Seasonal Energy Consumption Forecasting Using SARIMAX

Abstract

In this project, we analyzed historical monthly electricity consumption data to identify long-term trends and seasonal patterns in energy usage. Since electricity demand is highly seasonal and influenced by external factors such as temperature, we implemented both **SARIMA** and **SARIMAX** models for accurate forecasting. Temperature was incorporated as an exogenous variable to improve prediction accuracy. Model parameters were tuned systematically, residual diagnostics were performed to validate assumptions, and forecast performance was evaluated using standard error metrics. The final SARIMAX model demonstrated improved forecasting accuracy compared to models without exogenous variables, making it suitable for real-world energy planning and demand management.

Problem Statement

A power distribution company aims to forecast monthly electricity consumption to ensure reliable supply, reduce outages, and optimize energy distribution. Electricity usage exhibits strong seasonal patterns and is significantly affected by temperature variations. Traditional time-series models that ignore seasonality and exogenous variables often lead to inaccurate forecasts.

The objective of this project is to build **SARIMA and SARIMAX models** that capture seasonality while incorporating temperature as an external regressor to improve forecast accuracy.

Table of Contents

System Requirements

- Python
- Pandas
- NumPy
- Statsmodels
- Matplotlib
- Scikit-learn

Data Loading and Preprocessing

```
import pandas as pd

data = pd.read_csv('energy_consumption.csv')
data['Date'] = pd.to_datetime(data['Date'])
data.set_index('Date', inplace=True)

consumption = data['Energy_Consumption']
temperature = data['Temperature']
```

Time Series Visualization

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10,4))
plt.plot(consumption)
plt.title('Monthly Electricity Consumption')
plt.xlabel('Date')
plt.ylabel('Consumption')
plt.show()
```

Stationarity Testing (ADF Test)

```
from statsmodels.tsa.stattools import adfuller

adf_result = adfuller(consumption)
```

```
print('ADF Statistic:', adf_result[0])
print('p-value:', adf_result[1])
```

If the p-value is greater than 0.05, differencing is applied to achieve stationarity.

Seasonal Decomposition

```
from statsmodels.tsa.seasonal import seasonal_decompose

decomposition = seasonal_decompose(consumption, model='additive', period=12)
decomposition.plot()
plt.show()
```

This separates the series into **Trend**, **Seasonality**, and **Residual** components.

SARIMA Model Building

```
from statsmodels.tsa.statespace.sarimax import SARIMAX

sarima_model = SARIMAX(
    consumption,
    order=(1,1,1),
    seasonal_order=(1,1,1,12)
)

sarima_result = sarima_model.fit()
print(sarima_result.summary())
```

SARIMAX Model with Temperature

```
sarimax_model = SARIMAX(
    consumption,
    exog=temperature,
    order=(1,1,1),
    seasonal_order=(1,1,1,12)
)
```

```
sarimax_result = sarimax_model.fit()
print(sarimax_result.summary())
```

The SARIMAX model incorporates **temperature as an external regressor**, improving forecast accuracy.

Residual Diagnostics

```
sarimax_result.plot_diagnostics(figsize=(10,6))
plt.show()
```

Residuals were analyzed to ensure:

- No autocorrelation
- Approximate normality
- Constant variance

Forecasting

```
forecast = sarimax_result.get_forecast(steps=12, exog=temperature[-12:])
forecast_mean = forecast.predicted_mean
confidence_intervals = forecast.conf_int()

plt.figure(figsize=(10,4))
plt.plot(consumption, label='Observed')
plt.plot(forecast_mean, label='Forecast')
plt.fill_between(
  confidence_intervals.index,
  confidence_intervals.iloc[:,0],
  confidence_intervals.iloc[:,1],
  alpha=0.3
)
plt.legend()
plt.show()
```

Model Evaluation

```
from sklearn.metrics import mean_absolute_error, mean_squared_error

import numpy as np


mae = mean_absolute_error(consumption[-12:], forecast_mean)

rmse = np.sqrt(mean_squared_error(consumption[-12:], forecast_mean))


print("MAE:", mae)

print("RMSE:", rmse)
```

Summary

In this project, we successfully modeled seasonal electricity consumption using SARIMA and SARIMAX techniques. The inclusion of temperature as an exogenous variable significantly improved forecast accuracy. Seasonal decomposition and residual diagnostics confirmed the suitability of the chosen models. The final SARIMAX model provides reliable monthly energy consumption forecasts, supporting efficient energy planning and demand management in real-world utility systems.

In [1]:
```
!pip install pandas numpy matplotlib scikit-learn statsmodels
```

