Forecasting Electricity Consumption of the Local Government Agencies in Ubon Ratchathani Province, Thailand

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Abstract

This time series forecasting research aimed to forecast the electricity consumption of the local government agencies in Ubon Ratchathani Province and examine the strength of its relationship with temperature. Monthly electricity consumption data for the fiscal years 2022 to 2024 were obtained from the Energy Policy and Planning Office, while climate data from 2014 to 2024 were collected from the Northeastern Meteorological Center (Lower Part). The analysis focused on the five government agencies with the highest electricity consumption, using monthly data from June 2021 to January 2024. The training dataset comprised data from fiscal years 2021 to 2023. Descriptive statistics and correlation analysis were conducted using JAMOVI software, while the Box and Jenkins forecasting method was performed using the R program, package "forecast", function "auto.arima()". The results indicated that electricity consumption at Ubon Ratchathani Central Prison, Ubon Ratchathani Technical College, and Public Relations Office District 2 is expected to decrease. In contrast, Ubon Ratchathani Airport and Medical Sciences Center 10, Ubon Ratchathani, are projected to increase. Pearson's correlation analysis revealed a strong positive relationship between the monthly average daily maximum temperature and electricity consumption, with correlation coefficients ranging from 0.576 to 0.745, except for Ubon Ratchathani Technical College (College), which showed a lower correlation of 0.236. This study explores the increasing demand for precise electricity consumption forecasting in government agencies to support energy efficiency policies. The findings provide valuable insights for developing data-driven energy management strategies by analyzing historical consumption patterns and climatic factors. These results can help policymakers implement effective energy-saving measures, optimize resource allocation, and mitigate the impact of climatic variability.

Keywords: forecasting; electricity consumption; government agencies; Ubon Ratchathani province

Introduction

The initiative project to reduce energy consumption in the public sector was introduced following the Cabinet's approval of a national energy strategy on May 17, 2005, to resolve the country's energy problems. Under this policy, all government agencies and state enterprises were mandated to reduce their energy consumption by 10–15% compared to their electricity and fuel consumption in fiscal year 2003. This reduction target was formally established as a key performance indicator (KPI) for all agencies. Since fiscal year 2006, the Office of the Public Sector Development Commission (OPDC) has set KPI as an energy-saving target into the performance evaluation criteria for government agencies (Energy Policy and Planning Office (EPPO), Ministry of Energy, 2025a).

Additionally, the Ministry of Energy (MOE) has assembled a technical advisory team composed of experts from the Electricity Generating Authority of Thailand (EGAT), the Provincial Electricity Authority (PEA), the Metropolitan Electricity Authority (MEA), the Department of Alternative Energy Development and Energy Efficiency (DAE), and all 12 regional energy offices nationwide. This team provides technical guidance and support on equipment maintenance, optimization, and modification to enhance energy efficiency.

Electricity consumption among the local government agencies in Ubon Ratchathani province reported from this initiative project has been published. Of the 108 agencies in the province, 96 submitted 12-month electricity consumption reports for all three fiscal years (2022-2024). The five agencies with the highest electricity consumption during this period were: Ubon Ratchathani Airport, Ubon Ratchathani Central Prison, Ubon Ratchathani Technical College, Public Relations Office District 2, and Medical Sciences Center 10 (Energy Policy and Planning Office (EPPO), Ministry of Energy, 2025b). These five agencies vary in their operational characteristics. While most agencies exhibited a declining trend in electricity consumption, Public Relations Office District 2 (PRD2) recorded an increase. The characteristics of 36 months of time-series data of all five agencies and historical electricity consumption patterns can provide insights into future trends and possibilities using univariate time series forecasting principles.

Energy consumption is crucial for promoting sustainability and cost efficiency. By considering the affected environmental factors such as temperature, humidity, natural light, air quality, geographical location, building design, and renewable energy potential, the government agencies can implement energy-saving strategies that reduce environmental impact, enhance operational efficiency and further contribute to a more sustainable future (Kaufmann et al., 2013). Understanding the influence of climate on electricity consumption is crucial for the local government agencies in Ubon Ratchathani province to ensure adequate energy planning and policy development. Among various environmental factors, rising temperatures significantly affect electricity consumption patterns, leading to increased energy consumption. By analyzing these trends, policymakers can propose strategies to enhance energy efficiency and optimize resource utilization.

