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Comparative Performance of ARMA and ARIMAX Models in Time Series: A Case Study of Urban Electricity Consumption of Sulaymaniyah, Iraq

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ABSTRACT : Bridging the gap between supply and demand can be greatly assisted through modeling and forecasting daily energy consumption. The aim of this study is to utilize the Autoregressive Integrated Moving Average (ARIMA), and Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX), models to forecast and modelling energy consumption in Sulaymaniyah province, given the critical nature of this issue. The aforementioned models were developed employing daily electricity consumption and meteorological data from January 1, 2024, to December 31, 2024. The Akaike Information criteria (AIC) and Bayesian Information criteria (BIC) have been utilized in Google Colab software to determine the appropriate values of the parameters of the described models (p, d, q). The most effective models were determined to be ARIMA (3,0,4) and ARIMAX (3,0,3). It has been concluded from the comparison of the Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Coefficient of Determination values (R-Square) for the models. the ARIMA model with a (MAE = 0.0470), (RMSE = 0.060) and (R-Square = 70%) was more precise than the ARIMAX model in modeling and forecasting power consumption.
Keywords: Arima ,Arimax ,Electricity Consumption Forecasting ,Aic ,Rmse

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التحليل المقارن لنماذج ARMA و ARIMAX في السلاسل الزمنية: دراسة حالة لاستهلاك الكهرباء الحضري في السليمانية، العراق

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المستخلص.
يمكن سد الفجوة بين العرض والطلب بشكل كبير من خلال النمذجة والتنبؤ باستهلاك الطاقة اليومي. تهدف هذه الدراسة إلى استخدام نموذجي المتوسط المتحرك المتكامل الانحداري الذاتي (ARIMA) والمتوسط المتحرك المتكامل الانحداري الذاتي مع المتغيرات الخارجية (ARIMAX) للتنبؤ باستهلاك الطاقة ونمذجته في محافظة السليمانية، نظرًا لحساسية هذه القضية. طُوّرت النماذج المذكورة أعلاه باستخدام بيانات استهلاك الكهرباء اليومي والبيانات الجوية من 1 يناير 2024 إلى 31 ديسمبر 2024. استُخدمت معايير معلومات أكايكي (AIC) ومعايير المعلومات البايزية (BIC) في برنامج جوجل كولاب لتحديد القيم المناسبة لمعلمات النماذج الموصوفة (p, d, q) وُجد أن أكثر النماذج فعالية هما ARIMA (3،0،4) وARIMAX (3،0،3). وقد استنتج من مقارنة قيم متوسط الخطأ المطلق (MAE) وجذر متوسط خطأ التربيع (RMSE) ومعامل التحديد (R-Square) للنماذج أن

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نموذج ARIMA مع (MAE = 0.0470) و (RMSE = 0.060) و (R-Square = 70٪) كان أكثر دقة من نموذج ARIMAX في النمذجة والتنبؤ باستهلاك الطاقة.

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Introduction

Estimating the ANPG (Annual Net Power Generation) and ANC (Annual Net Consumption) of power in urban areas is highly desirable for both engineers involved in electrical and data science as a tool for trend recognition, as well as projection engineering of energy needs across different city regions. In planning systems for power generation and distribution as well as in energy resource management the relevance of this problem cannot be overemphasized.

Power generation and consumption time series are one of the fundamental topics in data science and electrical engineering. The reduction of the loss of energy, optimization of both production and consumption processes and ensuring a sustainable supply of energy are all strongly based on this research.

Numerous studies have been performed by researchers on time series forecasting in a range of domains based on the logic of recurring events occurring in the future. Box and Jenkins time series methodology uses Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX). These methods are commonly used time series forecasting methods because they are very easy to use [1].

To improve the model performance with the ARIMAX method, Robbie et al. (2020) employed population and GDP per capita as two exogenous variables. They predicted demand for the next three consecutive year to predict electric load, Shilpa (2019) proposed the AIMAX model which included a specific correlation factored with daily data. The input the ARIMAX model used were hourly load data over a month, plus exogenous variables, such as whether it was a weekday or weekend. [2]

Zainuddin et al. (2019) used ARIMA models to model soil temperature at two synoptic stations, and at three different depths. Again, this study utilized several preprocessing approaches for modeling. The suggested ARIMA model provided better performance when compared to a multi-layer perceptron neural network models, using the ARIMAX (1, 1, 0) methodology and 24 years of electrical consumption data.