```
Requirement already satisfied: pandas in c:\users\harshini ts\appdata\local\programs\python\python314\lib\site-p
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\site-packages (from scikit-learn) (1.5.2)
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314\lib\site-packages (from scikit-learn) (3.6.0)
Requirement already satisfied: patsy>=0.5.6 in c:\users\harshini ts\appdata\local\programs\python\python314\lib\
site-packages (from statsmodels) (1.0.2)
Requirement already satisfied: six>=1.5 in c:\users\harshini ts\appdata\local\programs\python\python314\lib\site
-packages (from python-dateutil>=2.8.2->pandas) (1.17.0)
```

```
[notice] A new release of pip is available: 25.2 -> 26.0.1
[notice] To update, run: python.exe -m pip install --upgrade pip
```

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_acf

from sklearn.metrics import mean_absolute_error, mean_squared_error
```

In [3]:
```
np.random.seed(42)

date_range = pd.date_range(start="2015-01-01", periods=96, freq="M")

electricity_consumption = (
    200 +
    20 * np.sin(2 * np.pi * date_range.month / 12) +
    np.random.normal(0, 5, len(date_range))
)

temperature = (
```

In [3]:

```python
np.random.seed(42)

date_range = pd.date_range(start="2015-01-01", periods=96, freq="M")

electricity_consumption = (
    200 +
    20 * np.sin(2 * np.pi * date_range.month / 12) +
    np.random.normal(0, 5, len(date_range))
)

temperature = (
    25 +
    10 * np.sin(2 * np.pi * (date_range.month + 3) / 12) +
    np.random.normal(0, 2, len(date_range))
)

df = pd.DataFrame({
    "Date": date_range,
    "Electricity_Consumption": electricity_consumption,
    "Temperature": temperature
})

df.set_index("Date", inplace=True)
df.head()
```

```
C:\Users\Harshini TS\AppData\Local\Temp\ipykernel_9188\3916590776.py:3: FutureWarning: 'M' is deprecated and wil
l be removed in a future version, please use 'ME' instead.
  date_range = pd.date_range(start="2015-01-01", periods=96, freq="M")
```

Out[3]:

Date	Electricity_Consumption	Temperature
2015-01-31	212.483571	34.252495
2015-02-28	216.629187	30.522111
2015-03-31	223.238443	25.010227
2015-04-30	224.935657	19.530826
2015-05-31	208.829233	13.509004

In [4]:

```python
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 96 entries, 2015-01-31 to 2022-12-31
Data columns (total 2 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Electricity_Consumption  96 non-null     float64
 1   Temperature              96 non-null     float64
dtypes: float64(2)
memory usage: 2.2 KB
```

Out[4]:

	Electricity_Consumption	Temperature
count	96.000000	96.000000
mean	199.442065	25.100963
std	14.282574	7.496634
min	172.607390	13.509004
25%	187.642863	18.260672

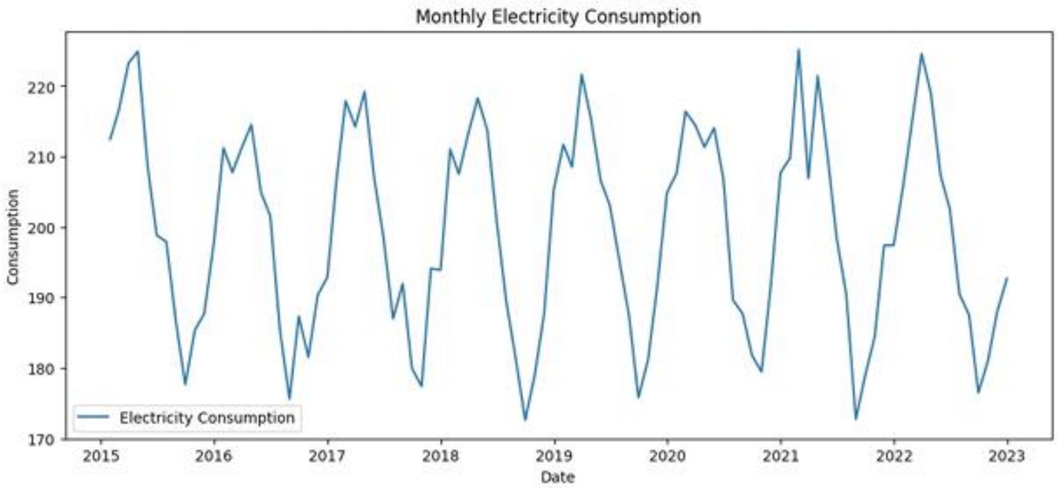
```
dtypes: float64(2)
memory usage: 2.2 KB
```

