49	2.58E+01	3.45E+00	1.87E+01	2.29E+01	2.68E+01	2.82E+01	3.09E+01
Exports of goods and services (% of GDP)	49	4.61E+01	1.96E+01	1.84E+01	2.41E+01	4.82E+01	6.60E+01	7.14E+01
GDP growth (annual %)	49	5.19E+00	4.09E+00	-7.63E+00	3.44E+00	5.37E+00	8.00E+00	1.33E+01
Foreign direct investment, net outflows (% of GDP)	49	8.38E-01	1.21E+00	-1.82E-02	9.37E-03	2.73E-01	1.24E+00	3.79E+00
Foreign direct investment, net inflows (% of GDP)	49	1.96E+00	1.50E+00	-9.89E-01	7.18E-01	1.79E+00	2.90E+00	6.44E+00
Trade (% of GDP)	49	9.10E+01	3.46E+01	3.87E+01	5.40E+01	9.51E+01	1.21E+02	1.40E+02
Current account balance (% of GDP)	49	-2.76E-01	5.68E+00	-8.53E+00	-4.93E+00	-1.23E+00	3.47E+00	1.25E+01

Table 2. Statistical description of the data. (continue).

	count	mean	std	min	25%	50%	75%	max
Population growth (annual %)	49	1.30E+00	7.16E-01	1.75E-01	7.18E-01	1.28E+00	1.91E+00	2.71E+00
Urban population growth (annual %)	49	3.06E+00	1.16E+00	1.59E+00	2.03E+00	2.74E+00	4.15E+00	5.28E+00
Households and NPISHs Final consumption expenditure (annual % growth)	49	4.69E+00	3.85E+00	-1.02E+01	2.60E+00	5.03E+00	7.43E+00	1.29E+01
Official exchange rate (LCU per US$, period average)	49	2.96E+01	7.03E+00	2.03E+01	2.49E+01	3.05E+01	3.43E+01	4.44E+01
Unemployment, total (% of total labor force) (national estimate)	49	1.57E+00	1.17E+00	2.50E-01	7.50E-01	1.21E+00	2.21E+00	5.77E+00
Domestic credit to private sector by banks (% of GDP)	49	8.75E+01	3.59E+01	2.25E+01	5.68E+01	9.31E+01	1.12E+02	1.67E+02
Gross fixed capital formation, private sector (% of GDP)	49	2.05E+01	5.69E+00	1.13E+01	1.71E+01	1.86E+01	2.07E+01	3.44E+01
Expense (% of GDP)	49	1.56E+01	3.22E+00	1.03E+01	1.30E+01	1.55E+01	1.83E+01	2.44E+01
Final consumption expenditure (% of GDP)	49	7.00E+01	5.12E+00	6.26E+01	6.60E+01	6.89E+01	7.57E+01	8.00E+01
Gross domestic savings (% of GDP)	49	3.00E+01	5.12E+00	2.00E+01	2.43E+01	3.11E+01	3.40E+01	3.75E+01

This statistical variability is further explored in Figure 1, which depicts the distribution of each variable. The alignment of the data in Table 2 and the graphical representations in Figure 1 highlights the intrinsic disparities between the variables.

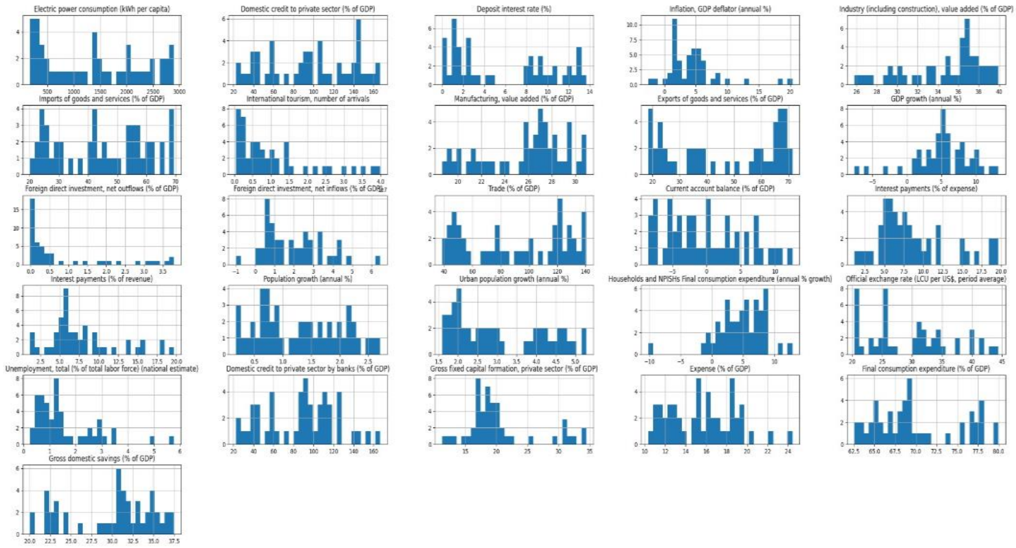

Figure 1. Frequency distribution chart of the data.

Given the diversity of the data, standardization processes were applied to ensure its accuracy. Two scaling algorithms, StandardScaler and RobustScaler, were compared to see how they handled data variability. This comparison tried to determine which technique better suited the dataset's specific characteristics. In the general structure, an economic macro variable acts as a control variable before scaling modifications are made using Normalization to reduce bias. The model is presented in equation (1) below.

$$Y = f(X1, X2, \ldots, X25) \quad (1)$$

Where
X1 = Domestic credit to private sector (% of GDP)
X2 = Deposit interest rate (%)
X3 = Inflation, GDP deflator (annual %)
X4 = Industry (including construction), value added (% of GDP)
X5 = Imports of goods and services (% of GDP)
X6 = International tourism, number of arrivals
X7 = Manufacturing, value added (% of GDP)
X8 = Exports of goods and services (% of GDP)
X9 = GDP growth (annual %)
X10 = Foreign direct investment, net outflows (% of GDP)
X11 = Foreign direct investment, net inflows (% of GDP)
X12 = Trade (% of GDP)
X13 = Current account balance (% of GDP)
X14 = Interest payments (% of expense)
X15 = Interest payments (% of revenue)
X16 = Population growth (annual %)

X17 = Urban population growth (annual %)
X18 = Households and NPISHs Final consumption expenditure (annual % growth)
X19 = Official exchange rate (LCU per US$, period average)
X20 = Unemployment, total (% of total labor force) (national estimate)
X21 = Domestic credit to private sector by banks (% of GDP)
X22 = Gross fixed capital formation, private sector (% of GDP)
X23 = Expense (% of GDP)
X24 = Final consumption expenditure (% of GDP)
X25 = Gross domestic savings (% of GDP)

The StandardScaler technique scales data by removing the mean and converting it to unit variance. While this strategy works well for normally distributed data, it is sensitive to outliers, as extreme values can greatly impact the mean and standard deviation. In contrast, the RobustScaler approach scales the data using the median and interquartile range (IQR), making it more resistant to outliers. Figure 2 depicts the data distribution following the use of both scaling approaches. The comparison shows that RobustScaler provides more consistent and reliable scaling, especially with outliers, which is common in macroeconomic data. Given the dataset's potential outliers from economic disruptions or rare events, RobustScaler helps prevent these from skewing the model's performance. Reducing outlier influence allows the model to focus on underlying patterns, improving prediction accuracy and generalizability. Therefore, RobustScaler was chosen for this study to ensure proper standardization and enhance analysis reliability.