Al-Sharif and Younis Wakim (2020) used ARIMA models to predict daily and monthly global solar radiation. They recognized the success of using the models to accurately estimate daily and monthly global solar radiation based on almost 37 years of data, which would help with planning solar power production [4].

In this current study, we are looking into the forecasting performance of ARIMA and ARIMAX using historical weather data and daily electricity consumption data from Sulaymaniyah province. The comparison forecasts will assess the models' accuracy using statistical metrics, including the Akaiki, BIC, MSE, and MAPE measures.

1.Methodology

First: The ARIMA process

In econometrics, the Autoregressive Integrated Moving Average models are known as ARMA and ARIMA. When there are no missing data points and the time series is stationary, these models perform incredibly well. These models typically consist of three components: Autocorrelation (AR), Difference(I), and Moving Average (MA). They are typically expressed as ARIMA (p, d, q). Relation (1) is used to express the autocorrelation component of this model, which shows the link between past and present observations. [5]

$$AR(p) = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + \epsilon_t \qquad 1$$

Where

φ: Autocorrelation Coefficient

X_t: Time Series Data
ϵ_t: Error Sentence
The difference component (I) of the time series, which can be expressed mathematically by equation 2, can be utilized to stationarize time series data.

$$I(d) = (1 - B)^d X_t \qquad 2$$

Where
B: Backshift operator
The equation (3) is utilized to express the moving average (MA) component, demonstrating the association between noise error and current observations.

$$MA(q) = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} \qquad 3$$

Where
θ: Moving average coefficients
All three of these components combine together to produce the ARIMA model, which is represented by equation (4).

$$(1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p)(1 - B)^d = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} \qquad 4$$

Equation (4) describes the relationship between the current observations of X and its past values, along with the historical white noise error, given this equation, it is essential to estimate the coefficients θ and φ so that the model can utilize the optimal values for (p, d, q) to forecast future data.
The autocorrelation (AC) and partial autocorrelation (PAC) functions based on the Box-Jenkins steps are typically used to determine the order of autoregressive terms and the number of moving average terms [6]. However, since other optimal models may be preferred over the aforementioned model, these models have been studied using the Akaike (AIC) [7,8].

Second: The ARIMAX process

There are commonalities between the (ARIMA) and (ARIMAX) techniques. The key difference is that the variable (X) includes exogenous variables that may be beneficial in forecasting the time series (Y) if the objective of the investigation is to do so. As a consequence, in addition to the variable itself, the forecast of the variable (Y) is additionally dependent on the past values of (X). In this instance, Equation 5 can be utilized to modify the model.

$$Y_t = \theta_0 + \sum_{i=1}^{p} \theta_i Y_{t-i} + \sum_{j=1}^{q} \theta_j e_{t-j} + \sum_{a=1}^{A} a_a X_{1t-a} + \sum_{b=1}^{B} b_b X_{2t-b} + \cdots + \epsilon_t \qquad 5$$

Utilizing historical power consumption data along with meteorological information, such as average air temperature, humidity, and wind speed, is one of the most crucial ways to forecast future urban electricity consumption. The present study discusses the subject [9].

Third: Time Series Analysis & Model Development

In this research, prior to any discussion of model accuracy metrics, all steps of time series analysis were performed. The first step was to test whether the electricity consumption and the meteorological variables were stationary using the Augmented Dickey-Fuller (ADF) test, and then non-stationary series were adjusted through differencing. The best ARIMA and ARIMAX models were selected based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), and the selected models were compared based on (MAE), (RMSE), and (R^2). Lastly, the observed and predicted series generated from the models were graphed and the series were assessed for normality using (QQ-Plots) and the Shapiro-Wilk test to validate models and prediction accuracy. All analyses of time series and modelling were performed using Google Colab.