Even though national energy conservation policies have been implemented, there remains a research gap in forecasting models tailored to specific provincial characteristics. Existing studies often emphasize broad national trends, overlooking the localized impact of climate variability and operational differences among government agencies. This study aims to bridge this gap by developing a more precise, region-specific electricity consumption forecasting model, facilitating the more effective implementation of energy policies.

For the local government agencies in Ubon Ratchathani province, forecasting electricity consumption for the next fiscal year and understanding the relationship between electricity consumption and climate will provide a valuable energy planning and policy development framework.

Research Objectives

To forecast the electricity consumption of the five government agencies for the fiscal year 2025 and to analyze the statistical correlation between climatic factors and electricity consumption in Ubon Ratchathani province.

Literature Reviews

Climate effects associated with energetic particle precipitation influence electricity consumption in Finland. Incorporating long-term space weather predictions into energy consumption forecasts could enhance accuracy (Juntunen & Asikainen, 2023). Household lifestyles play a crucial role in appliance energy consumption. How appliances are used can determine their optimal performance or contribute to inefficiencies and malfunctions. The rapid increase in residential electricity consumption has raised serious concerns about limited energy resources and rising electricity costs.

In Ghana (West Africa), the Electricity Company of Ghana (ECG) proposed a 134% increase in electricity tariffs during the height of the economic crisis caused by COVID-19, resulting in widespread public agitation. Additionally, unpredictable residential consumption patterns, driven by the pursuit of comfort and population growth, have significantly strained energy demand in the residential sector (Rauf & Adekoya, 2013). Similarly, a correlation study between climate data and maximum electricity demand in Qatar (Gastli et al., 2013) underscores the influence of climate conditions on energy consumption.

Pearson's Correlation Coefficient

Pearson's correlation is used to analyze the relationship between two variables. However, Spearman's correlation should be used if the data do not follow a normal distribution. According to Statistics Solutions (2022), the Pearson correlation coefficient is interpreted as follows:

- A value close to 1 indicates a perfect correlation, meaning that as one variable increases, the other increases or decreases proportionally.
- A value between 0.50 and 1.00 signifies a high correlation between the variables.
- A value between 0.30 and 0.49 indicates a moderate correlation.
- A value of 0.29 or below represents a weak correlation.
- A value approaching 0 suggests no correlation, indicating unrelated variables.

Box and Jenkins method

Univariate time series forecasting is applicable when two conditions are met: (1) historical numerical data is available, and (2) it is reasonable to assume that specific patterns observed in the past will persist into the future. The primary objective of time series forecasting is to predict how a sequence of observations will develop over time (Hyndman & Athanasopoulos, 2021).

A time series is a sequence of observations recorded over time. Time series analysis is used to identify patterns in historical data (in-sample data) and model these patterns to predict future values (out-of-sample data). A time series is considered stationary if it maintains a constant mean and variance.

The Box and Jenkins method employs the Auto-Regressive Integrated Moving-Average (ARIMA) model, denoted as ARIMA(p,d,q). This model generates forecasts by weighting p values of past actual values and a moving average of historical errors in the number of q values. Since ARIMA requires a stationary time series with a mean error of zero and constant variance, the data must be differenced d times until stationarity is achieved.

To determine the optimal parameters (p,d,q) in modelling, consider the correlation among the data's lag times. Autocorrelation is the correlation of a value at a point in time with a value q periods before it (lag q) from the self-correlation function (autocorrelation function; ACF) at various lags. A picture that shows self-correlation is called a correlogram.

The most consistent model is selected by choosing appropriate p, d, and q values for non-seasonal data. When seasonality is present, the SARIMA model (Seasonal ARIMA) is applied, expressed as ARIMA (p,d,q) (P, D, Q) [S] model, where P, D, and Q represent the parts with seasonal, and S is the amount of data in 1 season. SARIMA modeling requires numerous iterative calculations to optimize the parameters (p,d,q)(P, D, Q). Akaike's Information Criterion (AIC) and the corrected AIC (AICc) of the model with the lowest values are used as criteria for model selection (Makridakis, Wheelwright, Hyndman, 2008; Hyndman, Athanasopoulos, 2021). Appropriate data must be utilized to identify crucial structures and patterns effectively. The number of data points required for the ARIMA (p,d,q)(P, D, Q) [S] model is determined by p+d+q+P+Q+SD+1 (Hyndman & Kostenko, 2007). The general form of the seasonal model is presented below (NCSS Statistical Software, 2025).