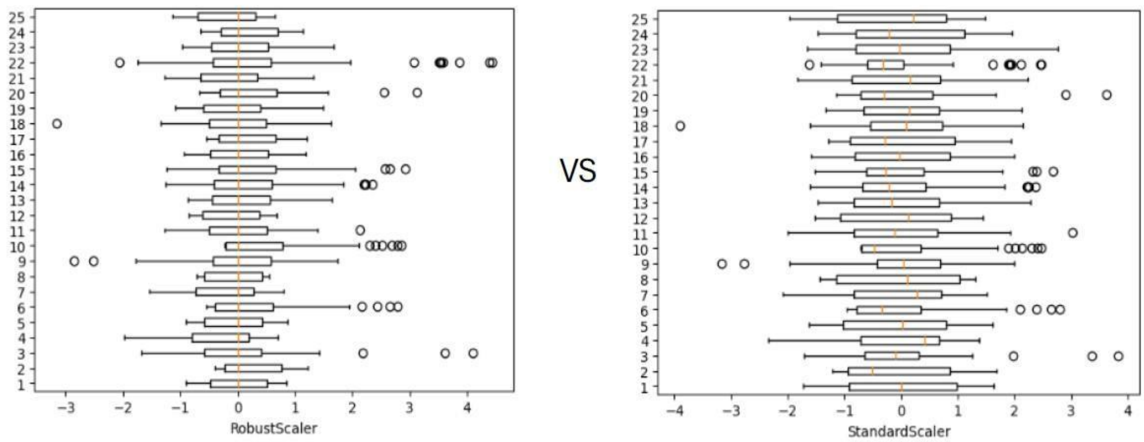

Figure 2. Comparison standardization.

A correlation analysis was conducted post-normalization to establish an understanding of how macroeconomic variables interact with electricity consumption. The correlation coefficients are summarized in Table 3, highlighting both positive and negative relationships between the variables and electricity consumption. For instance, variables like Export of Goods and industrial output showed strong positive correlations with electricity use, suggesting that economic expansion is typically accompanied by higher electricity demand. On the other hand, variables such as Deposit interest rate and inflation exhibited more complex and sometimes inverse relationships, indicating that economic instability could have varying effects on electricity usage depending on the specific context.

Table 3. Correlation between electric power consumption and macroeconomic variables.

	Electric power consumption (kWh per capita)
Exports of goods and services (% of GDP)	0.912497
Trade (% of GDP)	0.901606
Imports of goods and services (% of GDP)	0.868078
Domestic credit to private sector (% of GDP)	0.856935
International tourism, number of arrivals	0.827387
Foreign direct investment, net outflows (% of GDP)	0.812032
Manufacturing, value added (% of GDP)	0.725869
Domestic credit to private sector by banks (% of GDP)	0.708366
Expense (% of GDP)	0.680909
Official exchange rate (LCU per US$, period average)	0.678705
Industry (including construction), value added (% of GDP)	0.635421
Current account balance (% of GDP)	0.629633
Gross domestic savings (% of GDP)	0.568912
Foreign direct investment, net inflows (% of GDP)	0.380941
Gross fixed capital formation, private sector (% of GDP)	-0.227445
Unemployment, total (% of total labor force) (national estimate)	-0.364430
Households and NPISHs Final consumption expenditure (annual % growth)	-0.407281
Urban population growth (annual %)	-0.442354
GDP growth (annual %)	-0.518601
Inflation, GDP deflator (annual %)	-0.565526
Final consumption expenditure (% of GDP)	-0.568912
Deposit interest rate (%)	-0.606695
Interest payments (% of revenue)	-0.608866
Interest payments (% of expense)	-0.630804
Population growth (annual %)	-0.973860

The intensive data exploration and preprocessing methods provided a solid foundation for later model development. This study provides a credible and transparent framework for studying the determinants of power consumption in Thailand by verifying data quality, employing appropriate scaling approaches, and conducting a detailed correlation analysis. This method increases model accuracy and helps better comprehend the dynamic links between macroeconomic factors and electricity demand.

4.2 Model Performance Experiments

Before implementing and comparing the performance of different models for forecasting electricity consumption, all data underwent a standardized preprocessing procedure as described in Section 4.1. This ensured consistency and fairness across all models, allowing for reliable comparisons. Following this preprocessing stage, various models were applied, including the Multilayer Perceptron Regressor (MLP), Long Short-Term Memory Networks (LSTM), 1D Convolutional Neural Network combined with LSTM (1D CNN + LSTM), Autoregressive Integrated Moving Average (ARIMA), Decision Trees, Random Forests, and Generalized Additive Models (GAMs), to determine the most efficient approach for predicting electricity consumption.

The Grid Search technique was used to tune hyperparameters and improve model performance. This strategy searched methodically throughout a preset set of hyperparameters for each model, allowing for a thorough examination of all potential combinations. Hyperparameters such as the number of layers and neurons in neural network models, the maximum depth and number of estimators in tree-based models, and ARIMA parameters such as p, d, and q were fine-tuned to produce the optimum results.

The main advantage of Grid Search is that it performs an exhaustive search across all combinations, ensuring that no potential parameter configuration is overlooked. Unlike random search, which samples combinations randomly, Grid Search ensures that the entire search space is explored, making it more thorough in finding the best possible hyperparameters.

The evaluation of model performance was conducted using multiple metrics to capture various aspects of prediction accuracy and model behavior:

- Mean Absolute Error (MAE): A measure of the average magnitude of errors in the predictions, offering a straightforward interpretation of how much predictions deviate from actual values.
- Mean Squared Error (MSE): Emphasizes larger errors, making it sensitive to outliers. It evaluated the models' performance in scenarios where significant deviations from the actual values could occur.
- Root Mean Squared Error (RMSE): Serves as the square root of MSE and is particularly useful in understanding how model errors translate back to the original scale of electricity consumption.
- R^2 (Coefficient of Determination): Measures the proportion of variance in the dependent variable that is predictable from the independent variables, offering insights into how well each model explains the variation in electricity consumption.

The modeling process for all models involved splitting the data into training and testing sets with a 70/30 ratio to ensure consistent conditions across all models. The results after hyperparameter tuning using GridSearchCV for each model are summarized in Table 4. Following the model training and tuning through GridSearchCV, the performance of each model was measured using the previously mentioned metrics: MAE, MSE, RMSE, and R^2. The evaluation results for each model's performance are presented in Table 5.