Fourth: Model accuracy indicators

Forecasting models using time series have been evaluated with various statistical measures. In this study, we measured the following indices to evaluate the models: Akaike Information Criterion (AIC), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Correlation Coefficient (R). These measures are intended to establish the best model and assess model accuracy levels. A

lower value of the Akaike Information Criterion (AIC), a factor related to model complexity, indicates a less complicated and more accurate model. The AIC is determined by the amount of parameterization and the standard deviation of prediction error. For both MAE and RMSE measures, each is more accurate when values approach zero. The correlation coefficient (R) is assessed in value approaching (1) and shows greater agreement between actual data and forecasted values. The RMSE measure is sensitive to large errors; therefore, absolute error criteria (MAE and RMSE) provide an overall assessment of model performance estimates of actual values. As a comparison metric, R2 demonstrates how well the model demonstrates the variation of the real data. Akaike information criterion is important for finding the best model, especially with time series models, since it examines the differences in model complexity, and how well the model fits. Another important factor in selecting the best model is the Bayesian Information Criterion (BIC), which works well when the models have varying numbers of parameters [10,11].
The model evaluation indicators are defined as follows.

$$AIC = N_o * \log((RMSE)^2) + 2 * K_0 \qquad 6$$

$$RMSE = \frac{1}{N_o}\sqrt{\sum_{t=1}^{n}(St_{0(t)} - St_{p(t)})^2} \qquad 7$$

$$MAE = \frac{1}{N_o}\sum_{t=1}^{n}\left|(St_{0(t)} - St_{p(t)})\right| \qquad 8$$

$$R = \frac{\sum_{t=1}^{n}(St_{0(t)} - \overline{St_o})(St_{p(t)} - \overline{St_p})}{\sqrt{\sum_{t=1}^{n}(St_{0(t)} - \overline{St_o})^2 (St_{p(t)} - \overline{St_p})^2}} \qquad 9$$

$$BIC = -2\ln(L) + K_0 ln(N_o) \qquad 10$$

Where
$St_{0(t)}$: the real value
$St_{p(t)}$: the forecasted Value
$\overline{St_o}$: the average of real value
$\overline{St_p}$: the average of forecasted value
N_o:number of data
K_0:number of parameters
L: maximum likelihood of model

2. Results and discussion:

First: Statistical Properties of Variables

The study utilized data on daily electricity consumption in Sulaymaniyah province and the meteorological variables average temperature, humidity, and wind speed. The data was collected from January 1, 2024 to December 31, 2024, and provided by the Provincial Synoptic Center and the Electricity Directorate. Summary statistics for each variable, including count, mean, standard deviation, and Augmented Dickey–Fuller (ADF) test results for stationarity are presented in the table below. This summary of statistics is a basis for formulating an understanding of data behavior and stationarity including the assessment of time series data for the purpose of establishing potential ARIMA and ARIMAX modeling approaches.

Table 1. represent the descriptive, normality and stationarity test of data

Variable	Count	Mean	Std	ADF Stat	ADF p-value
Consumption	366	580.725	64.191	-5.416	0.000
Temp		17.352	9.414	-1.115	0.709
Humidity		44.148	13.255	-0.878	0.795
Wind		2.666	0.938	-1.304	0.627

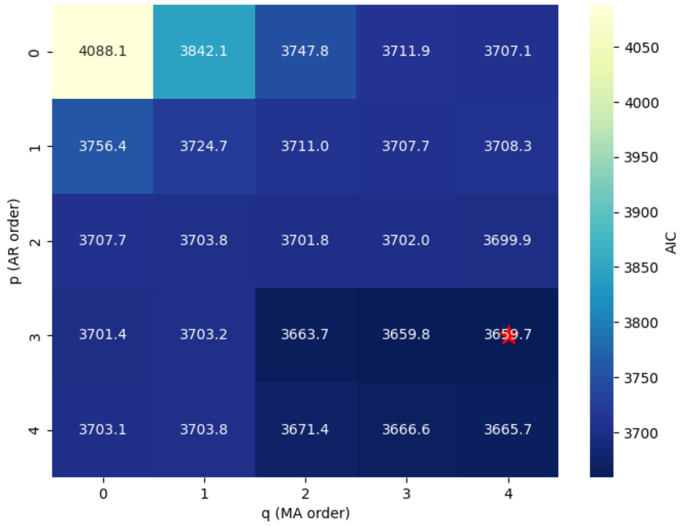
The p-values from Table 1 demonstrate that electricity consumption is stationary; the other variables, however, are not. As a result, the differencing approach was used such that after first differencing, all variables became stationary. The Variance Inflation Factor (VIF), which was also calculated, yielded values close to 1; hence indicating that there is not significant multicollinearity among the variables. Table 2 presents the final results which include VIF values as well as Dickey-Fuller test results for all variables after differencing.