The ARIMA(p,q) model,

$$X_t = \phi_1 X_{t-1} + \ldots + \phi_p X_{t-p} + a_t - \theta_1 a_{t-1} - \ldots - \theta_q a_{t-q}$$

The ϕ's (phis) are the autoregressive parameters to be estimated, the θ's (thetas) are the moving average parameters to be estimated, the X's are the original series, and the a s are a series of unknown random errors (or residuals) assumed to follow the normal probability distribution.

The backshift operator, B has the effect of changing the period t to the period $t-1$. Thus $BX_t = X_{t-1}$ and $B^2X_t = X_{t-2}$. Using this backshift notation, the above model may be rewritten as:

$$(1-\phi_1 B - \ldots - \phi_p B^p)X_t = (1-\theta_1 B - \ldots - \theta_q B^q)a_t$$

This may be abbreviated even further by writing:

$$\phi_p(B)X_t = \theta_q(B)a_t$$

where

$$\phi_p(B) = (1-\phi_1 B - \ldots \phi_p B^p)$$

$$\theta_q(B) = (1-\theta_1 B - \ldots - \theta_q B^q)$$

These formulas show the operators. $\phi_p(B)$ and $\theta_q(B)$ Are polynomials in B of orders p and q Respectively. One benefit of writing models in this fashion is that we can see why several models may be equivalent.

Nonstationary Models

$$W_t = X_t - X_{t-1} \quad \text{or} \quad W_t = (1-B)X_t$$

A more general form of this equation is:

$$\phi_p(B)(1-B)^d X_t = \theta_q(B)a_t$$

where d Is the order of differencing? This is known as the ARIMA(p,d,q) model.

To deal with series containing seasonal fluctuations, Box–Jenkins recommends the following general model ARIMA(p,d,q)(P, D, Q)[S]:

$$\phi_p(B)\Phi(B)(1-B)^d\left(1-B^S\right)^D X_t = \theta_q(B)\Theta_Q\left(B^S\right)a_t$$

where d Is the order of differencing? s The number of seasons per year, and D is the order of seasonal differencing.

Note that

$$\left(1-B^{S}\right)X_{t}=X_{t}-X_{t-S}$$

Selecting the optimal model based on the Box and Jenkins method is complex and requires a properly trained person to select model parameters consistent with the data. Therefore, a program has been developed that can automatically select the appropriate model, namely the “auto.. Arima ()” function in the package “forecast” developed with the “program R” running on R Studio (Hyndman, & Khandakar, 2008).

Model accuracy

Mean Absolute Percentage Error (MAPE) is a widely used statistic for comparing the accuracy of different models (Makridakis, Wheelwright & Hyndman, 2008).

When given y_i as actual period value, and y_i as periodic forecast values for the period i and $i=1,2,...,n$ (In-sample data),

$$\text{MAPE}=\frac{1}{n-1}\sum_{i=2}^{n}\left|\frac{\hat{y}_i-y_i}{y_i}\right|\times 100$$

The model's accuracy is determined by MAPE, which is expressed as a percentage of the actual value. MAPE if less than 10 has high accuracy, 10-20 is suitable for forecasting, 20-50 is reasonable enough for forecasting, and more than 50 is not accurate (Lewis, 2023).

The ARIMA model predicting electrical energy consumption using the training data collected ranges from October 2004 to May 2014, with 116 data points, while the test data collected ranges from May 2014 to July 2018, with 48 data points, the experiment recommended that ARIMA was maximum accuracy for the medium-term predictions (Fathin, Widhiyasana & Syakrani, 2021). The study employed the ARIMA model with three sets of parameters (ARIMA (1,1,1), ARIMA(1,1,2), and ARIMA (1,1,7)) to forecast residential consumption on two different datasets. Their experimental results show that ARIMA (1, 1, 1) had high precision and stable predictions on both datasets (Mahia et al., 2019).