Model performance is evaluated using MSE, MAE, RMSE, and R^2 measures. These measurements provide insights into the effectiveness of each paradigm, as seen below:

Mean Squared Error (MSE) measures the average squared differences between the predicted and actual values. It significantly emphasizes larger errors, making it helpful in identifying models sensitive to extreme deviations. A lower MSE indicates a model's ability to reduce substantial prediction errors in electricity consumption, which is critical when analyzing the impact of sudden economic shifts or outliers in electricity demand.

Mean Absolute Error (MAE) provides an average measure of absolute differences between predicted and actual values. Unlike MSE, it treats all errors equally, making it suitable for assessing models that need to minimize consistent errors across predictions. Concerning electricity use, a lower MAE suggests that the model can consistently track demand patterns, which is valuable in understanding regular economic activities and their energy implications.

Root Mean Squared Error (RMSE) is the square root of MSE, bringing the error measure back to the original scale of electricity consumption. It is beneficial for interpreting how large typical errors are in practical terms, allowing for a direct understanding of prediction accuracy in units of electricity demand. Lower RMSE values indicate models that provide accurate forecasts, which are crucial for planning and managing energy supply and are aligned with economic growth.

R-squared (R^2) indicates the proportion of variance in electricity consumption that the independent variables in the model can explain. A higher R^2 suggests that the model effectively captures the relationship between economic factors and electricity use, demonstrating how well macroeconomic variables like GDP growth, inflation, and industrial output contribute to changes in electricity demand.

Table 4. The result of each model using hyperparameter tuning.

Model						
MLPRegresspr	**LSTM**	**1D CNN+LSTM**	**RANDOM_FORESTS**	**DECISION_TREES**	**ARIMA**	**GAMs**
Activation = relu	activation = tanh	hidden_units = 150	bootstrap = FALSE	depth = 5	p = 5	intercept = TRUE
Alpha = 0.01	dropout_rate = 0.3	learning_rate = 0.1	depth = 10	gestures = log2	q = 3	lam = 0.3
Hidden_layer_sizes = (100, 50)	hidden_units = 150	activation = relu	features = sqrt	samples_leaf = 2	d = 2	max_iter = 50
Learning_rate = constant	learing_rate = 0.01	filters = 32	samples_leaf = 1	samples_split = 5	trend = n	n_splines = 4
Learning_rate_init = 0.01	optmizer = adam	epochs = 150	samples_split = 2			spline_order = 3
Max_iter = 50		optimizer = SGD	extimators = 200			
Solver = adam						

By understanding these metrics, we can better interpret model performance in terms of its ability to predict electricity consumption accurately, which has direct implications for economic planning and policy development.

Table 5. Comparison of model performance metrics.

Model	MAE	MSE	RMSE	R-squared
MLPRegressor	0.09	0.01	0.12	0.95
LSTM	01.15	0.04	0.2	0.88
1D CNN+LSTM	0.14	0.03	0.17	0.91
RANDOM_FORESTS	0.25	0.09	0.3	0.7
DECISION_TREES	0.09	0.02	0.13	0.93
ARIMA	0.06	0.02	0.15	0.93
GAMs	0.13	0.03	0.18	0.89

Table 5 demonstrates that MLP and ARIMA outperformed the other models examined. MLP had the lowest errors (MSE: 0.01, RMSE: 0.12) and the best R^2 (0.95), suggesting its ability to capture complex patterns in the data. ARIMA fared well with a low MAE (0.06) and high R^2 (0.93), indicating its capacity to handle temporal patterns in electricity usage. Overall, MLP outperformed the other two models. It beat ARIMA with lower MSE and RMSE and a better R^2, indicating superior accuracy in modeling both linear and nonlinear interactions. MLP's advantage lies in its ability to handle complex, multi-dimensional patterns in the data, making it more adaptable to diverse factors affecting electricity consumption. While strong in modeling temporal trends, ARIMA is more limited in capturing nonlinear interactions, which may explain its slightly lower performance than MLP. On the other hand, Random Forests and LSTM exhibited the weakest performance. Random Forests had the highest errors (MAE: 0.25, MSE: 0.09) and the lowest R^2 (0.7), suggesting difficulty modeling the data's non-linearity. LSTM also struggled, with relatively high errors (MAE: 0.15, RMSE: 0.2) and a lower R^2 (0.88), indicating its limitations in this context. These findings highlight the benefits of utilizing MLP, especially when capturing complicated, nonlinear correlations in data, which is critical for effective forecasting. The complete comparison in Table 4 provides a clear standard for assessing the efficacy of various models in projecting power usage.

4.3 Feature Importance and Explainability

As shown in Table 5, the MLP model demonstrates strong predictive performance in forecasting electricity consumption, having been trained with the same variable set and consistent train-test split throughout the experiment. Following this evaluation, SHAP and LIME were applied to interpret the model's predictions and identify the macroeconomic variables with the most significant influence. While both SHAP and LIME offer local explanations by estimating feature contributions at the individual observation level, they rely on fundamentally different algorithms. To compare their effectiveness, an unsupervised clustering approach was employed using dissimilarity matrices derived from LIME weights and SHAP values, with standardized Euclidean distance as the metric. This method enabled the evaluation of which technique better captures local feature importance and provides clearer insights into variable contributions to electricity consumption.

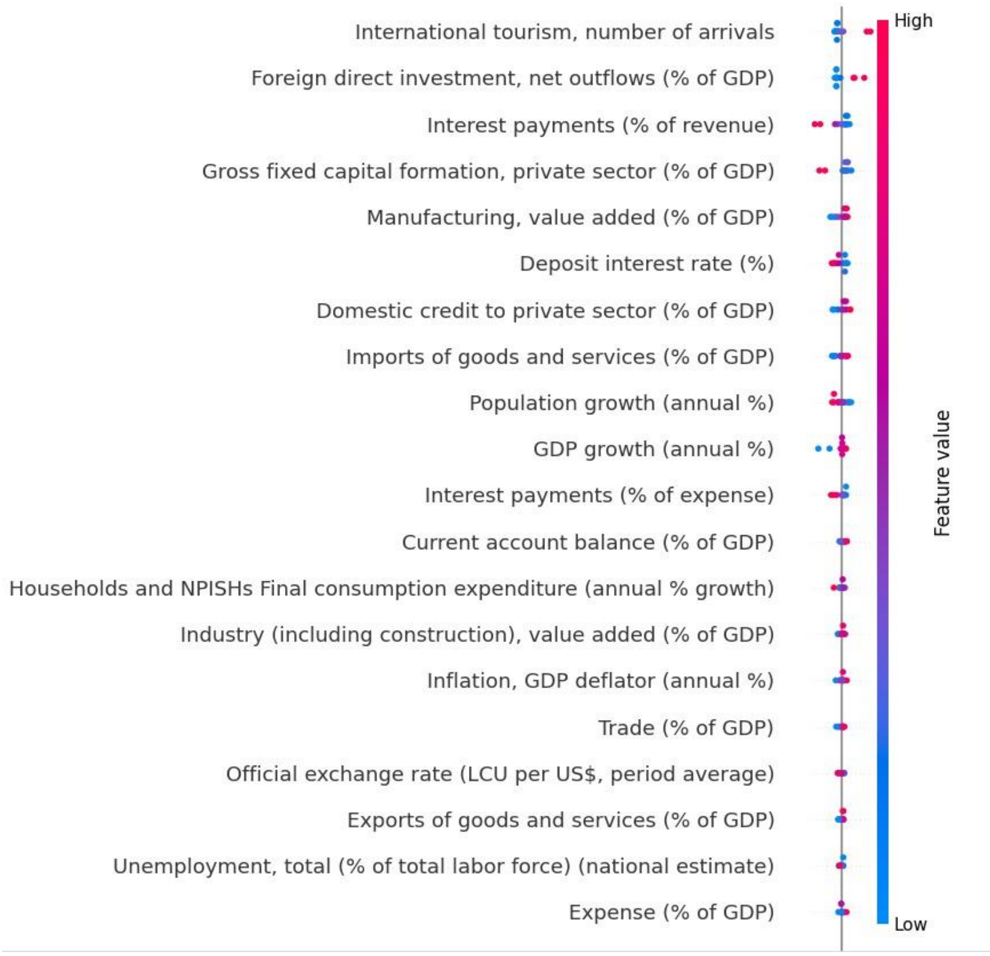

Figure 3. SHAP summary plot for feature importance and impact on model predictions.

Figure 3 shows the SHAP analysis results, identifying key macroeconomic factors influencing electricity consumption. International tourism and manufacturing value-added consistently show strong positive SHAP values, indicating that growth in these sectors is linked to higher energy demand. In contrast, rising interest payments (% of revenue) are associated with negative SHAP values, suggesting that increased debt servicing may suppress electricity use due to reduced fiscal flexibility or investment capacity. As shown in Figure 4, these relationships remain consistent across individual cases, offering clearer insights into how specific variables drive or inhibit consumption. While foreign direct investment (FDI) and private sector capital formation contribute positively, their impact is generally weaker. These patterns highlight the dual role of macroeconomic variables, some acting as key drivers and others as constraints that provide helpful guidance for effective energy planning and policy design.

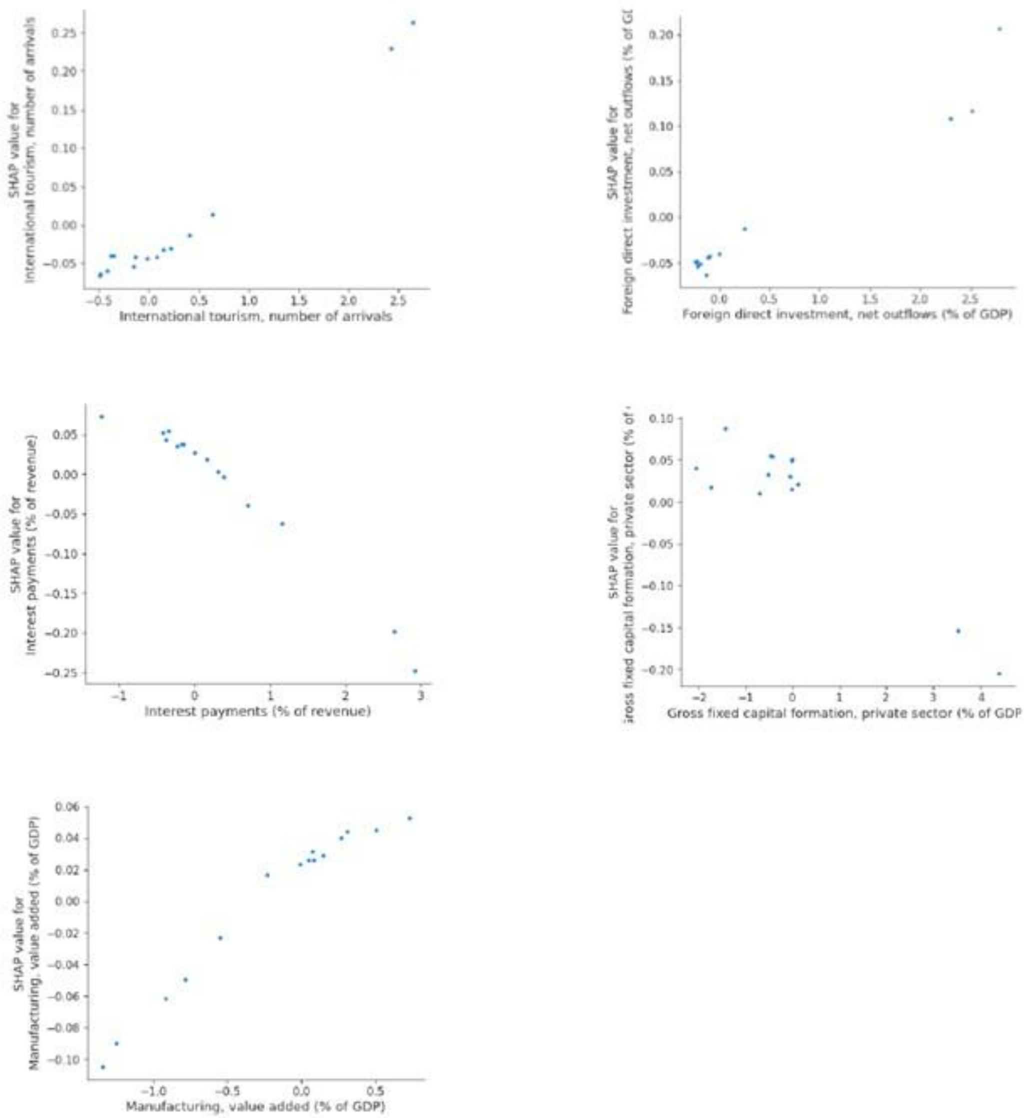

Figure 4. Top 5 SHAP for feature impact.

Locally Interpretable Model Agnostic Explanations (LIME) is a post hoc model agnostic explanation technique aiming to approximate any black box machine learning model with a local, interpretable model to explain each prediction. LIME works locally, which means it is observation-specific and provides explanations for the prediction relative to each observation, just like SHAP. It fits a local model using sample data points similar to the observation being explained, with the local model chosen from interpretable models such as linear models or decision trees. This analysis applied LIME to the MLP to understand how individual macroeconomic variables impact electricity consumption predictions at the observation level. The results of the LIME analysis are illustrated in Figure 5, which showcases the top macroeconomic factors influencing specific predictions.

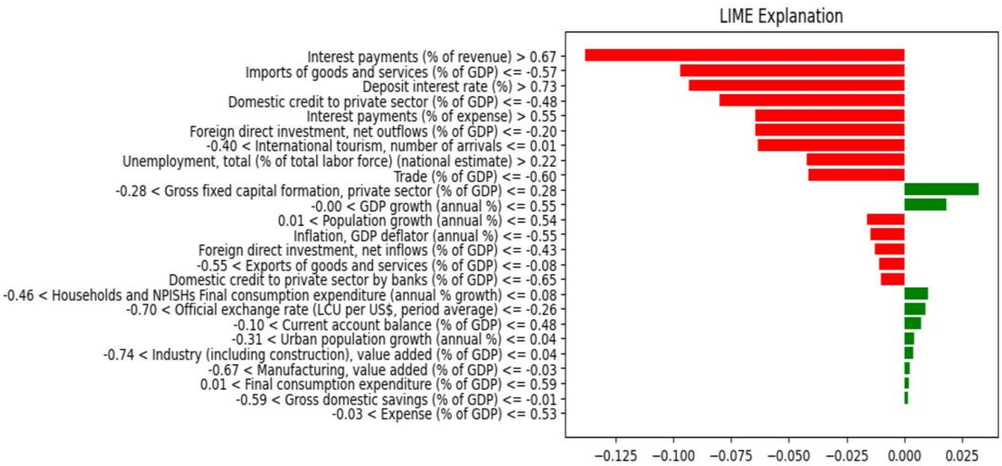

Figure 5. LIME explanation.

As shown in Figure 5, interest payments (% of revenue) have the most significant negative impact on electricity consumption, as indicated by the largest red SHAP bar, suggesting that higher financial burdens may reduce energy demand by limiting economic activity. Other variables, such as Imports of goods and services (% of GDP), Deposit interest rate (%), and Domestic credit to the private sector (% of GDP), also show negative contributions, indicating their tendency to suppress consumption in certain contexts. In contrast, Gross fixed capital formation in the private sector (% of GDP) positively influences electricity usage, reflecting increased energy needs linked to investment-driven growth. To further evaluate the interpretability of the MLP model, SHAP and LIME were compared to assess their effectiveness in explaining feature contributions. Although both methods offer local interpretability, their differing algorithms lead to unique insights. The comparison involved clustering analysis, visual inspection, and AUC-based performance evaluation. Standardized Euclidean distance was used to construct dissimilarity matrices based on SHAP values and LIME weights, followed by assessing clustering quality using Silhouette scores and the Davies-Bouldin Index (DBI) where higher Silhouette values indicate clearer cluster separation, and lower DBI suggests better internal cohesion. This analysis reveals the strengths and limitations of each method in interpreting electricity consumption forecasts under different economic scenarios.

Table 6. Clustering evaluation results.

Method	LIME	SHAP
K-means Silhouette	0.377905	0.436423
Spectral Clustering Silhouette	0.362149	0.436423
K-means DBI	1.062711	0.804729
Spectral Clustering DBI	1.008351	0.804729

Table 6 shows that SHAP outperformed LIME in terms of clustering performance. In the K-means clustering study, SHAP had a better Silhouette score (0.436423) than LIME (0.377905), indicating a clearer separation of groups. Similarly, SHAP had a lower Davies-Bouldin Index (0.804729) than LIME (1.062711), indicating that clusters were more compact. The spectral clustering analysis yielded consistent findings, with SHAP again outperforming LIME, with a higher Silhouette score (0.436423 vs. 0.362149) and a lower DBI (0.804729 vs. 1.008351). These findings indicate that SHAP is more effective at capturing the structural patterns of feature contributions, resulting in more distinct and coherent grouping.

Further, to evaluate the clustering performance of SHAP and LIME, spectral clustering was employed to visualize how each method distinguishes observations based on feature importance. This analysis aimed to assess the ability of both techniques to form distinct groups, thereby capturing different patterns of feature contributions. The results are presented in Figure 6, with Panel A illustrating the clustering outcomes from LIME, while Panel B shows the clusters formed by SHAP.

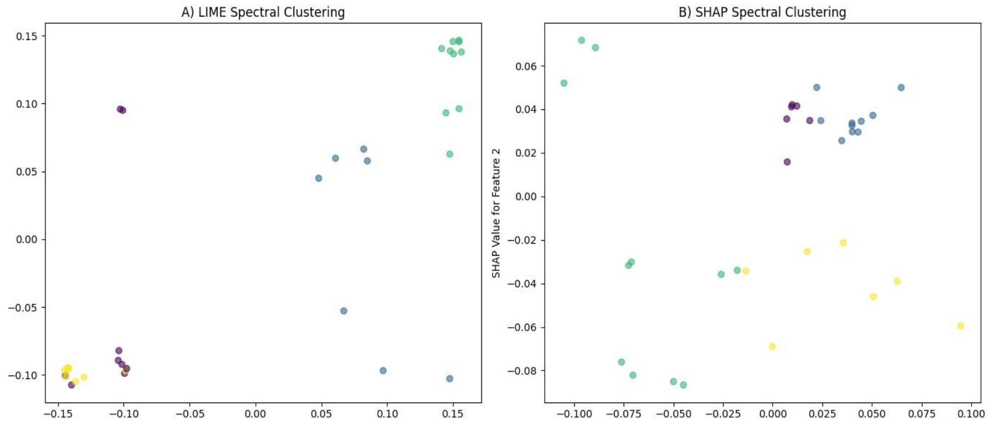

Figure 6. (A) LIME spectral clustering; (B) SHAP spectral clustering.

Figure 6 reveals key differences between the two methods. In panel A, LIME's clustering shows overlap, indicating difficulty in clearly defining boundaries based on feature importance, which may hinder local feature interpretation. In contrast, panel B shows SHAP's clusters with clearer boundaries and minimal overlap, offering a more accurate depiction of macroeconomic variable impacts on electricity consumption. SHAP better distinguishes feature influences, allowing for clearer identification of individual variable contributions to energy demand changes. Following this, ROC curves were generated to assess the predictive power of SHAP and LIME parameters.

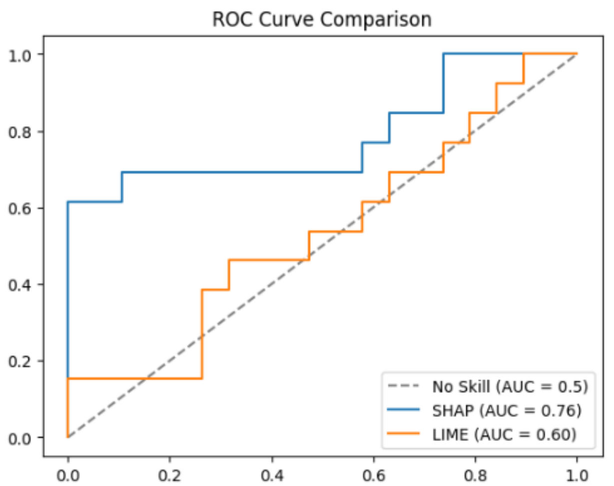

Figure 7. LIME and SHAP ROC curves.

Figure 7 shows that SHAP achieved a higher AUC (0.76) than LIME (0.60), indicating greater precision in capturing feature contributions for predicting electricity consumption. The lower AUC of LIME reflects its weaker discriminative capability. These results confirm SHAP's superiority in model interpretation.