Table 2. Represents the result of differencing

Variable	Count	ADF Stat	ADF p-value	VIF
Temp	365	-18.536	0.000	1.032
Humidity		-12.606	0.000	1.018
Wind		-13.227	0.000	1.015

Second: ARMA Model Development

The ARMA method can be used to determine the best model for the data under consideration, according on the results shown in Table 1. The Akaki values were computed using Equation 5 to establish the best delay time for forecasting power consumption in the data under investigation. The outcomes are contrasted with various autocorrelation and moving average ranks in Figure 1. ARMA (3,4), which has the lowest Akaki value (3659.8), is the best model based on the data.



Figue.1. Represent the compression between AIC values

Third: ARMAX Model Development

Normality and stationarity are considered to be real for the electricity consumption data, as indicated by the results of the normality and stationarity tests in Table 2. Nevertheless, meteorological variables (also known as external variables) do not contain the stationarity property. Such variables include average air temperature, humidity, and wind speed. The cointegration was investigated using the Johansen cointegration test to make sure that these variables could have been used. The test's findings confirmed the notion that there is a considerable and long-term relationship between weather and power use. Therefore, it is conceivable to verify the validity of these claims in spite of their lack of stationarity from a statistical and empirical viewpoint.

This section focuses on the internal patterns of the time series in addition to the impacts of the external variables under study on power usage utilizing the ARIMA model. The Autoregressive (AR), the difference over stationarity (I), moving average (MA) and the external variables (X) will all be utilized concurrently in this model. It is essential to point out that the difference over stationarity in this model is (I = 0) considering the stationarity of the electricity consumption data. furthermore, ARMAX is the expression for the previously mentioned model [12].

The AutoRegressive Integrated Moving Average with eXogenous variables (ARIMAX) method can be used to determine the best model for the data under consideration, according on the results shown in Figure 2. The Akaki values were computed using Equation 5 to establish the best delay time for forecasting power consumption in the data under investigation. The outcomes are contrasted with various autocorrelation and moving average ranks with eXginuse variables in Figure 2. ARMAX (3,0,3) with exogenous variables: Temp, Humidity, Wind, which has the lowest Akaki value (3707.8), is the best model based on the data.

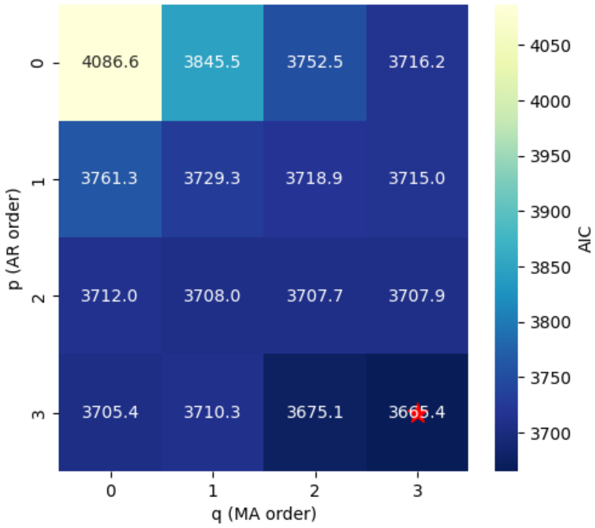


Figure.2. Represent the compression between AIC values

Fourth: Model Performance Evaluation

The comparison of the ARIMA and ARIMAX models will be discussed in this section. The performance of these two models has been compared utilizing criteria MAE, RMSE, and the coefficient of determination (R-Square). Additionally, the residuals of the models of study will be investigated for autocorrelation and normality.

The results shown in (Table 3) reveal that criteria (MAE = 0.0470) and (RMSE=0. 060) of the ARIMA (3,0,4) model have shown superior results compared to (MAE = 0.0475) and (RMSE=0.065) of the ARIMAX (3,0,3) model (although the difference is not considerable) And the Diebold-Mariano test results also confirm this. This discrepancy applies to the coefficient determination (R-Square) additionally. Even though the ARIMA (3,0,4) model appears to be more interpretable than the ARIMAX (3,0,3) model, this difference is negligible. Additionally, the ARIMA model's Akaike and Bayesian Information Criterion (BIC) values were (3659.65) and (3694.77) respectively, demonstrating its numerical superiority above the ARIMAX (3,0,3) results, which were (3707.85) and (3746.88), respectively.

Table.3. Represent comparative assessment of ARIMA and ARIMAX Models

Models	AIC	BIC	MAE	RMSE	R-Square	Diebold-Mariano	
ARIMA (3,0,4)	3659.65	3694.77	0.0470	0.060	72%	Statistic	P-value
ARIMAX (3,0,3)	3707.85	3746.88	0.0475	0.065	70%	-0.733	0.46

A comparison of the actual electricity consumption figures and the models' projections is presented in Figure 3. Both models have done an effective task of following the general pattern of the data, as demonstrated in the figure 3. This graph illustrates that both models' forecasting and the actual data are essentially in accordance. residual tests indicate that both ARIMA (3,0,4) and ARIMAX (3,0,3) models are generally adequate in relation to residual assumptions since, in the case of both models, the Shapiro-Wilk test indicates that the residuals are adequately normal. The normality assumption is justified with a p-value of 0.051 for ARIMA and 0.058 for ARIMAX. The Ljung-Box test indicates that the residuals are not correlated since the p-values are 0.058 and 0.051 respectively, suggesting that the models adequately preserve the independence of the residuals, as Table 4 and Figure 4 demonstrates.

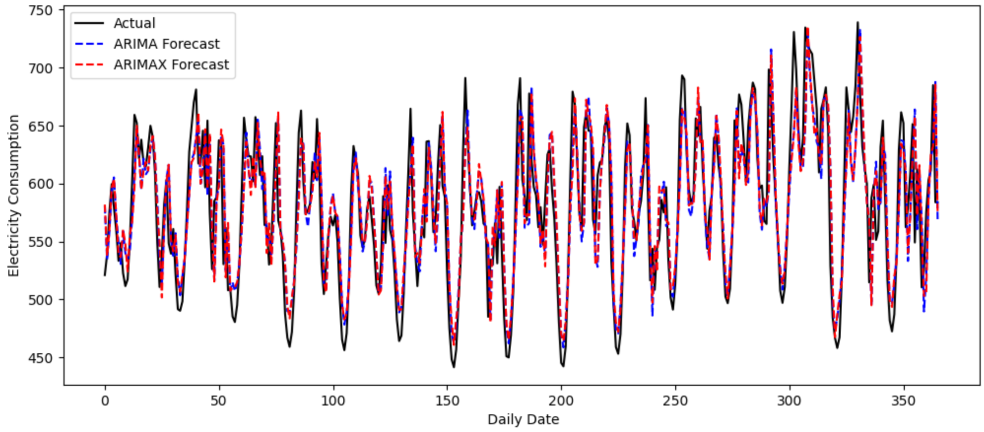


Figure 3. Represent the comparison the real, ARIMA and ARIMAX model forecasting

The ACF and PACF plots of the residuals also indicate that almost all values are within the confidence intervals which indicate that there is no autocorrelation. Therefore, these tests suggest that both models are adequately capturing the temporal structure of the data and that residuals can be assumed to act like white noise. From this analysis, it can be concluded that both models are statistically defensible.

Table.4. represent the Stationarity test for Residuals

Models	Shapero Wilk. Test	P- Value	Ljung-Box Test	P- Value
ARIMA (3,0,4)	0.992	0.051	30.760379	0.058434
ARIMAX (3,0,3)	0.991	0.058	31.329137	0.050993

