Comparing the Effectiveness of ARIMA and SARIMA Models in Forecasting Seasonal Energy Consumption: A Case Study

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ABSTRACT

Determining an appropriate time series analysis model is essential to achieve accurate forecasts with minimal errors. This study analyzes the type of forecasting and time series analysis methods which are ARIMA and SARIMA by testing and comparing the forecast result and their error. The dataset used in this research comprises 3,686 energy consumption records, with 3,600 data points allocated for training and 86 data points for testing. The evaluation metric applied in this study is the Mean Absolute Percentage Error (MAPE). Empirical results indicate that the choice of forecasting methods and models significantly impacts performance, depending on the characteristics of the dataset. Notably, the SARIMA model demonstrates its capability to effectively capture the patterns in the data.

Keywords: Energy Consumption, Time Series Analysis,MAPE

1. INTRODUCTION

With the ever increasing number of human population, daily consumption is also on the rise, including energy. Energy is inseparable from human life. It is used from individual scale, such as cooking and lighting rooms, to national interest, such as manufacturing and supplying electricity nationwide. To ensure its supply in the further years, it is mandatory for scholars and policy makers to predict future demands by using the data available in the present. In doing so, forecasting methods are introduced to solve the problem.

Forecasting is a time series analysis method that predicts future values of variables that change over time by using the previous data (Hendikawati, 2020). To start forecasting, a stationary dataset will be needed. However, in a real life scenario it is rare to be found. Stationarity is also the prerequisite of using ARIMA and SARIMA methods. If the data isn’t stationary, all of the results would be wrong. To combat this issue, data is usually transformed using box-cox transformation and differencing with their seasonality and data. Stationary is split into two categories, which are stationary with variance that could be resolved with box-cox or other transformation and stationary with mean that could be resolved with differencing. To prove that the data is already stationary in mean and variance, it could be proven by lambda value in box cox as one or Augmented Dickey Fuller (ADF) Test is failed to reject the null hypothesis.

Mean Absolute Percentage Error or MAPE is a popular metric in econometrics that is used to evaluate the accuracy of predictions. MAPE is categorized in 5 group with great forecasting with the value of MAPE percentage are between 0 until 10 percent, good forecasting with the value of MAPE percentage are between 11 until 20 percent, mediocre forecasting with the value of MAPE percentage are between 21 until 30 percent, bad forecasting with the value of MAPE percentage are between 31 until 40 percent, very bad forecasting with the value of MAPE percentage are between 41 until 50 percent, and data that needed a remodeling with the value of MAPE percentage are between 51 until 100 percent .In this research, researcher wanted to compare between the forecasting of ARIMA and SARIMA on a data that have seasonality pattern using MAPE and the forecasting, in hope to proving the base knowledge regarding ARIMA and SARIMA.

2. ARIMA AND SARIMA MODELS

ARIMA (Autoregressive Integrated Moving Average) is a widely used statistical method for analyzing and forecasting time series data. ARIMA itself combines 3 different components : AR (Autoregression), I (Differencing), and MA (Moving Average). The Autoregressive component captures dependencies between an observation and a specified number of lagged observations. The differencing component ensures stationarity in the time series by removing trends or seasonality, while the moving average component models the relationship between an observation and a residual error from a moving average model applied to lagged observations. ARIMA is particularly effective for modeling non-seasonal data but may not perform optimally when seasonality is present (Box et al., 2015).

`SARIMA (Seasonal ARIMA) model extends ARIMA by incorporating seasonal components. SARIMA adds seasonal autoregressive, differencing, and moving average terms to address seasonal patterns in the data. These seasonal components are defined by additional parameters that capture periodic behavior in the time series, making SARIMA an appropriate choice for data with clear seasonal variations. By combining both seasonal and non-seasonal components, SARIMA provides a more comprehensive modeling framework for forecasting time series data with seasonal characteristics (Hyndman & Athanasopoulos, 2018).