The analysis of feature importance in predicting electricity consumption demonstrates that combining predictive accuracy with interpretability is feasible and advantageous for informed decision-making. By employing a highly accurate predictive model alongside explainability tools such as SHAP and LIME, this study reveals the value of eXplainable AI (XAI) in enhancing model performance and transparency. The results from the clustering analysis, visualization of feature importance, and overall clustering performance indicate that SHAP consistently outperforms LIME in providing clearer and more reliable feature information.

These findings affirm that SHAP is more adept at capturing the underlying structure of feature contributions, making it a more effective tool for model interpretation.

4.5 Long-term and Short-term Prediction Scenarios

Short- and long-term analyses are essential to understand the performance of the MLP in predicting electricity consumption over different time horizons. This analysis helps determine whether the model can accurately capture short-term fluctuations and predict longer-term trends. Comparing these predictions is crucial for effective energy planning and management, as economic changes have immediate and prolonged impacts. The use of interpretability tools such as SHAP and LIME in this analysis enhances our understanding of the economic factors that drive electricity consumption. SHAP provides global interpretations that cover all variables, while LIME offers localized explanations for individual predictions, making it helpful in analyzing the impact of variables over different time frames.

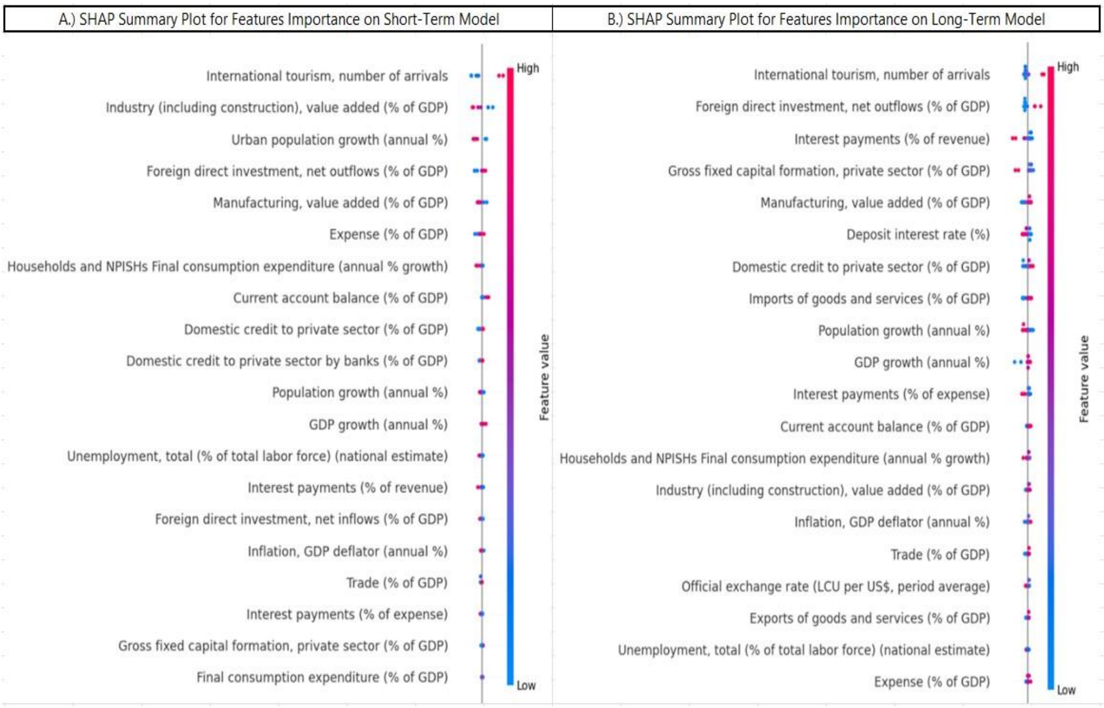

Figure 8. Comparison of the SHAP summary plot between short and long-term models.

The use of SHAP allows each model to analyze and present the influence of various variables on electricity consumption. As shown in Figure 8, the SHAP Summary Plot illustrates the importance of different features in predicting electricity consumption, separated into short-term (Panel A) and long-term (Panel B) prediction models. The results indicate that the most significant feature in both time frames is International tourism, the number of arrivals, which strongly influences electricity consumption. Additionally, in Manufacturing, value added also plays an important role, but the results differ between short-term and long-term models regarding the direction and magnitude of the influence.

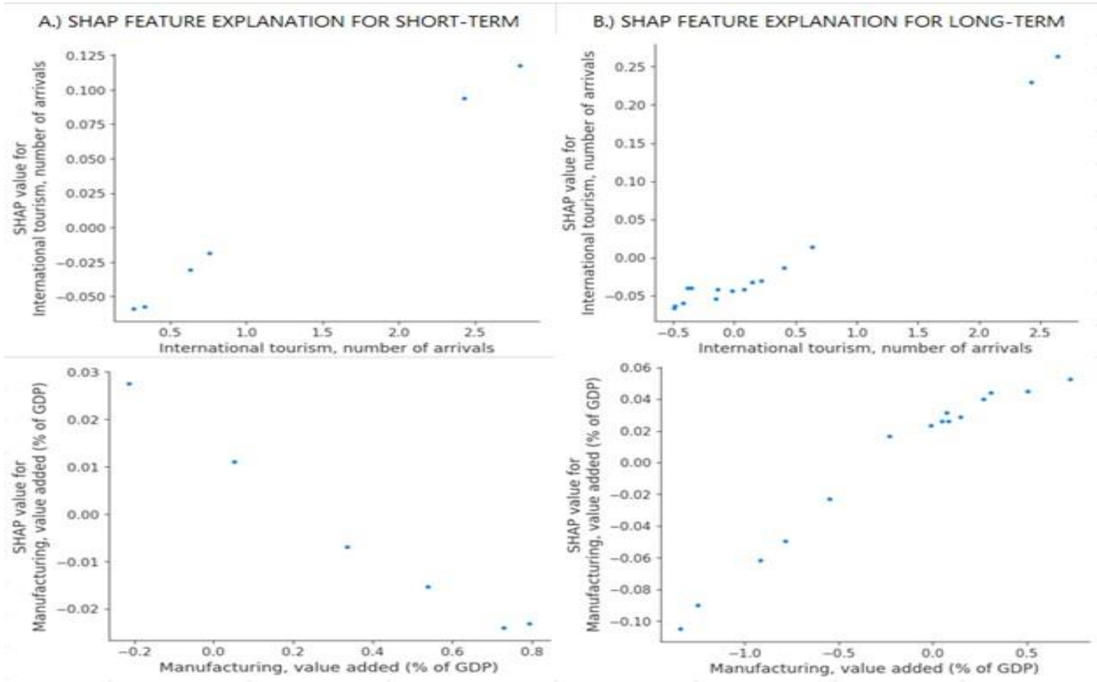

Figure 9. SHAP features explanations for short-term and long-term.

Figure 9 shows a clearer picture of how SHAP values relate to two key variables—International tourism and Manufacturing, value added—in both short-term and long-term electricity consumption predictions. For International tourism (Panels A and B), the pattern is consistent across both models: SHAP values increase as the number of tourists rises, showing a strong positive link with electricity use. However, the pattern for Manufacturing value-added changes depending on the time frame. In the short term, SHAP values decrease as manufacturing increases, suggesting that improved efficiency or temporary production adjustments might lower electricity use. In the long term, SHAP values increase with more manufacturing activity, indicating higher electricity demand as the industry grows.

SHAP helps explain which variables impact electricity consumption most, giving a broad, long-term perspective. However, a local explanation method is needed to understand how variables affect each individual prediction. That's where LIME comes in. As shown in Figure 10, LIME explains the influence of variables for each case, helping uncover how different factors affect electricity use across various periods.

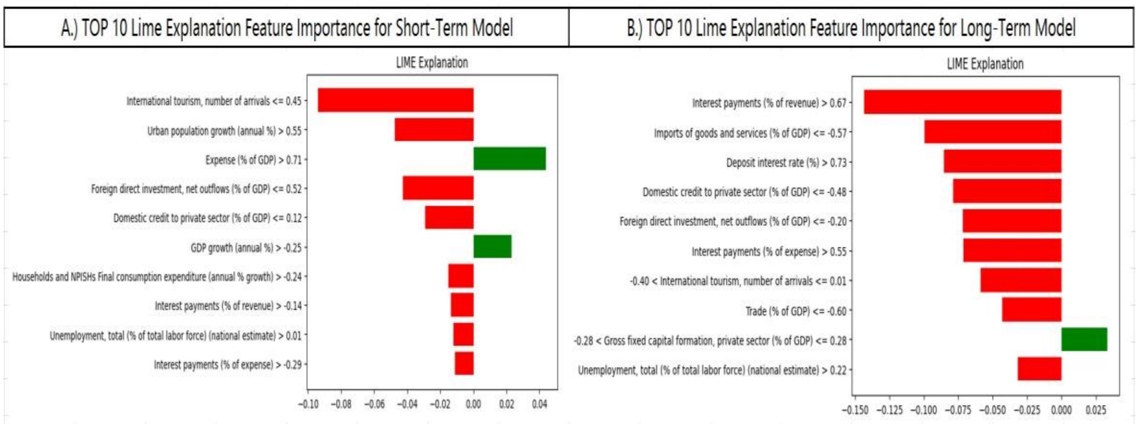

Figure 10. Top 10 LIME explanations feature importance for short-term and long-term models.

Figure 10 presents the results of the LIME analysis, comparing short-term and long-term electricity consumption predictions. This analysis highlights how the importance of variables changes over time. In the short term, international tourism has a negative impact—when tourist numbers fall below 0.5 million, electricity use drops, reflecting lower demand. Similarly, Urban population growth and Expenses (% of GDP) also have negative effects, possibly due to decreased urban energy use and short-term reductions in government spending. In contrast, the long-term analysis shows that Interest payments (% of revenue) have a strong negative influence, suggesting that rising debt payments can suppress electricity consumption over time. Other variables, like Imports of goods and services, Deposit interest rate, and Domestic credit to the private sector, also show negative effects, pointing to ongoing structural influences. Meanwhile, Trade (% of GDP) has a slight positive impact, indicating a potential rise in energy demand as trade grows. Comparing SHAP and LIME highlights their complementary roles. SHAP captures overall trends and the global influence of variables, while LIME focuses on local, case-specific explanations. LIME is beneficial for identifying short-term effects, such as the immediate impact of tourism and debt, whereas SHAP is better for understanding broader, long-term patterns. Using both methods together provides a fuller understanding of electricity consumption and supports more effective energy planning.

4.6 Comparative Study

To understand the relationship between economic determinants and electricity consumption across varying economic contexts, this study conducts a comparative analysis by grouping countries into three GDP-based categories: similar GDP (e.g., Singapore, Israel, Malaysia), higher GDP (e.g., United States, United Kingdom, Japan), and lower GDP (e.g., Iceland, Senegal, Togo). This classification enables an exploration of how economic development levels influence electricity usage and key contributing factors within each group. Using an MLP model and interpretable AI techniques—specifically SHAP and LIME—the analysis examines feature influence across different GDP levels to identify context-specific drivers of electricity consumption. All data are sourced from the World Development Indicators (WDI) to maintain consistency and comparability, following the same methodological framework used in the Thailand case study to minimize bias. The experimental process aims to determine whether GDP levels affect the significance of macroeconomic variables and how those relationships vary across countries. SHAP analysis results, illustrated in Figure 11, highlight the top five most influential economic indicators in each country, while LIME provides deeper insights into localized effects. Together, these tools offer valuable perspectives for enhancing forecasting accuracy and informing strategic energy planning tailored to diverse economic settings.

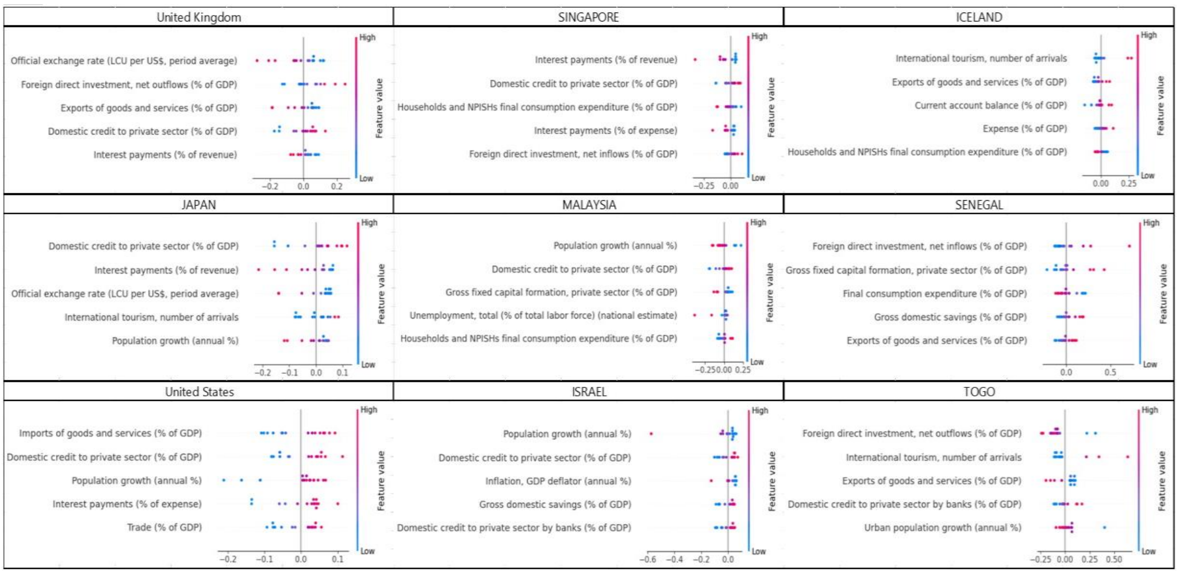

Figure 11. SHAP summary plot of feature importance for electricity consumption with different GDP levels.

The SHAP summary plot analysis comparing the influence of economic variables on electricity consumption across countries with varying GDP levels reveals distinct patterns. In high-GDP nations (e.g., the United States, United Kingdom, Japan), electricity consumption is strongly influenced by Domestic credit to the private sector and the Official exchange rate, reflecting economies driven by trade and investment. In countries with moderate GDP levels similar to Thailand (e.g., Singapore, Israel, Malaysia), Domestic credit to the private sector remains a key factor, alongside Foreign direct investment and Interest payments, which show patterns consistent with Thailand's economic context. For low-GDP countries (e.g., Iceland, Senegal, Togo), electricity usage is primarily shaped by external drivers such as Foreign direct investment and International tourism. These findings highlight how GDP level corresponds to differing economic structures and variable significance in energy demand. Building on this global SHAP analysis, we proceed to a local interpretation using LIME (see Figure 12), which offers case-specific insights into how individual variables impact electricity consumption within each country. This helps clarify which factors hold localized importance and illustrates how economic disparities influence variable behavior in electricity forecasting.

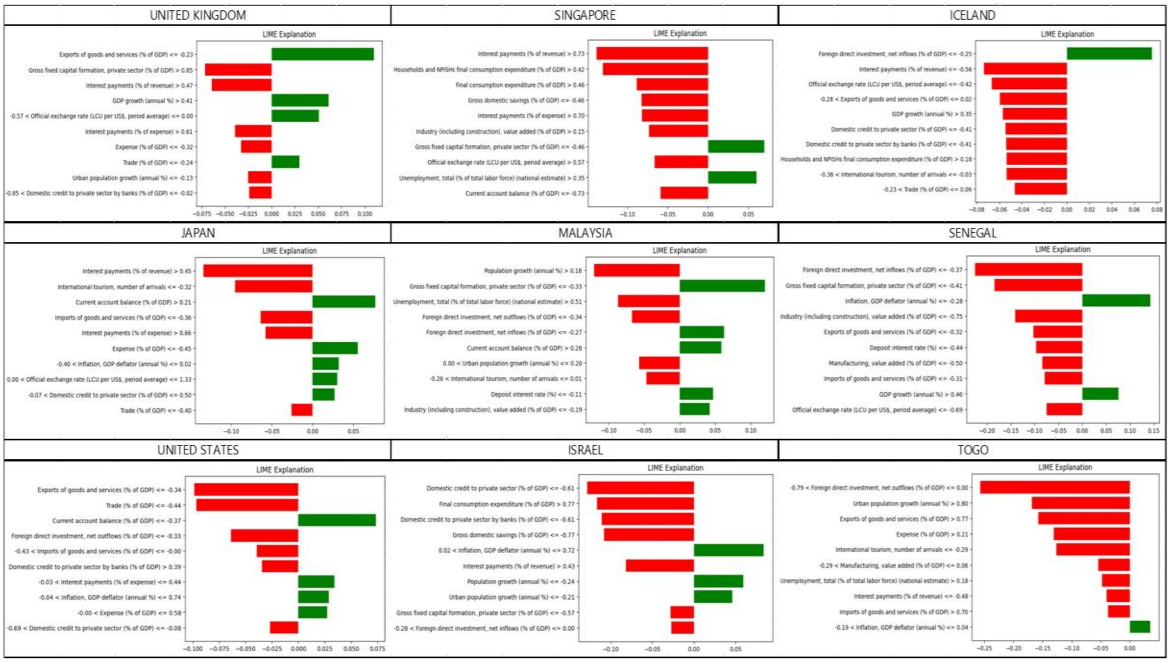

Figure 12. LIME summary plot of feature importance for electricity consumption with different GDP levels.

The LIME analysis by GDP level reveals distinct economic drivers of electricity consumption. In high-GDP countries (e.g., the UK, Japan, and the US), key factors include trade and investment, such as exports, imports, and capital formation. In mid-GDP countries (e.g., Singapore, Malaysia, Israel), population growth and domestic consumption, like household spending and FDI, are more influential. Low-GDP countries (e.g., Iceland, Senegal, Togo) rely on external factors like FDI and tourism. These findings highlight how GDP levels shape the economic variables impacting electricity consumption. SHAP and LIME analysis reveals how economic variables influence electricity consumption across GDP levels. SHAP provides a global view, showing that high-GDP countries are driven by trade and investment factors, while LIME highlights country-specific effects. Population growth and household spending are key in mid-GDP nations, whereas low-GDP countries rely on external factors like FDI and tourism. Combining SHAP and LIME offers a comprehensive understanding of economic influences on electricity consumption at both global and local scales.

4.7 Discussion

This study introduces a robust and interpretable machine learning model for forecasting electricity consumption; however, a key limitation lies in the exclusion of environmental factors such as temperature and humidity, which significantly influence energy demand—particularly in regions with extreme climates. Without these variables, the model may offer an incomplete representation of electricity usage. Future research should address this gap by incorporating environmental data and testing the model across various regions, climates, and economic contexts to enhance both accuracy and adaptability. Additionally, while the selected macroeconomic indicators and modeling techniques are appropriate, they may not fully capture the complexity of electricity consumption. Exploring alternative or ensemble methods, alongside integrating local economic factors, environmental variables, and stakeholder input, could improve predictive performance and increase the model's practical relevance in real-world energy planning.

5. Conclusion

In conclusion, this study demonstrates the effectiveness of using interpretable machine learning specifically a multilayer perceptron (MLP) integrated with SHAP and LIME to accurately forecast short- and long-term electricity consumption in Thailand while enhancing transparency into how macroeconomic variables influence energy demand. This interpretable approach offers a practical alternative to traditional black-box models, allowing stakeholders to better understand the role of economic drivers such as tourism, industrial growth, and interest rates. These insights can inform targeted policy decisions, including adjusting national energy budgets, prioritizing infrastructure in tourism-driven areas, and coordinating energy and monetary policies to manage demand more effectively. The findings show that MLP outperforms ARIMA and Random Forest models, while SHAP and LIME highlight how factors like tourism and industrial activity increase consumption, whereas interest rates and private sector investment tend to reduce it. These results support more adaptive, region-specific strategies for sustainable energy planning. However, limitations remain, such as the exclusion of geographic and environmental data—e.g., population distribution, temperature, and seasonality which future research should integrate to enhance accuracy. Incorporating regional-level data and advanced models like Transformers or other time-series techniques may also improve long-term forecasting by capturing complex, multidimensional relationships. Further, evaluating model robustness under economic uncertainty and adopting more advanced interpretability methods (e.g., integrated gradients or DeepLIFT) could deepen understanding of variable impacts and strengthen decision-making. Overall, this study advances interpretable electricity forecasting in Thailand by connecting economic indicators with energy use and lays a foundation for future improvements that support resilient, sustainable policy planning.

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