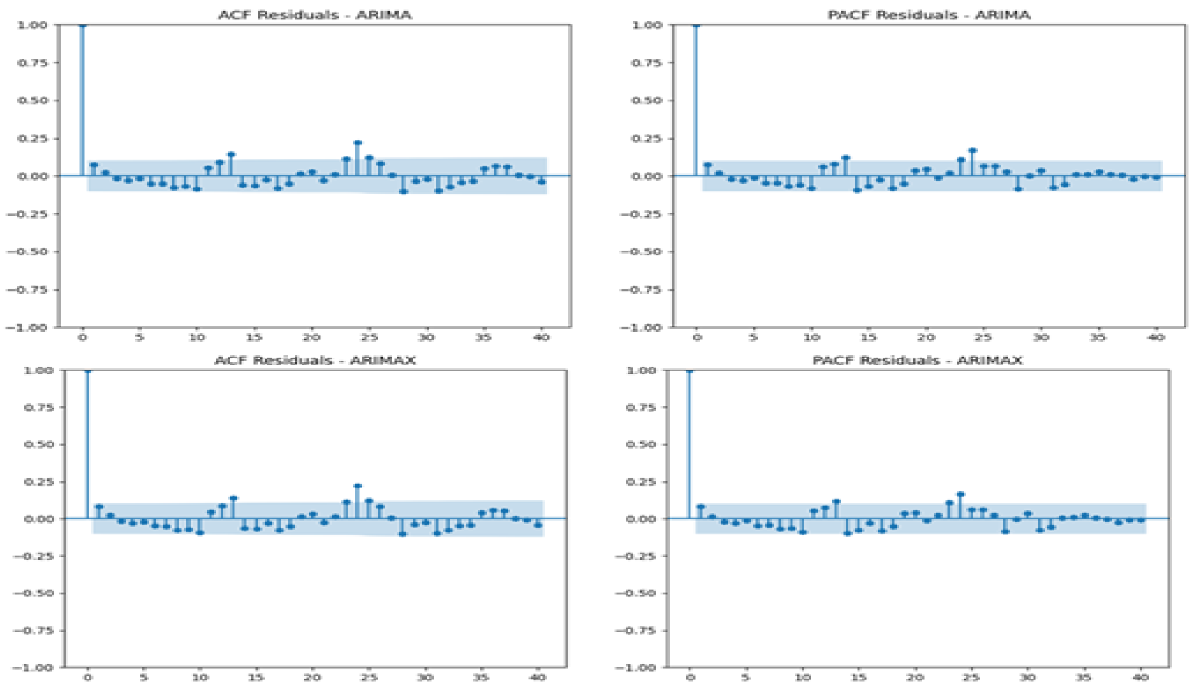


Figure.4. Represent the ACF and PACF plot ARIMAX and ARIMA Residuals

Conclusion

This study studied the ARIMA and ARIMAX models for forecasting Sulaymaniyah province's daily power consumption. Electricity consumption statistics and daily meteorological data, such as average air temperature, humidity, and wind speed, were taken into consideration for this purpose throughout the statistical period of January 1, 2024, to December 31, 2024. Before utilizing time series methods, the stationarity of the electricity consumption time series was established through statistical techniques in order to confirm and verify the stationarity of the data under study. The difference method was utilized to render the meteorological data stationary although it contained non-stationary external variables. All of the data became stationary in the first difference, therefore it's appropriate to use for time series modelling methods.

Several combinations have been investigated and the (AIC) criterion was established for each combination in order to determine the optimal combination of (p, d, q) for the models under study. Following these computations, the ARIMA and ARIMAX models with the lowest (AIC) values were found to have the best combinations, (3659.65) and (3707.88), respectively. The ARIMA (3,0,4) was determined as the best model according to the results that were collected. Additionally, criteria (MAE), (RMSE) and (R-Square) were utilized to assess the accuracy of the previously indicated models. The findings demonstrated that the ARIMA (3,0,4) model was better at forecasting the province's electricity consumption, with (MAE), (RMSE) and (R-Square) for the ARIMA (3,0,4) being(MAE=0.470), (RMSE=0.60) and (R-Square=72%) for respectively, and for the model ARIMAX(3,0,3) being (MAE=0.474), (RMSE=0.604) and (R-Square=70%).

Lastly, the accuracy of the models under study was demonstrated using the residual test.

Recommendation

Future ARIMAX model evaluations should incorporate more external factors, including economic or industrial indices, as these may have different impacts on forecasts of power consumption. The ability for identifying complicated patterns and variations can be enhanced by combining this model with methods based on machine learning. Furthermore, the impact of seasonal and annual oscillations is more probable to be identified when longer time periods are utilized.

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