Out[4]:

	Electricity_Consumption	Temperature
count	96.000000	96.000000
mean	199.442065	25.100963
std	14.282574	7.496634
min	172.607390	13.509004
25%	187.642863	18.260672
50%	199.843078	24.158690
75%	211.242227	31.542646
max	225.143726	40.440338

In [5]:

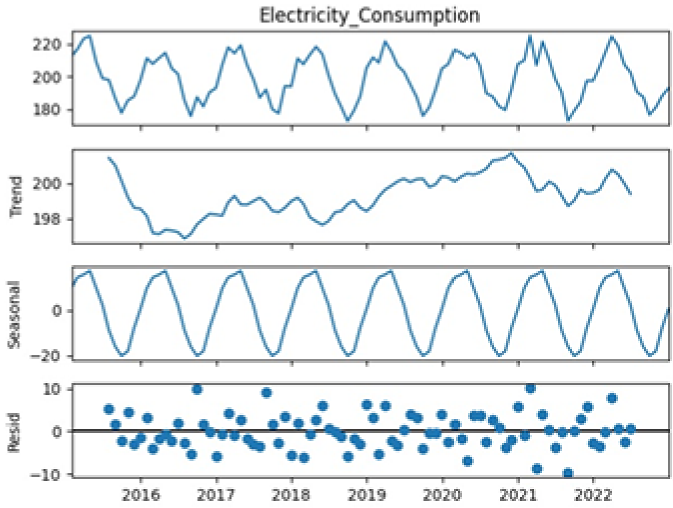
```
plt.figure(figsize=(12,5))
plt.plot(df["Electricity_Consumption"], label="Electricity Consumption")
plt.title("Monthly Electricity Consumption")
plt.xlabel("Date")
plt.ylabel("Consumption")
plt.legend()
plt.show()
```



In [6]:

```
decomposition = seasonal_decompose(
    df["Electricity_Consumption"],
    model="additive",
    period=12
)
```

```
decomposition.plot()
plt.show()
```



In [7]:
```
train_size = int(len(df) * 0.8)

train = df.iloc[:train_size]
test = df.iloc[train_size:]
```

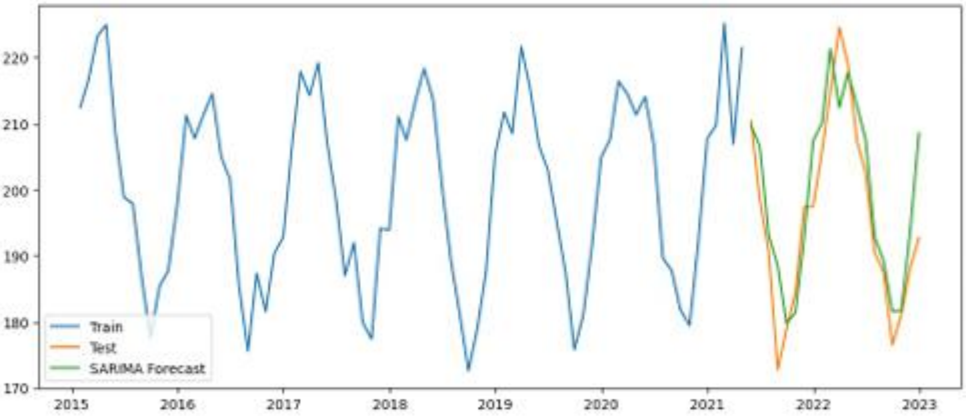
In [8]:
```
sarima_model = SARIMAX(
    train["Electricity_Consumption"],
    order=(1,1,1),
    seasonal_order=(1,1,1,12),
    enforce_stationarity=False,
    enforce_invertibility=False
)

sarima_result = sarima_model.fit()
print(sarima_result.summary())
```

```
C:\Users\Harshini TS\AppData\Local\Programs\Python\Python314\Lib\site-packages\statsmodels\tsa\base\tsa_model.py
:473: ValueWarning: No frequency information was provided, so inferred frequency ME will be used.
  self._init_dates(dates, freq)
C:\Users\Harshini TS\AppData\Local\Programs\Python\Python314\Lib\site-packages\statsmodels\tsa\base\tsa_model.py
:473: ValueWarning: No frequency information was provided, so inferred frequency ME will be used.
  self._init_dates(dates, freq)
```