The Box and Jenkins method employs the Auto-Regressive Integrated Moving-Average (ARIMA) model, which was applied to forecast the electricity demand in Thailand, the Philippines, and Pakistan. The ARIMA model was used in forecasting electricity consumption by sector of the

Provincial Electricity Authority (PEA) in Thailand, using the past annual consumption from 2017 to 2023, and the model had good accuracy with the Mean Absolute Percent Error (MAPE) of 2.13 to 16.16 percent (Kumjinda et al., 2023). Forecasting electricity consumption in the Philippines, the annual electricity consumption from 1973 to 2020 was in gigawatt-hours (GWh). The first 43 data points, from 1973 to 2015, had been used as a training set for model building. The remaining 5 data points, 2016 to 2020, had been used for forecast evaluation. The best model to forecast the annual electricity consumption in the Philippines was ARIMA (0,2,1) (Parreño, 2022). Forecasting of hydroelectricity consumption in Pakistan based on the historical data of the past 53 years from 1965 to 2017 using the ARIMA model to predict up to the year 2030, the most appropriate model had the lowest variance, AIC, and SBIC values and the highest adjusted R2 value (Jamil, 2020).

Research Methodology

Electrical energy used

Electricity consumption data (in kWh) for the local government agencies in Ubon Ratchathani province was collected from the Energy Policy and Planning Office, Ministry of Energy (2025b). The public sector energy reduction project publishes electricity consumption reports for five categories of agencies: provincial government agencies, district government agencies, local government organizations, higher education institutions, and state enterprises, covering the 12-month fiscal cycle from October to September for the fiscal years 2022–2024.

In the reporting system, electricity consumption data for the local government agencies in Ubon Ratchathani province is displayed by selecting "Province" and then "Ubon Ratchathani Province". The five agencies with the highest electricity consumption during this period were as follows: Ubon Ratchathani Airport (Airport), Ubon Ratchathani Central Prison (Prison), Ubon Ratchathani Technical College (College), Public Relations Office District 2 (PRD2), Medical Sciences Center 10, Ubon Ratchathani (MSC10).

The climatic factors

The Northeastern Meteorological Center (Lower Part) (2025) provides the meteorological information as a self-downloading, offering monthly climatic records from 2014 to 2024, with an area of responsibility covering nine provinces in Ubon Ratchathani. The dataset includes: daily highest-lowest temperature (degrees Celsius), length of sunlight (hours), water evaporated (mm), relative humidity (percent), and total rainfall (mm). The monthly average daily maximum temperature (ADMaxT) and monthly maximum temperature (MaxTemp) were used in the analysis. The electricity consumption forecasting dataset comprised 36 months, covering the fiscal years from 2021 to 2023. Electric consumption and climatic factor data were analyzed over 33 months, from June 2021 to January 2024, for descriptive statistics and correlation analysis.

The population in this study refers to the total electricity consumption records of the local government agencies in Ubon Ratchathani province, covering all relevant agencies included in the Public Sector Energy Reduction Project's database.

The sample size is determined based on a systematic selection process to ensure that the dataset is representative of electricity consumption trends. If using a rule-of-thumb approach for time series forecasting, a minimum of 30–50 observations is generally recommended for robust statistical analysis. This study uses electricity consumption data spanning 36 months (three fiscal years: 2021–2023) for forecasting, while a 33-month dataset (June 2021 – January 2024) is used for descriptive statistics and correlation analysis.

This structured approach ensures that the sample is comprehensive and statistically sound, providing reliable insights into electricity consumption patterns and their correlation with climatic factors.

Statistical Analysis

The statistical analysis software for descriptive statistics and correlation analysis is "jamovi" (JAMOVI, 2022), and the software for time series forecasting is "Program R" (The R Core Team, 2021), package "forecast" with "auto.arima()" function (DataCamp, 2025; Hyndman & Khandakar, 2008).

Research Results

Table 1 shows the descriptive statistics of electricity consumption of the five highest usages and the climatic factors, and Table 2 also shows the Pearson correlation coefficients.

The Pearson correlation coefficient between the monthly average daily maximum temperature (ADMaxT) and the monthly maximum temperature (MaxTemp) was exceptionally high at 0.922, indicating that these variables can be used interchangeably.

Correlation analysis between the monthly average daily maximum temperature (ADMaxT) and electricity consumption across five agencies revealed strong relationships, with correlation coefficients of 0.745, 0.704, 0.665, and 0.576 for Ubon Ratchathani Central Prison (Prison), Medical Sciences Center 10, Ubon Ratchathani (MSC10), Ubon Ratchathani Airport (Airport), and Public Relations Office District 2 (PRD2), respectively. In contrast, Ubon Ratchathani Technical College (College) 's weak correlation was 0.236.

The strong correlation between maximum temperature and electricity consumption suggests that electricity consumption can be effectively projected based on temperature forecasts.

Table 1 The descriptive statistics of electricity consumption and climatic factors of Ubon Ratchathani province

	Agencies					Climatic factors	
	Airport	**Prison**	**College**	**PRD2**	**MSC10**	**ADMaxT**	**MaxTemp**
Mean	270,338	103,082	23,273	37,748	35,785	33.60	36.80
Median	249,175	103,788	23,921	33,450	35,505	33.20	36.10
Standard deviation	67,521	18,641	2,660	9,086	5,821	2.35	2.53
Minimum	164,227	63,500	17,332	23,995	24,766	29.50	33.10
Maximum	430,296	134,315	30,500	47,119	49,682	40.50	43.10
Shapiro–Wilk W	0.925	0.955	0.95	0.787	0.977	0.952	0.904
Shapiro–Wilk p	0.026	0.190	0.132	< .001	0.704	0.153	0.007

Table 2 Pearson's correlations between climatic factors and the top five electricity users

Users		ADMaxT	MaxTemp
MaxTemp	Pearson's r	**0.922**	—
	p-value	< .001	—
Airport	Pearson's r	**0.665**	**0.673**
	p-value	< .001	< .001
Prison	Pearson's r	**0.745**	0.649
	p-value	< .001	< .001
College	Pearson's r	**0.236**	0.137
	p-value	0.186	0.445
PRD2	Pearson's r	**0.576**	0.488
	p-value	< .001	0.004
MSC10	Pearson's r	**0.704**	0.633
	p-value	< .001	< .001

The auto.arima () found the models fitted to the 36 months training data set as shown in Table 3. The MAPE was less than 10 percent, which meant it was suitable for forecasting. The monthly forecast for the fiscal year 2025 is shown in Table 4. Ubon Ratchathani Central Prison (Prison), Ubon Ratchathani Technical College (College), and Public Relations Office District 2 (PRD2) showed a decrease from 2024, while Ubon Ratchathani Airport (Airport) and Medical Sciences Center 10, Ubon Ratchathani (MSC10) showed an increase from 2024. The forecast models for each electricity user were as follows;

At Ubon Ratchathani Airport (Airport), the best-fitted model was the seasonal ARIMA (0,0,1)(0,1,0)[12] with drift. The model achieved an MAPE of 6.07, indicating high forecasting accuracy. The total monthly forecasts for the fiscal year 2025 showed a 13.18 percent increase compared to the fiscal year 2024.

At Ubon Ratchathani Central Prison (Prison), the best-fitted model was the ARIMA(0,0,0) with a non-zero mean. The MAPE of 3.92 indicates high forecasting accuracy. The total sum of monthly forecasts for the fiscal year 2025 showed a 3.17 percent decrease compared to the fiscal year 2024.

Table 3 The ARIMA models and coefficients of the top five agencies

Agencies		Model and Coefficients	MAPE
Airport	Model	ARIMA(0,0,1)(0,1,0)[12] with drift	6.07
	Coefficients:		
	ma1	0.5235	
	drift	3,318.69	
Prison	Model	ARIMA(0,0,0) with non-zero mean	3.92
	Coefficients:		
	sar1	-0.7979	
	drift	770.70	
College	Model	ARIMA(0,0,0) with non-zero mean	8.14
	Coefficients:		
	mean	23,234.61	
PRD2	Model	ARIMA(0,1,0)	4.87
MSC10	Model	ARIMA(0,1,0)(0,1,0)[12]	4.86

Ubon Ratchathani Technical College (College) 's best–fitted model was the ARIMA(0,0,0) with a non–zero mean. The MAPE of 8.14 indicates high forecasting accuracy. The total sum of monthly forecasts for the fiscal year 2025 showed a 9.28 percent decrease compared to the fiscal year 2024.

Public Relations Office District 2 (PRD2): The best–fitted model was the ARIMA(0,1,0). The MAPE of 4.87 indicates high forecasting accuracy. The total monthly forecasts for the fiscal year 2025 showed a 1.22 percent decrease compared to the fiscal year 2024.

Medical Sciences Center 10, Ubon Ratchathani (MSC10), the best–fitted model was the seasonal ARIMA(0,1,0)(0,1,0)[12]. The model achieved an MAPE of 4.86, indicating high forecasting accuracy. The total monthly forecasts for the fiscal year 2025 showed a 35.34 percent increase compared to the fiscal year 2024.

Table 4 Monthly Electricity (kWh) Forecast for the fiscal year 2025

A.D.	Description	Airport	Prison	College	PRD2	MSC10
2024	October	299,800	108,504	23,235	45,980	54,815
2024	November	273,721	111,774	23,235	45,980	50,945
2024	December	240,757	91,225	23,235	45,980	47,988
2025	January	277,857	88,859	23,235	45,980	51,413
2025	February	256,850	104,746	23,235	45,980	54,615
2025	March	275,035	123,852	23,235	45,980	61,239
2025	April	470,120	141,639	23,235	45,980	60,545
2025	May	466,566	143,305	23,235	45,980	61,939
2025	June	437,642	136,097	23,235	45,980	65,618
2025	July	428,790	133,974	23,235	45,980	73,047
2025	August	409,264	134,630	23,235	45,980	79,823
2025	September	408,275	127,793	23,235	45,980	70,332
	Total 2025	4,244,677	1,337,894	255,581	551,760	732,319
	Fiscal Year 2024	3,750,284	1,381,709	281,739	558,576	541,087
	+/– % Chage	13.18	–3.17	–9.28	–1.22	35.34

Discussion

The Pearson correlation coefficients revealed a strong relationship between the monthly average daily maximum temperature and electricity consumption, ranging from 0.576 to 0.745, except for Ubon Ratchathani Technical College (College), which showed a weaker correlation of 0.236. Implementing air conditioning monitoring measures could effectively help reduce energy consumption.

The articles related to forecasting electricity demand mainly demonstrated how the model fit, but did not present the accuracy in terms of MAPE. A study by an electricity provider from the State of Pennsylvania, using monthly data from January 1, 1973, to March 1, 2021, in Terawatts (TW), reported a MAPE of approximately 4.96 percent (Sharma & Mishra, 2023). This study showed an MAPE ranging from 3.92 to 8.14, indicating that the ARIMA model was applicable.

The findings indicate that agencies with rising electricity consumption may require stricter energy control measures, such as improving air conditioning efficiency or integrating renewable energy sources. Conversely, agencies with declining energy consumption can serve as models of best practices, contributing to the development of more effective energy-saving policies in the public sector.

The univariate time series forecasting model utilizes only historical data to project future electricity consumption. Once actual data is reported into the system, analysts can assess the model's accuracy and determine the appropriate measures to implement for each agency.

Conclusion

Understanding the relationship between climate factors and electricity consumption is essential for establishing effective measures to monitor and manage energy consumption.

The R programming utilizes the forecast module and the auto. The arima () function can predict electricity consumption in government agencies. These forecasts enable authorities to implement strategic energy management and optimization measures.

The study’s findings provide valuable insights for government agencies to implement data-driven energy saving measures. By leveraging time series forecasting models, policymakers can optimize electricity consumption planning, allocate resources efficiently, and enhance sustainability efforts in the public sector.

Suggestion

The electricity consumption in Ubon Ratchathani province is related to the monthly average daily maximum temperature; this will lead to strategies to reduce electricity consumption. Electricity demand is nonlinearly related to temperature, increasing in response to lower and higher temperatures (Sharma & Mishra, 2023).

Classify the influencing factors such as environmental (temperature, humidity), structural (building design, insulation), operational (working hours, energy policies), and technological (use of energy-efficient devices or systems), and use statistical methods or econometric models to study correlations or causal relationships between factors and energy usage. Tools like regression analysis, time-series analysis, and machine learning models can help identify patterns. Based on findings, suggest policies for reducing energy consumption, enhancing energy efficiency, and incorporating renewable energy sources.

New Knowledge

Electricity consumption in Ubon Ratchathani province is related to the monthly average daily maximum temperature. The Box and Jenkins method is a univariate time series forecasting model that utilizes historical data to project future electricity consumption. This ARIMA model can be an initial guideline for future electricity consumption planning—the fitted model from the auto. The arima() function presented the model's accuracy in terms of MAPE and the range of high forecasting accuracy.

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