3. ANALYSIS AND DISCUSSION

Given the energy consumption rate from February 1 to February 26, 2020. The data from Analysis started with plotting the time series for energy consumption data that have a time range every 10 minutes between each data. According to Figure 1, energy consumption data created seemingly very stationary and additive seasonal data with a constant model.

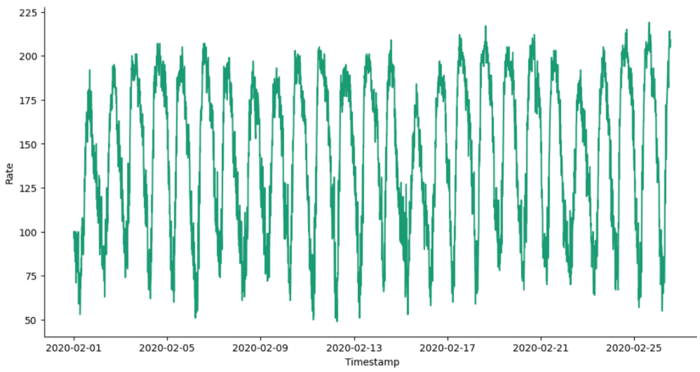

Figure 1. Time Series Plot Energy Consumption Data

Even though according to Figure 1 the data is stationary, the data itself needed a stationary test to foolproof the interpretation. Stationary is important because the long-term equilibrium relationship between related variables is essential for making forecasts. (Maruddani D.A., Tarno, and Anisah R.A, 2008)

To ensure that the dataset was appropriately utilized for both training and evaluation purposes, it was divided into two subsets: a training set and a testing set. The training set was selected from February 1, 2020, to February 25, 2020. This range was chosen to provide a substantial amount of data for the model to learn and identify patterns effectively. The testing set, on the other hand, consisted of data from February 26, 2020. This specific date was reserved exclusively for testing to evaluate the model's performance on unseen data, ensuring a fair assessment of its generalization capabilities. We can see the data are splitten from graph below,

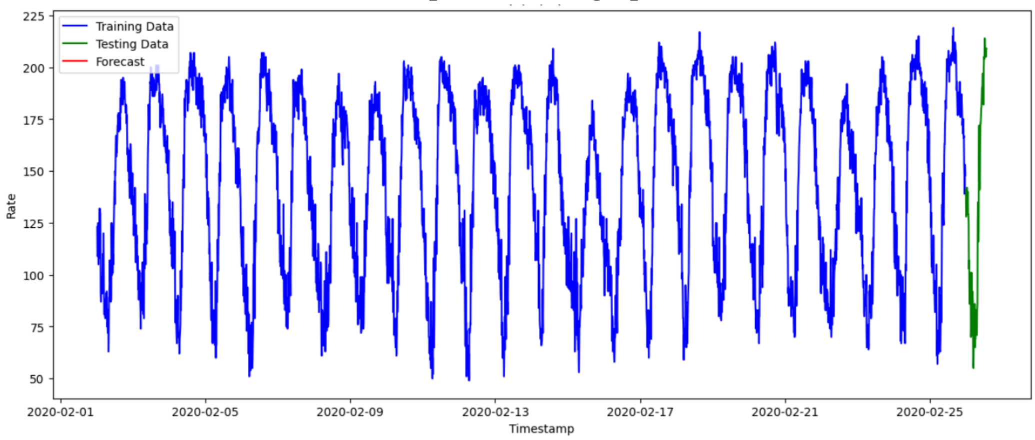

Figure 2. Time Series Plot After Splitting Data

To check the stationary of variance is with transforming the data according to box cox transformation. According to Figure 3 and 4, energy consumption data is transformed because the lambda rounded value in the first box cox transformation isn't equal to one. After that, the data is already stationary with variance because the lambda for second box cox transformation is equal to one. The graph are shown below,

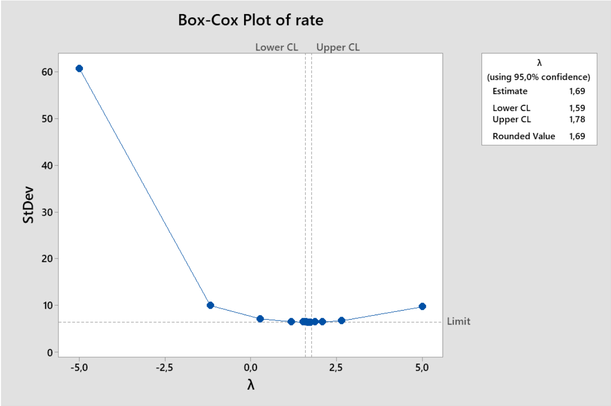

Figure 3. First Box Cox Transformation

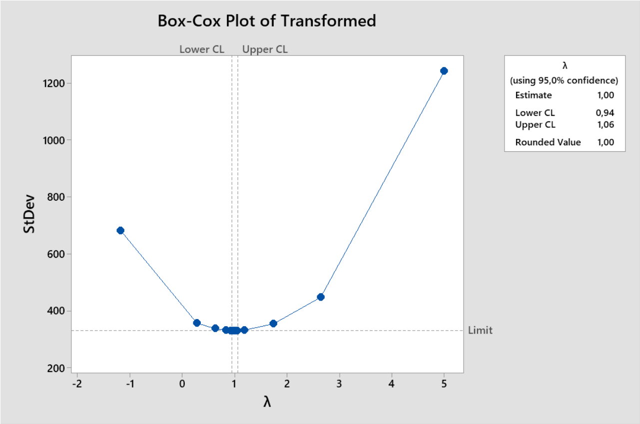

Figure 4. Second Box Cox Transformation

To further analyze the time series data after applying the Box-Cox transformation, decomposition was performed to separate the data into its trend, seasonal, and residual components. This process allows for a clearer understanding of the underlying patterns and variations in the data. Additionally, the differencing parameter d=1 was selected, as it makes the trend component more stationary compared to d=0, ensuring better suitability for time series modeling. The decomposition results are shown in the graph below.

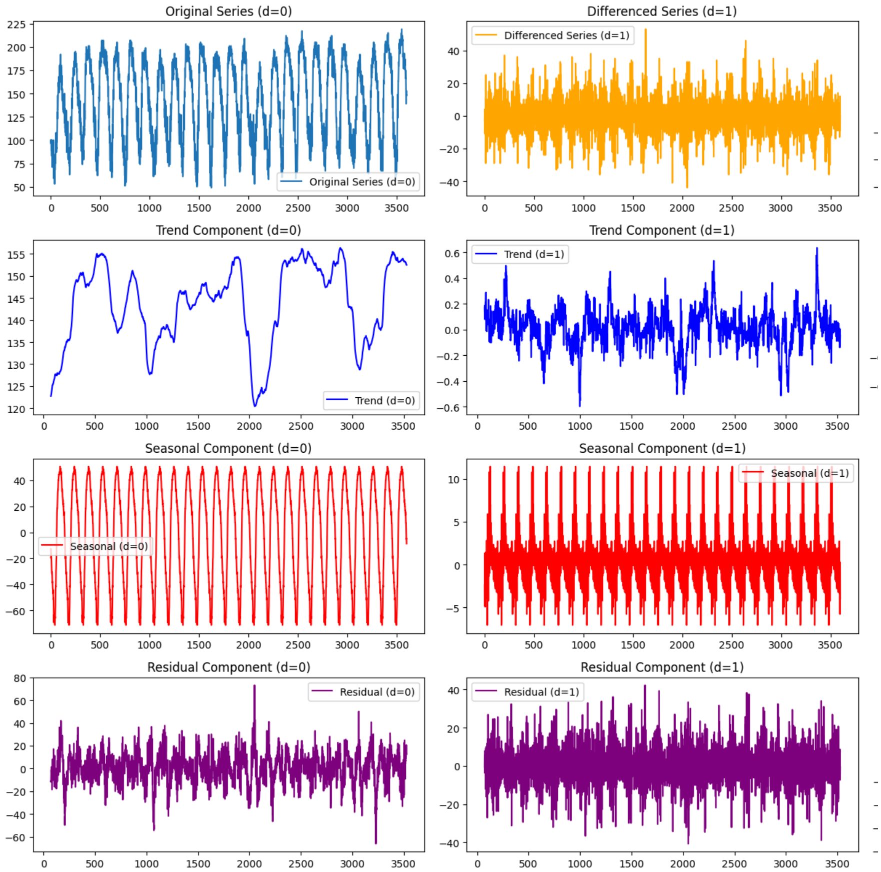

Figure 5. Decomposition between d=0 and d=1

The graph illustrated the original series along with the decomposed components. The trend component captures the long-term progression of the data, which appears more stationary after applying d=1. The seasonal component reflects recurring patterns, while the residual component represents random noise. This decomposition, along with the selected differencing parameter, provides a clearer understanding of the time series, facilitating the development of a more accurate forecasting model. To proceed with further analysis, the next step involves examining the ACF and PACF graphs, the graph can be shown below,

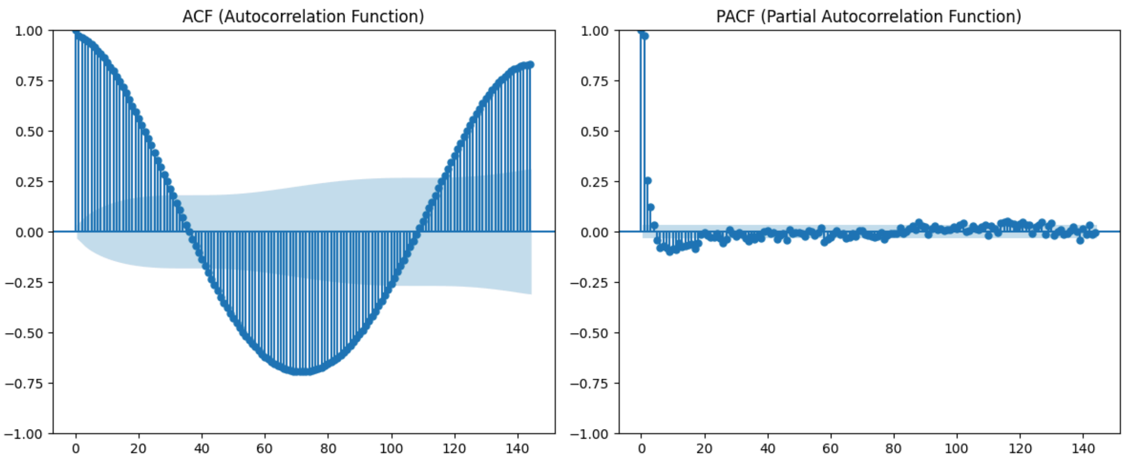

Figure 6. ACF and PACF for Transformed Data

From the decomposition graph in Figure 5 also ACF and PACF for transformed data in Figure 6, data is shown to have been influenced by a seasonal trend. It’s shown in ACF is creating a seasonal model and trend in a decomposition graph. For that reason the data still show the characteristics of non stationary with mean. Transformed box-cox data needed a differencing to fix the issue.

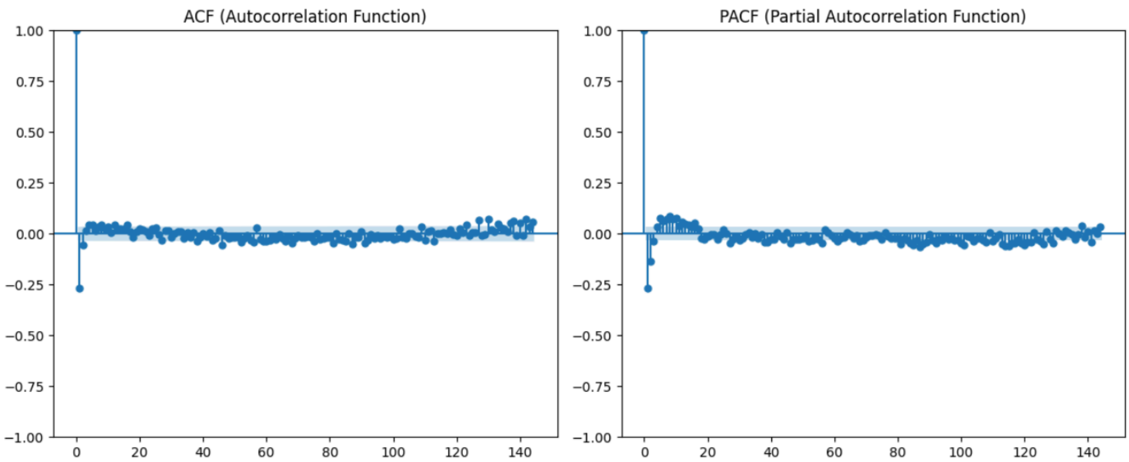

Figure 7. ACF and PACF for One Differencing

```
ADF Statistic: -9.197399
p-value: 0.000000
Critical Values:
        1%: -3.432178442676204
        5%: -2.8623479033634767
        10%: -2.5672000600324405
```

Figure 8. Augmented Dickey Fuller Test

ACF and PACF for one differencing in Figure 7 and the result of Augmented Dickey Fuller Test in Figure 8, shown that the data is already stationary both in mean and variance. Interpretation is the result of p-value of ADF test is less than 0,05 and the ACF/PACF didn’t have a seasonal tendencies (Muzhtaq R.,2011) .According to ACF and PACF in Figure 7, the best ARIMA model for energy consumption data is ARIMA([0,1,2,3],1,[0,1,2]) model.

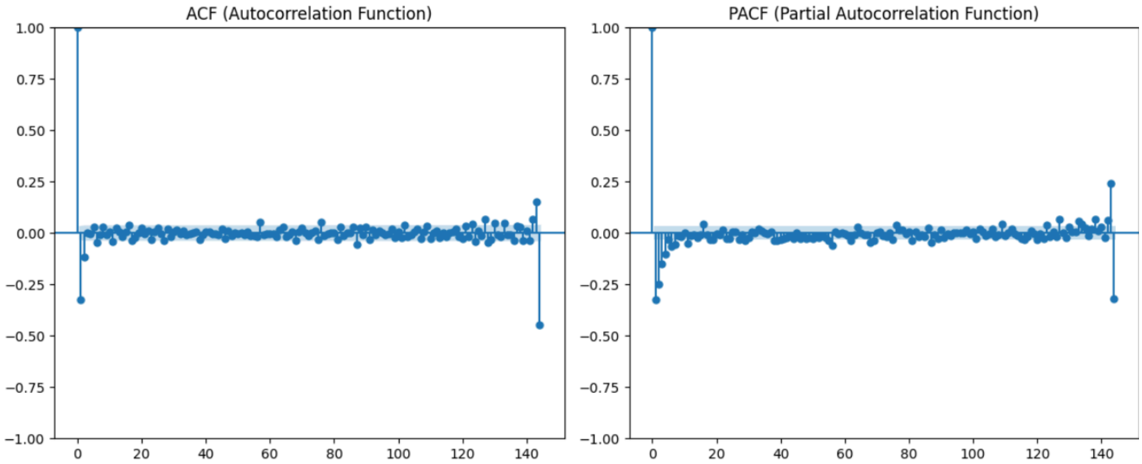

Figure 9. ACF and PACF After 144 Seasonal Differencing

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Best ARIMA order (p, d, q): (2, 1, 1)
Best AIC: 25437.669613990307
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Figure 10. Best Parameter for ARIMA

According to the ACF and PACF for 144 seasonal differencing in Figure 9 and best parameter estimation such as in Figure 10, we could interpret that the best model for ARIMA is ARIMA(2,1,1) model with the smallest AIC compared with another model. Another best model that the researcher found so far for SARIMA is SARIMA(2,1,1)(1,0,1,144) model.

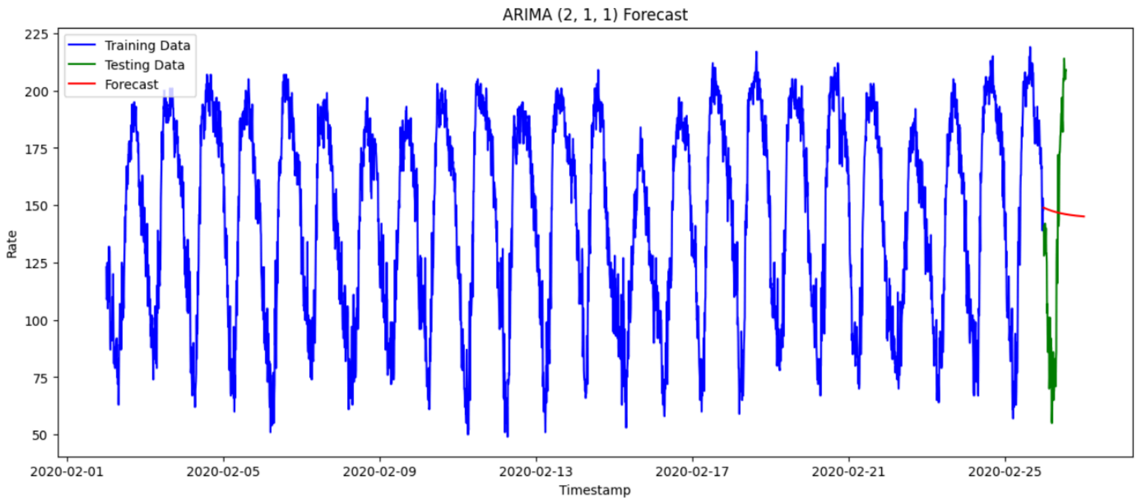

Figure 11. ARIMA(2,1,1) Forecast

```
Kolmogorov-Smirnov Test:
KS Statistic: 0.3878367177483398
p-value: 0.0

Ljung-Box Test:
```

	lb_stat	lb_pvalue
144	1325.340910	4.339852e-190
288	2623.176141	0.000000e+00
432	3865.887755	0.000000e+00

Figure 12. Normality and Ljung-Box Test

ARIMA(2,1,1) forecast in Figure 11 show that the forecast of energy consumption has a decreasing tendency with no characteristics to go up in the future. According to Figure 11 ARIMA isn't that great to forecast energy consumption data because it can't capture the seasonality characteristics. Normality and Ljung-Box Test in Figure 12 could be interpreted as data isn't normally distributed and have autocorrelation tendencies. Both of these showed that the current model isn't the best model to use because it can't capture all underlying pattern and temporal tendency that is shown with MAPE percentage with testing data at 46,85 percent, which is considered a very bad forecast and needed a remodeling. The researcher needed to search for better model but because the time constrict, researcher decided to use this model.

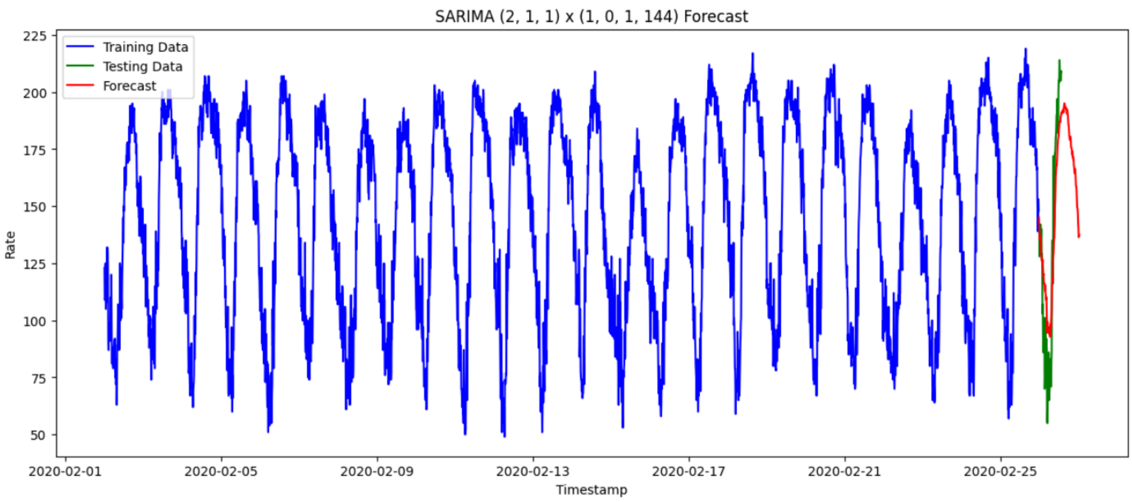

Figure 13. SARIMA(2,1,1)(1,0,1,144)

The forecasting model SARIMA(2,1,1)(1,0,1,144) in Figure 13 shows that this model is better suited for energy consumption data because it can capture the seasonal characteristics of the data. Based on the forecasting results, the MAPE for the test data is 18.38%. This indicates that the SARIMA forecast is better compared to ARIMA for this case study, with the SARIMA model (2,1,1)(1,0,1,144) being categorized as a good forecast. However, the result is not the best, as it fails to meet the Ljung-Box test and the Normality Assumption, suggesting the need for further exploration of other potential models. Due to time constraints, the researcher used both models to draw conclusions

```
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                                 rate   No. Observations:                 3600
Model:             SARIMAX(2, 1, 1)x(1, 0, 1, 144)   Log Likelihood              -12685.254
Date:                             Thu, 14 Nov 2024   AIC                          25382.508
Time:                                     16:39:34   BIC                          25419.390
Sample:                                          0   HQIC                         25395.680
                                            - 3600
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.0808      0.077     -1.047      0.295      -0.232       0.070
ar.L2         -0.0977      0.028     -3.508      0.000      -0.152      -0.043
ma.L1         -0.2527      0.078     -3.256      0.001      -0.405      -0.101
ar.S.L144      0.1786      0.067      2.646      0.008       0.046       0.311
ma.S.L144     -0.0437      0.069     -0.631      0.528      -0.180       0.092
sigma2        90.8344      1.656     54.865      0.000      87.589      94.079
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):               407.94
Prob(Q):                              0.93   Prob(JB):                         0.00
Heteroskedasticity (H):               0.92   Skew:                             0.32
Prob(H) (two-sided):                  0.18   Kurtosis:                         4.55
===================================================================================
```

Figure 14. Results

Based on the result on python , we can model the Yt. The models are :

$$Y_t = -0.8888 \cdot Y_{t-1} - 0.8957 \cdot Y_{t-2} + 0.8207 \cdot \epsilon_{t-1} + \epsilon_t$$

4. SUMMARY

The conclusion of this study is that the SARIMA(2,1,1)(1,0,1,144) method is the best model identified by the researcher compared to the ARIMA(2,1,1) model. This is due to the seasonal pattern in energy consumption data, which is influenced by the daily habits and routines of the community. This is further supported by the MAPE value, where ARIMA(2,1,1) has a MAPE of 46.85 percent, compared to SARIMA(2,1,1)(1,0,1,144), which has a MAPE of 18.38 percent.

5. RECOMMENDATIONS

The recommendation in this study is to conduct forecasting using better models that satisfy the assumptions of normality and white noise from the obtained SARIMA and ARIMA models. In future studies, it is necessary to present the complete models of the best SARIMA and ARIMA, as well as to apply more robust methods and data transformation techniques to address autocorrelation in the data.

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