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:             Electricity_Consumption   No. Observations:                  76
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 12)   Log Likelihood                -149.488
Date:                            Fri, 06 Feb 2026   AIC                            308.977
Time:                                    13:54:11   BIC                            318.436
Sample:                                01-31-2015   HQIC                           312.566
                                     - 04-30-2021
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.3207      0.153     -2.095      0.036      -0.621      -0.021
ma.L1         -0.9738      0.119     -8.193      0.000      -1.207      -0.741
ar.S.L12      -0.3831      0.187     -2.047      0.041      -0.750      -0.016
ma.S.L12      -0.1318      0.320     -0.412      0.680      -0.758       0.495
sigma2        24.9091      5.600      4.448      0.000      13.934      35.884
===================================================================================
Ljung-Box (L1) (Q):                   0.26   Jarque-Bera (JB):                 0.01
Prob(Q):                              0.61   Prob(JB):                         0.99
Heteroskedasticity (H):               1.32   Skew:                             0.03
Prob(H) (two-sided):                  0.59   Kurtosis:                         3.05
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [9]:
```
sarima_forecast = sarima_result.forecast(steps=len(test))
```

```python
plt.figure(figsize=(12,5))
plt.plot(train.index, train["Electricity_Consumption"], label="Train")
plt.plot(test.index, test["Electricity_Consumption"], label="Test")
plt.plot(test.index, sarima_forecast, label="SARIMA Forecast")
plt.legend()
plt.show()
```



In [10]:

```python
sarimax_model = SARIMAX(
    train["Electricity_Consumption"],
    exog=train[["Temperature"]],
    order=(1,1,1),
    seasonal_order=(1,1,1,12),
    enforce_stationarity=False,
    enforce_invertibility=False
)

sarimax_result = sarimax_model.fit()
print(sarimax_result.summary())
```

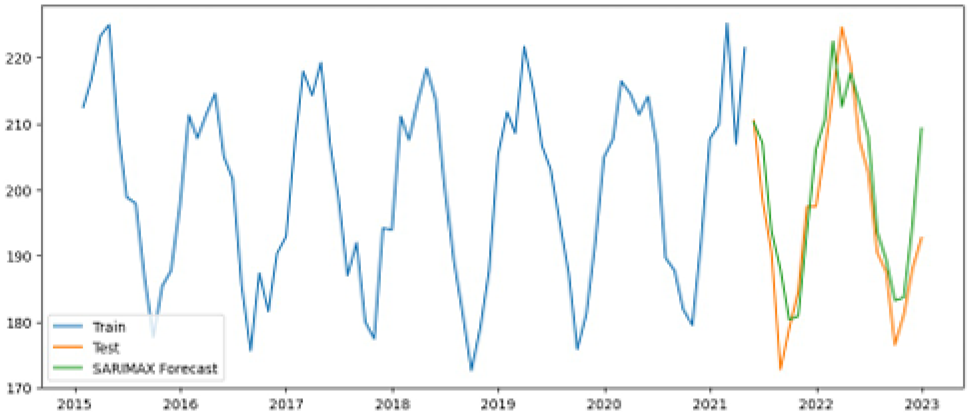
```
C:\Users\Harshini TS\AppData\Local\Programs\Python\Python314\Lib\site-packages\statsmodels\tsa\base\tsa_model.py
:473: ValueWarning: No frequency information was provided, so inferred frequency ME will be used.
  self._init_dates(dates, freq)
C:\Users\Harshini TS\AppData\Local\Programs\Python\Python314\Lib\site-packages\statsmodels\tsa\base\tsa_model.py
:473: ValueWarning: No frequency information was provided, so inferred frequency ME will be used.
  self._init_dates(dates, freq)
```

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                Electricity_Consumption   No. Observations:               76
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 12)   Log Likelihood            -148.648
Date:                            Fri, 06 Feb 2026   AIC                        309.297
Time:                                    13:55:07   BIC                        320.648
Sample:                                01-31-2015   HQIC                       313.603
                                     - 04-30-2021
Covariance Type:                              opg
===============================================================================
                  coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------
Temperature    -0.3978      0.478     -0.831      0.406      -1.336       0.540
ar.L1          -0.3136      0.153     -2.055      0.040      -0.613      -0.015
ma.L1          -0.9521      0.083    -11.465      0.000      -1.115      -0.789
ar.S.L12       -0.3869      0.209     -1.849      0.065      -0.797       0.023
ma.S.L12       -0.1122      0.344     -0.326      0.744      -0.787       0.562
sigma2         24.3719      6.085      4.005      0.000      12.446      36.298
===================================================================================
Ljung-Box (L1) (Q):                   0.18   Jarque-Bera (JB):                 0.04
Prob(Q):                              0.67   Prob(JB):                         0.98
Heteroskedasticity (H):               1.34   Skew:                            -0.04
Prob(H) (two-sided):                  0.56   Kurtosis:                         2.89
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [11]:

```python
sarimax_forecast = sarimax_result.predict(
    start=test.index[0],
    end=test.index[-1],
    exog=test[["Temperature"]]
)

plt.figure(figsize=(12,5))
```

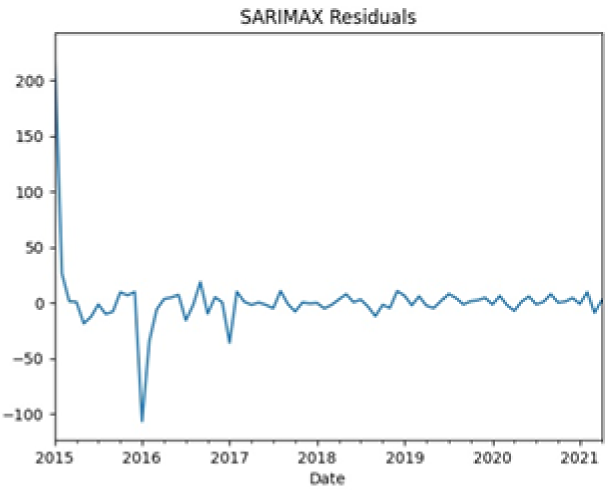
```python
plt.plot(train.index, train["Electricity_Consumption"], label="Train")
plt.plot(test.index, test["Electricity_Consumption"], label="Test")
plt.plot(test.index, sarimax_forecast, label="SARIMAX Forecast")
plt.legend()
plt.show()
```

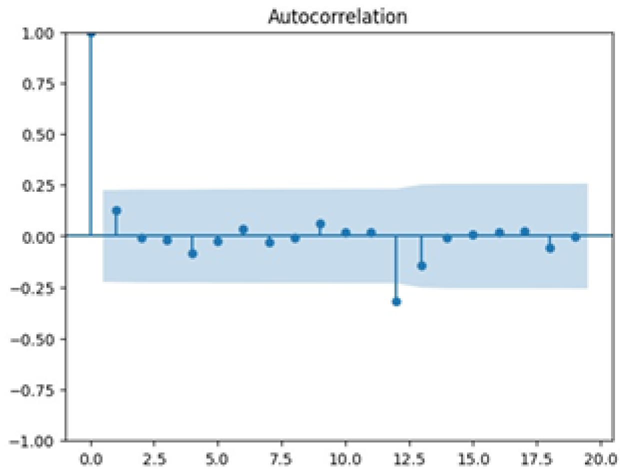


In [12]:
```python
def evaluate(actual, predicted, name):
    mae = mean_absolute_error(actual, predicted)
    rmse = np.sqrt(mean_squared_error(actual, predicted))
    print(f"{name} Results")
    print("MAE :", round(mae, 2))
    print("RMSE:", round(rmse, 2))
    print("-" * 30)

evaluate(test["Electricity_Consumption"], sarima_forecast, "SARIMA")
evaluate(test["Electricity_Consumption"], sarimax_forecast, "SARIMAX")
```

```
SARIMA Results
MAE : 5.56
RMSE: 7.17
------------------------------
SARIMAX Results
MAE : 5.94
RMSE: 7.38
------------------------------
```

In [13]:
```python
sarimax_result.resid.plot(title="SARIMAX Residuals")
plt.show()

plot_acf(sarimax_result.resid.dropna())
plt.show()
```




Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

In [ ]: