[220]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import pandas as pd
from statsmodels.tsa.seasonal import seasonal_decompose
import warnings
# Suppress all warnings
warnings.filterwarnings("ignore")


# Load the sales data file into a Pandas DataFrame
file_path = r"C:\Users\marsh\Documents\Jupyter\final_data.csv"
file_path2= r"C:\Users\marsh\Documents\Jupyter\external_data.
↪csv"
# Check sheet names to decide how to load the data
sales_data = pd.read_csv(file_path)
external_data = pd.read_csv(file_path2)
```

[222]:
```python
sales_data.head()
```

[222]:

	Month-Year	Service Parts	Equipment
0	Apr-2015	3486.9	21505.1
1	May-2015	3891.3	11021.8
2	Jun-2015	3505.2	14929.5
3	Jul-2015	4081.1	27340.9
4	Aug-2015	3141.4	6405.1

[224]:
```python
external_data.head()
```

[224]:

	Month-Year	Print Production Volume
0	Apr-2015	1023.33
1	May-2015	1023.33
2	Jun-2015	1023.33
3	Jul-2015	1023.33
4	Aug-2015	1023.33

[226]:
```python
sales_data.set_index('Month-Year', inplace=True)
print(sales_data.describe())
sales_data.head()
```

```
       Service Parts     Equipment
count     120.000000    120.000000
mean     6965.528333  11903.305417
std      2342.014706   8454.806727
min      2959.600000     40.900000
25%      3994.050000   5574.375000
50%      7873.400000  11370.225000
75%      8666.100000  16679.525000
max     10687.600000  32352.000000
```

[226]:

Month-Year	Service Parts	Equipment
Apr-2015	3486.9	21505.1
May-2015	3891.3	11021.8
Jun-2015	3505.2	14929.5

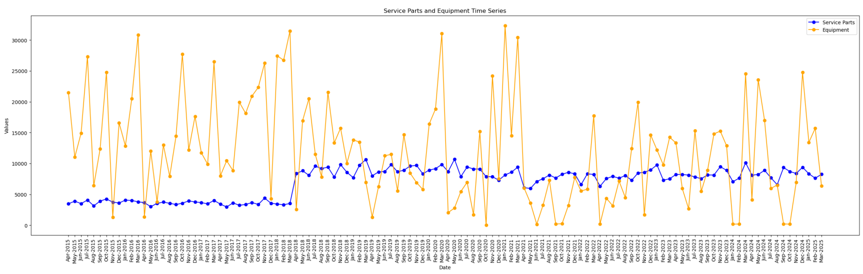
```
75%                   872.000000
max                  1023.330000
```

[228]:

```
                Print Production Volume
Month-Year
Apr-2015                        1023.33
May-2015                        1023.33
Jun-2015                        1023.33
Jul-2015                        1023.33
Aug-2015                        1023.33
```

[230]:

```python
plt.figure(figsize=(30, 8))
# Plot for Service Parts
plt.plot(sales_data['Service Parts'], label='Service Parts',␣
 ↪marker='o', color='blue')
# Plot for Equipment
plt.plot(sales_data['Equipment'], label='Equipment',␣
 ↪marker='o', color='orange')
plt.title('Service Parts and Equipment Time Series')
plt.xlabel('Date')
plt.ylabel('Values')
plt.xticks(rotation=90)  # Rotate x-axis labels
plt.legend()
plt.show()
```



[231]:

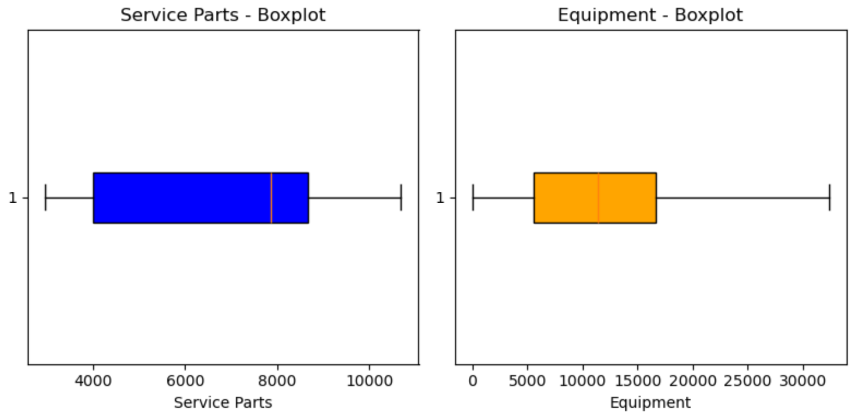
```python
def detect_outliers_iqr(series):
    Q1 = series.quantile(0.25)  # First quartile
    Q3 = series.quantile(0.75)  # Third quartile
    IQR = Q3 - Q1               # Interquartile range
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return series[(series < lower_bound) | (series >␣
 ↪upper_bound)]
```

```
outliers_service_parts = ␣
↪detect_outliers_iqr(sales_data['Service Parts'])
outliers_equipment = ␣
↪detect_outliers_iqr(sales_data['Equipment'])

print("Outliers in Service Parts:\n", outliers_service_parts)
print("\nOutliers in Equipment:\n", outliers_equipment)
```

```
Outliers in Service Parts:
 Series([], Name: Service Parts, dtype: float64)

Outliers in Equipment:
 Series([], Name: Equipment, dtype: float64)
```

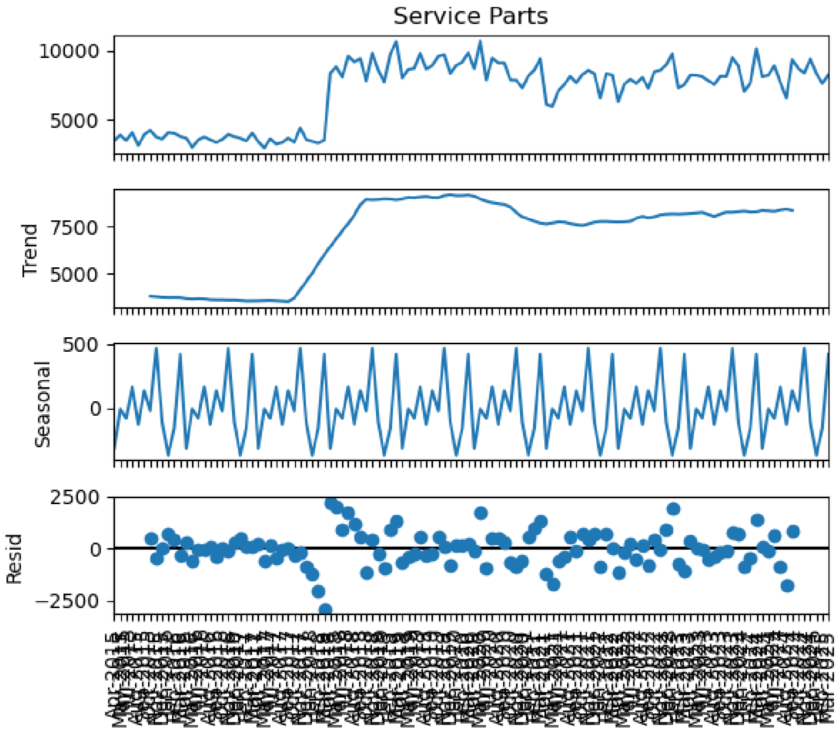
[234]:

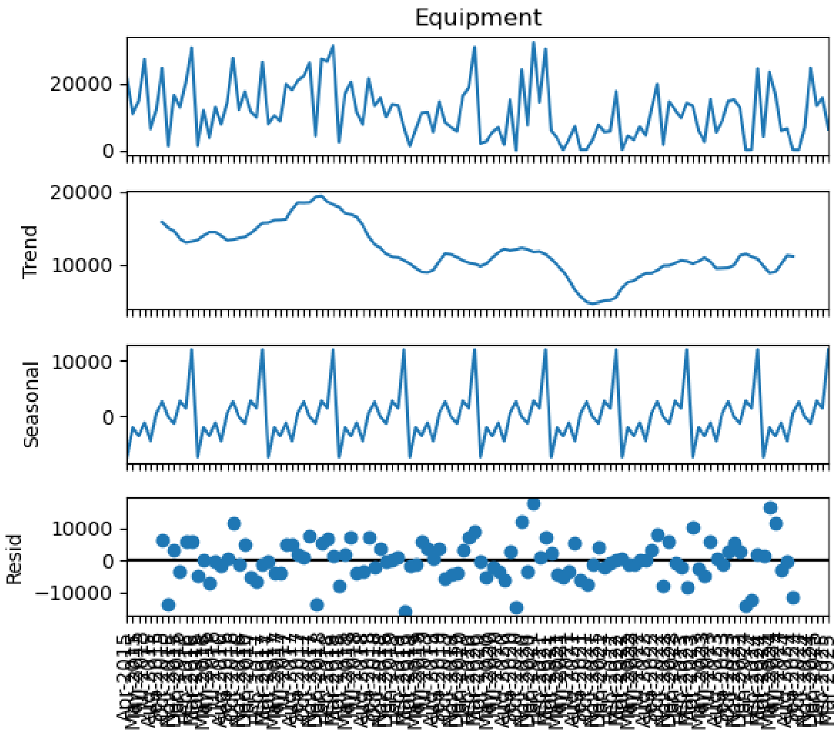
```
# Plot boxplots to visualize outliers
plt.figure(figsize=(8, 4))

# Service Parts Boxplot
plt.subplot(1, 2, 1)
plt.boxplot(sales_data['Service Parts'], vert=False, ␣
↪patch_artist=True,
            boxprops=dict(facecolor='blue', color='black'))
plt.title('Service Parts - Boxplot')
plt.xlabel('Service Parts')

# Equipment Boxplot
plt.subplot(1, 2, 2)
plt.boxplot(sales_data['Equipment'], vert=False, ␣
↪patch_artist=True,
            boxprops=dict(facecolor='orange', color='black'))
plt.title('Equipment - Boxplot')
plt.xlabel('Equipment')

plt.tight_layout()
plt.show()
```



0.0.1 Decomposition

[237]:
```
# Decompose Service Parts
decompose_service_parts = seasonal_decompose(sales_data['Service Parts'], model='additive', period=12)
decompose_service_parts.plot()
plt.xticks(rotation=90)
plt.show()

# Decompose Equipment
decompose_equipment = seasonal_decompose(sales_data['Equipment'], model='additive', period=12)
decompose_equipment.plot()
plt.xticks(rotation=90)  # Rotate x-axis labels
plt.show()
```

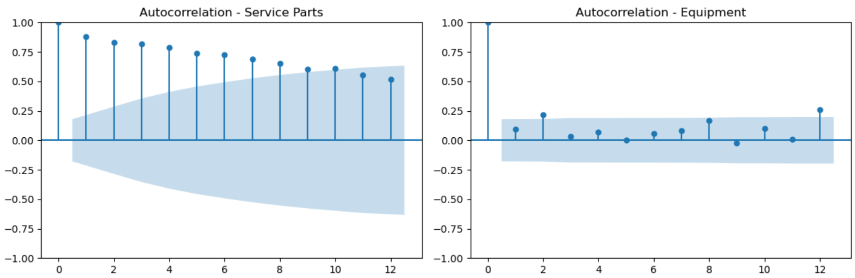

Service Parts
10000
5000
Trend
7500
5000
Seasonal
500
0
Resid
2500
0
−2500


Equipment
20000
0
Trend
20000
10000
Seasonal
10000
0
Resid
10000
0
−10000

Both the Service Parts and Equipments have seasonality

Looking for correlation

[241]:
```
from statsmodels.graphics.tsaplots import plot_acf

fig, axes = plt.subplots(1, 2, figsize=(12, 4))

# ACF for Service Parts
plot_acf(sales_data['Service Parts'], lags=12, ax=axes[0])
axes[0].set_title('Autocorrelation - Service Parts')

# ACF for Equipment
plot_acf(sales_data['Equipment'], lags=12, ax=axes[1])
axes[1].set_title('Autocorrelation - Equipment')

# Show the plots
plt.tight_layout()  # Adjust layout to prevent overlap
plt.show()
```



[243]:
```
data = sales_data
```

Checking if the data is stationary or not

[246]:
```
from statsmodels.tsa.stattools import adfuller
# ADF Test
def adf_test(series):
    result = adfuller(series, autolag='AIC')
    print(f'ADF Statistic: {result[0]}')
    print(f'p-value: {result[1]}')
    print(f'Critical Values: {result[4]}')
    if result[1] <= 0.05:
        print("The data is stationary.")
    else:
```

```
        print("The data is non-stationary.")

print('Service Parts Data')
adf_test(data['Service Parts'])

print('\nEquipment Data')
adf_test(data['Equipment'])
```

```
Service Parts Data
ADF Statistic: -1.759051719427676
p-value: 0.4009723907208821
Critical Values: {'1%': -3.487517288664615, '5%': -2.
 ↪8865777180380032, '10%':
-2.5801239192052012}
The data is non-stationary.

Equipment Data
ADF Statistic: -5.837274711750817
p-value: 3.850206794269265e-07
Critical Values: {'1%': -3.4870216863700767, '5%': -2.
 ↪8863625166643136, '10%':
-2.580009026141913}
The data is stationary.
```

Target Variable: Service Parts

[249]:

```
service_parts = sales_data['Service Parts']
service_parts.describe()
```

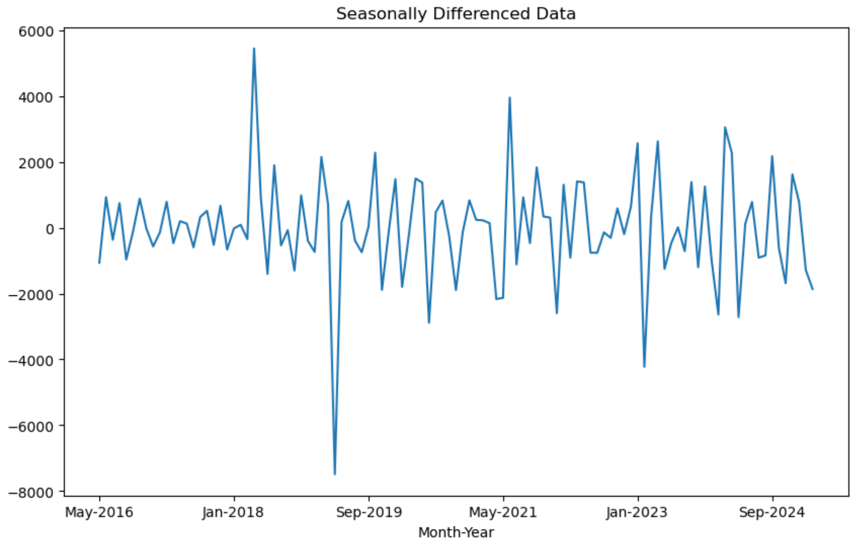
[249]:

```
count      120.000000
mean      6965.528333
std       2342.014706
min       2959.600000
25%       3994.050000
50%       7873.400000
75%       8666.100000
max      10687.600000
Name: Service Parts, dtype: float64
```

[251]:

```
# First-order differencing
data_diff = sales_data['Service Parts'].diff().dropna()

# Seasonal differencing (e.g., if seasonality is monthly,␣
 ↪period=12)
data_seasonal_diff = data_diff.diff(12).dropna()

# Plot the differenced data
```

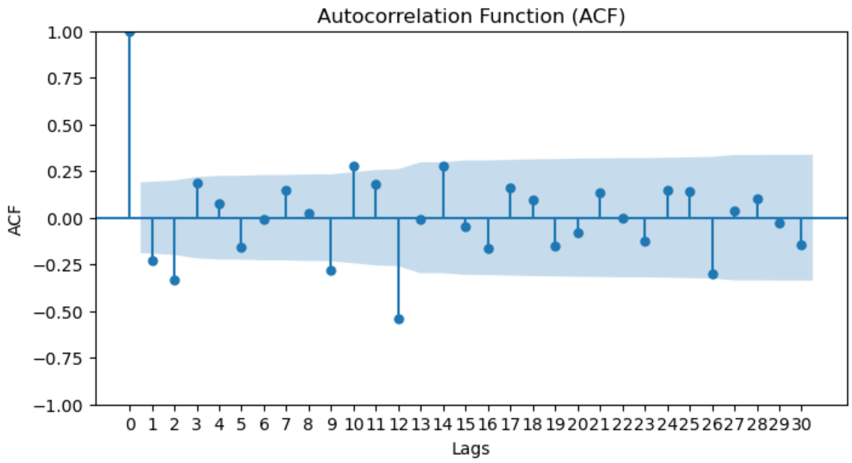
```
data_seasonal_diff.plot(title='Seasonally Differenced Data',␣
↪figsize=(10, 6))
plt.show()

# Check stationarity again
adf_test(data_seasonal_diff)
```

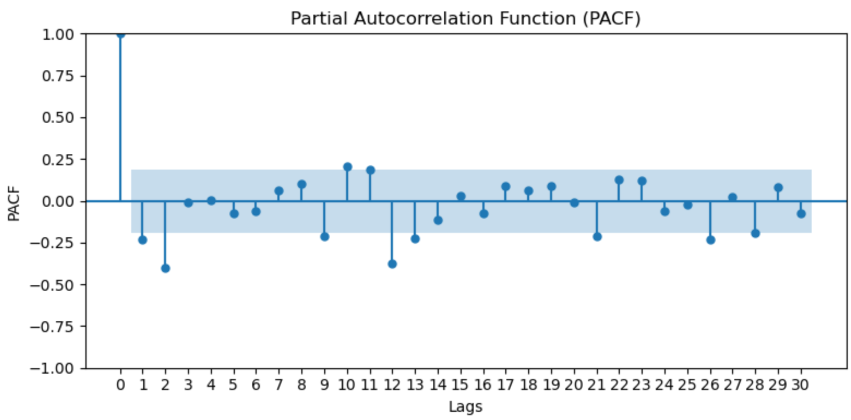



```
ADF Statistic: -4.012301546321255
p-value: 0.0013474490108212707
Critical Values: {'1%': -3.5019123847798657, '5%': -2.
↪892815255482889, '10%':
-2.583453861475781}
The data is stationary.
```

[253]:
```
fig, ax = plt.subplots(figsize=(8, 4))
plot_acf(data_seasonal_diff, lags=30, ax=ax)
ax.set_title('Autocorrelation Function (ACF)')
ax.set_xlabel('Lags')
ax.set_ylabel('ACF')

ax.set_xticks(range(0, 31))  # Set the x-ticks to range from␣
↪0 to 30 (lags)
ax.set_xticklabels(range(0, 31))  # Set the labels for each␣
↪lag

from statsmodels.graphics.tsaplots import plot_pacf
fig, ax = plt.subplots(figsize=(8, 4))
plot_pacf(data_seasonal_diff, lags=30, ax=ax)
ax.set_title('Partial Autocorrelation Function (PACF)')
```

```
ax.set_xlabel('Lags')
ax.set_ylabel('PACF')
ax.set_xticks(range(0, 31))  # Set the x-ticks to range from␣
↪0 to 30 (lags)
ax.set_xticklabels(range(0, 31))  # Set the labels for each␣
↪lag

# Show plots
plt.tight_layout()
plt.show()
```





[255]:
```
data_seasonal_diff.head()
```

[255]:
```
Month-Year
May-2016    -1064.2
Jun-2016      925.5
```

```
Jul-2016    -369.5
Aug-2016     746.3
Sep-2016    -967.3
Name: Service Parts, dtype: float64
```

[257]:
```
data_seasonal_diff.describe()
```

[257]:
```
count     107.000000
mean      -19.140187
std      1608.991918
min     -7484.200000
25%      -753.750000
50%       -32.000000
75%       814.800000
max      5440.200000
Name: Service Parts, dtype: float64
```

[259]:
```
start_date = 'May-2016'
end_date = 'Mar-2026'
filtered_df = external_data.loc[start_date:end_date]

sp = pd.concat([data_seasonal_diff, filtered_df], axis=1)

exog = sp['Print Production Volume']
```

[261]:
```
y = sp['Service Parts']

# Train-test split (last 12 months for testing)
train_size = len(sp) - 24
y_train, y_test = y[:train_size], y[train_size:train_size+12]
exog_train, exog_test, exog_future = exog[:train_size],␣
↪exog[train_size:train_size+12], exog[train_size:]

from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error
from math import sqrt
import matplotlib.pyplot as plt
```

[263]:
```
# Fit SARIMA model
sarima_model = SARIMAX(y_train, order=(1, 0, 1),␣
↪seasonal_order=(1, 0, 1, 12))
sarima_result = sarima_model.fit(disp=False)

# Make predictions
predictions_sarima = sarima_result.predict(start=y_test.
↪index[0], end=y_test.index[-1])
```

```python
# Evaluate the model
rmse = sqrt(mean_squared_error(y_test, predictions_sarima))

print(f'RMSE: {rmse}')
sarima_result.summary()
```

RMSE: 1218.7906496697528

[263]:

Dep. Variable:	Service Parts	**No. Observations:**	95
Model:	SARIMAX(1, 0, 1)x(1, 0, 1, 12)	**Log Likelihood**	-804.894
Date:	Mon, 16 Dec 2024	**AIC**	1619.788
Time:	13:05:55	**BIC**	1632.557
Sample:	05-01-2016	**HQIC**	1624.947
	- 03-01-2024		
Covariance Type:	opg		

	coef	std err	z	P> |z|	[0.025	0.975]
ar.L1	0.1869	0.244	0.764	0.445	-0.292	0.666
ma.L1	-0.5798	0.225	-2.581	0.010	-1.020	-0.139
ar.S.L12	-0.0695	0.076	-0.911	0.362	-0.219	0.080
ma.S.L12	-0.9952	0.094	-10.532	0.000	-1.180	-0.810
sigma2	1.002e+06	9.57e-08	1.05e+13	0.000	1e+06	1e+06

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	45.13
Prob(Q):	0.97	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.83	**Skew:**	0.26
Prob(H) (two-sided):	0.59	**Kurtosis:**	6.34

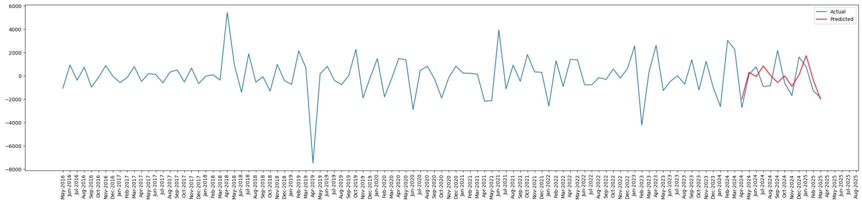
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 3.19e+28. Standard errors may be unstable.

[265]:
```python
predictions_sarima = predictions_sarima.reindex(y.index)
print(predictions_sarima.index)
print(y.index)
```

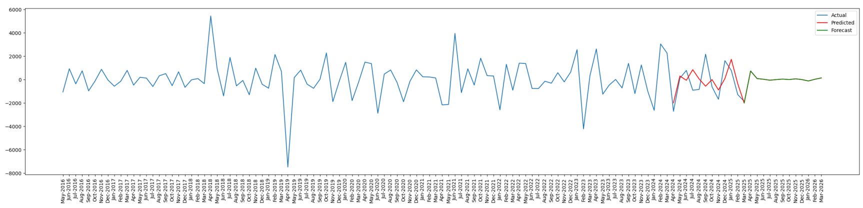
```
Index(['May-2016', 'Jun-2016', 'Jul-2016', 'Aug-2016',␣
↪'Sep-2016', 'Oct-2016',
       'Nov-2016', 'Dec-2016', 'Jan-2017', 'Feb-2017',
       ...
       'Jun-2025', 'Jul-2025', 'Aug-2025', 'Sep-2025',␣
↪'Oct-2025', 'Nov-2025',
       'Dec-2025', 'Jan-2026', 'Feb-2026', 'Mar-2026'],
      dtype='object', name='Month-Year', length=119)
Index(['May-2016', 'Jun-2016', 'Jul-2016', 'Aug-2016',␣
↪'Sep-2016', 'Oct-2016',
       'Nov-2016', 'Dec-2016', 'Jan-2017', 'Feb-2017',
```

```
       ...
       'Jun-2025', 'Jul-2025', 'Aug-2025', 'Sep-2025',␣
↪'Oct-2025', 'Nov-2025',
       'Dec-2025', 'Jan-2026', 'Feb-2026', 'Mar-2026'],
      dtype='object', name='Month-Year', length=119)
```

[267]:
```
plt.figure(figsize=(30, 6))
plt.plot(y, label='Actual')
plt.plot(predictions_sarima, label='Predicted', color='red')
plt.legend()
plt.xticks(rotation=90)
plt.show()
```



[268]:
```
predictions_sarima = sarima_result.predict(start=y_test.
↪index[0], end=exog_future.index[-1])

predictions_sarima = predictions_sarima.reindex(y.index)


plt.figure(figsize=(30, 6))
plt.plot(y, label='Actual')
plt.plot(predictions_sarima, label='Predicted', color='red')
plt.plot(predictions_sarima[-13:], label='Forecast',␣
↪color='green')
plt.legend()
plt.xticks(rotation=90)
plt.show()
```



[269]:
```
predictions_df = pd.DataFrame({'Forecast':␣
↪predictions_sarima[-13:]})
predictions_df['Forecast'] = predictions_df['Forecast'].
↪map(lambda x: '{:.2f}'.format(x))
predictions_df
```

[269]:
```
           Forecast
Month-Year
Mar-2025   -2006.89
Apr-2025     733.40
May-2025      90.09
Jun-2025      25.21
Jul-2025     -54.91
Aug-2025      -2.26
Sep-2025      39.51
Oct-2025       0.13
Nov-2025      61.95
Dec-2025      -5.53
Jan-2026    -120.21
Feb-2026      24.66
Mar-2026     139.53
```

[273]:
```
#predictions_df.to_csv("Service_Parts_SARIMA.csv")
```

[275]:
```
# Fit SARIMA-X model
sarima_x_model = SARIMAX(y_train, exog=exog_train, order=(1,␣
↪0, 1), seasonal_order=(1, 0, 1, 12))
sarima_x_result = sarima_x_model.fit(disp=False)

# Make predictions
predictions_sarima_x = sarima_x_result.predict(start=y_test.
↪index[0], end=y_test.index[-1], exog=exog_test)

# Evaluate the model
rmse = sqrt(mean_squared_error(y_test, predictions_sarima_x))

print(f'RMSE: {rmse}')
sarima_x_result.summary()
```

```
RMSE: 1215.3859200239535
```

[275]:

Dep. Variable:	Service Parts	**No. Observations:**	95
Model:	SARIMAX(1, 0, 1)x(1, 0, 1, 12)	**Log Likelihood**	-804.839
Date:	Mon, 16 Dec 2024	**AIC**	1621.677
Time:	13:06:10	**BIC**	1637.000
Sample:	05-01-2016	**HQIC**	1627.869
	- 03-01-2024		
Covariance Type:	opg		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Print Production Volume	-0.0094	0.026	-0.355	0.722	-0.061	0.042
ar.L1	0.1861	0.236	0.787	0.431	-0.277	0.649
ma.L1	-0.5846	0.217	-2.694	0.007	-1.010	-0.159
ar.S.L12	-0.0770	0.080	-0.960	0.337	-0.234	0.080
ma.S.L12	-0.9691	0.101	-9.630	0.000	-1.166	-0.772
sigma2	1.022e+06	1.09e-07	9.39e+12	0.000	1.02e+06	1.02e+06

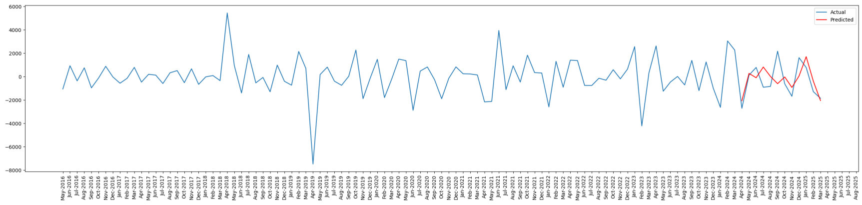
Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	43.64
Prob(Q):	0.98	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.82	**Skew:**	0.26
Prob(H) (two-sided):	0.57	**Kurtosis:**	6.28

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.76e+29. Standard errors may be unstable.

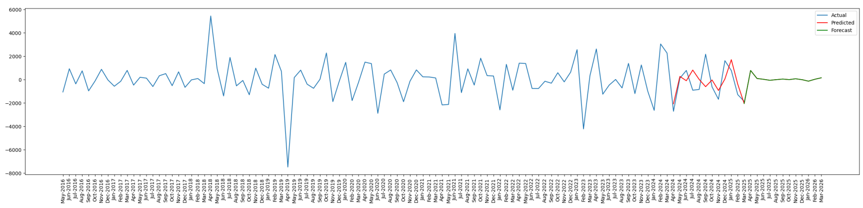
[277]:
```python
predictions_sarima_x = predictions_sarima_x.reindex(y.index)
print(predictions_sarima_x.index)
print(y.index)
```

```
Index(['May-2016', 'Jun-2016', 'Jul-2016', 'Aug-2016',␣
↪'Sep-2016', 'Oct-2016',
       'Nov-2016', 'Dec-2016', 'Jan-2017', 'Feb-2017',
       ...
       'Jun-2025', 'Jul-2025', 'Aug-2025', 'Sep-2025',␣
↪'Oct-2025', 'Nov-2025',
       'Dec-2025', 'Jan-2026', 'Feb-2026', 'Mar-2026'],
      dtype='object', name='Month-Year', length=119)
Index(['May-2016', 'Jun-2016', 'Jul-2016', 'Aug-2016',␣
↪'Sep-2016', 'Oct-2016',
       'Nov-2016', 'Dec-2016', 'Jan-2017', 'Feb-2017',
       ...
       'Jun-2025', 'Jul-2025', 'Aug-2025', 'Sep-2025',␣
↪'Oct-2025', 'Nov-2025',
       'Dec-2025', 'Jan-2026', 'Feb-2026', 'Mar-2026'],
      dtype='object', name='Month-Year', length=119)
```

[279]:
```python
plt.figure(figsize=(30, 6))
plt.plot(y, label='Actual')
plt.plot(predictions_sarima_x, label='Predicted', color='red')
plt.legend()
plt.xticks(rotation=90)
plt.show()
```



[280]:
```python
# Make predictions
predictions_sarima_x = sarima_x_result.predict(start=y_test.
↪index[0], end=exog_future.index[-1], exog=exog_future)

predictions_sarima_x = predictions_sarima_x.reindex(y.index)


plt.figure(figsize=(30, 6))
plt.plot(y, label='Actual')
plt.plot(predictions_sarima_x, label='Predicted', color='red')
plt.plot(predictions_sarima_x[-13:], label='Forecast',␣
↪color='green')
plt.legend()
plt.xticks(rotation=90)
plt.show()
```



[281]:
```python
predictions_sarima_x_df = pd.DataFrame({'Forecast':␣
↪predictions_sarima_x[-13:]})
predictions_sarima_x_df['Forecast'] =␣
↪predictions_sarima_x_df['Forecast'].map(lambda x: '{:.2f}'.
↪format(x))
predictions_sarima_x_df
```

[281]:
```
            Forecast
Month-Year
Mar-2025    -2051.72
Apr-2025      778.73
May-2025       90.30
Jun-2025       23.95
Jul-2025      -63.96
Aug-2025       -5.48
Sep-2025       41.59
Oct-2025       -2.71
Nov-2025       66.31
Dec-2025       -8.93
Jan-2026     -136.36
Feb-2026       25.02
Mar-2026      152.52
```

[285]:
```
#predictions_sarima_x_df.to_csv("Service_Parts_SARIMAX.csv")
```

Target Variable: Equipments

[288]:
```
Equipment = sales_data['Equipment']
Equipment.head()
```

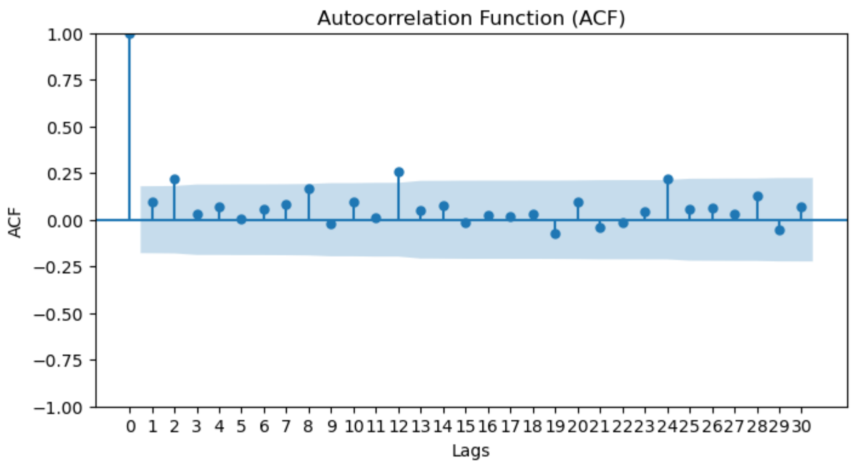
[288]:
```
Month-Year
Apr-2015    21505.1
May-2015    11021.8
Jun-2015    14929.5
Jul-2015    27340.9
Aug-2015     6405.1
Name: Equipment, dtype: float64
```

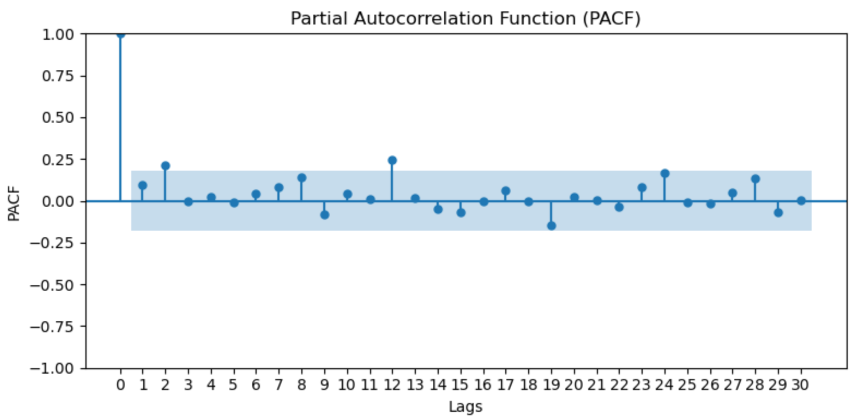
[290]:
```
adf_test(Equipment)
```

```
ADF Statistic: -5.837274711750817
p-value: 3.850206794269265e-07
Critical Values: {'1%': -3.4870216863700767, '5%': -2.
↪8863625166643136, '10%':
-2.580009026141913}
The data is stationary.
```

[292]:
```
fig, ax = plt.subplots(figsize=(8, 4))
plot_acf(Equipment, lags=30, ax=ax)
ax.set_title('Autocorrelation Function (ACF)')
ax.set_xlabel('Lags')
ax.set_ylabel('ACF')

ax.set_xticks(range(0, 31))  # Set the x-ticks to range from␣
↪0 to 30 (lags)
```

```
ax.set_xticklabels(range(0, 31))  # Set the labels for each␣
↪lag

from statsmodels.graphics.tsaplots import plot_pacf
fig, ax = plt.subplots(figsize=(8, 4))
plot_pacf(Equipment, lags=30, ax=ax)
ax.set_title('Partial Autocorrelation Function (PACF)')
ax.set_xlabel('Lags')
ax.set_ylabel('PACF')
ax.set_xticks(range(0, 31))  # Set the x-ticks to range from␣
↪0 to 30 (lags)
ax.set_xticklabels(range(0, 31))  # Set the labels for each␣
↪lag

# Show plots
plt.tight_layout()
plt.show()
```





[293]:
```
Equipment.head()
```

[293]:
```
Month-Year
Apr-2015    21505.1
May-2015    11021.8
Jun-2015    14929.5
Jul-2015    27340.9
Aug-2015     6405.1
Name: Equipment, dtype: float64
```

[294]:
```
Equipment.describe()
```

[294]:
```
count      120.000000
mean     11903.305417
std       8454.806727
min         40.900000
25%       5574.375000
50%      11370.225000
75%      16679.525000
max      32352.000000
Name: Equipment, dtype: float64
```

[298]:
```
start_date = 'Apr-2015'
end_date = 'Mar-2026'
filtered_df = external_data.loc[start_date:end_date]

sp = pd.concat([Equipment, filtered_df], axis=1)

exog = sp['Print Production Volume']
```

[300]:
```
y = sp['Equipment']

# Train-test split (last 12 months for testing)
train_size = len(sp) - 24
y_train, y_test = y[:train_size], y[train_size:train_size+12]
exog_train, exog_test, exog_future = exog[:train_size],␣
↪exog[train_size:train_size+12], exog[train_size:]

from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error
from math import sqrt
import matplotlib.pyplot as plt
```

[302]:
```
# Fit SARIMA model
sarima_model = SARIMAX(y_train, order=(1, 0, 1),␣
↪seasonal_order=(1, 0, 1, 12))
```

```
sarima_result = sarima_model.fit(disp=False)

# Make predictions
predictions_sarima = sarima_result.predict(start=y_test.
↪index[0], end=y_test.index[-1])

# Evaluate the model
rmse = sqrt(mean_squared_error(y_test, predictions_sarima))

print(f'RMSE: {rmse}')
sarima_result.summary()
```

```
RMSE: 9756.453282283997
```

[302]:

Dep. Variable:	Equipment	**No. Observations:**	108
Model:	SARIMAX(1, 0, 1)x(1, 0, 1, 12)	**Log Likelihood**	-1120.308
Date:	Mon, 16 Dec 2024	**AIC**	2250.616
Time:	13:06:29	**BIC**	2264.027
Sample:	04-01-2015 - 03-01-2024	**HQIC**	2256.054
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	0.9832	0.019	51.588	0.000	0.946	1.021
ma.L1	-0.8550	0.075	-11.335	0.000	-1.003	-0.707
ar.S.L12	0.9974	0.019	52.032	0.000	0.960	1.035
ma.S.L12	-0.9537	0.173	-5.522	0.000	-1.292	-0.615
sigma2	5.165e+07	3.43e-09	1.51e+16	0.000	5.17e+07	5.17e+07

Ljung-Box (L1) (Q):	0.78	**Jarque-Bera (JB):**	0.89
Prob(Q):	0.38	**Prob(JB):**	0.64
Heteroskedasticity (H):	0.69	**Skew:**	0.19
Prob(H) (two-sided):	0.28	**Kurtosis:**	2.76

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 4.76e+31. Standard errors may be unstable.

[303]:

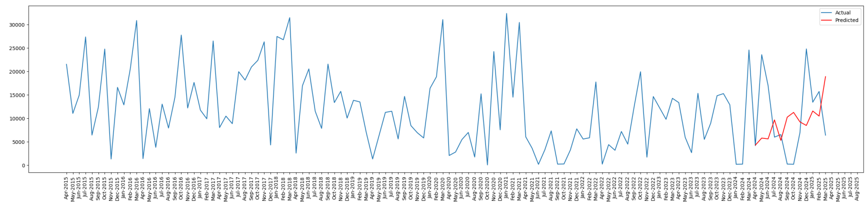
```
predictions_sarima = predictions_sarima.reindex(y.index)
print(predictions_sarima.index)
print(y.index)
```

```
Index(['Apr-2015', 'May-2015', 'Jun-2015', 'Jul-2015',␣
↪'Aug-2015', 'Sep-2015',
       'Oct-2015', 'Nov-2015', 'Dec-2015', 'Jan-2016',
       ...
```

```
       'Jun-2025', 'Jul-2025', 'Aug-2025', 'Sep-2025',␣
↪'Oct-2025', 'Nov-2025',
       'Dec-2025', 'Jan-2026', 'Feb-2026', 'Mar-2026'],
      dtype='object', name='Month-Year', length=132)
Index(['Apr-2015', 'May-2015', 'Jun-2015', 'Jul-2015',␣
↪'Aug-2015', 'Sep-2015',
       'Oct-2015', 'Nov-2015', 'Dec-2015', 'Jan-2016',
       ...
       'Jun-2025', 'Jul-2025', 'Aug-2025', 'Sep-2025',␣
↪'Oct-2025', 'Nov-2025',
       'Dec-2025', 'Jan-2026', 'Feb-2026', 'Mar-2026'],
      dtype='object', name='Month-Year', length=132)
```

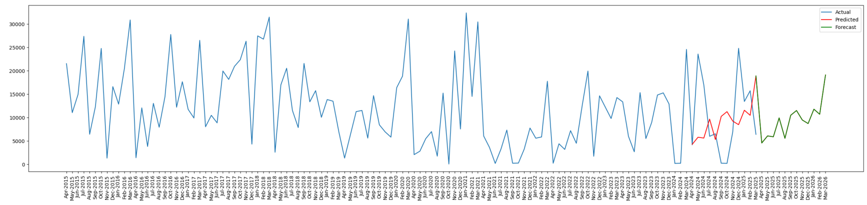
[306]:

```
plt.figure(figsize=(30, 6))
plt.plot(y, label='Actual')
plt.plot(predictions_sarima, label='Predicted', color='red')
plt.legend()
plt.xticks(rotation=90)
plt.show()
```



[307]:

```
predictions_sarima = sarima_result.predict(start=y_test.
↪index[0], end=exog_future.index[-1])

predictions_sarima = predictions_sarima.reindex(y.index)


plt.figure(figsize=(30, 6))
plt.plot(y, label='Actual')
plt.plot(predictions_sarima, label='Predicted', color='red')
plt.plot(predictions_sarima[-13:], label='Forecast',␣
↪color='green')
plt.legend()
plt.xticks(rotation=90)
plt.show()
```



[309]:
```python
predictions_df = pd.DataFrame({'Forecast': predictions_sarima[-13:]})
predictions_df['Forecast'] = predictions_df['Forecast'].map(lambda x: '{:.2f}'.format(x))
predictions_df
```

[309]:
```
           Forecast
Month-Year
Mar-2025   18878.47
Apr-2025    4536.67
May-2025    6046.39
Jun-2025    5863.42
Jul-2025    9902.58
Aug-2025    5535.96
Sep-2025   10471.25
Oct-2025   11478.58
Nov-2025    9448.44
Dec-2025    8694.75
Jan-2026   11765.32
Feb-2026   10679.06
Mar-2026   19076.63
```

[314]:
```python
#predictions_df.to_csv("Equipments_SARIMA.csv")
```

[316]:
```python
# Fit SARIMA-X model
sarima_x_model = SARIMAX(y_train, exog=exog_train, order=(1, 0, 1), seasonal_order=(3, 0, 3, 12))
sarima_x_result = sarima_x_model.fit(disp=False)

# Make predictions
predictions_sarima_x = sarima_x_result.predict(start=y_test.index[0], end=y_test.index[-1], exog=exog_test)

# Evaluate the model
rmse = sqrt(mean_squared_error(y_test, predictions_sarima_x))

print(f'RMSE: {rmse}')
sarima_x_result.summary()
```

```
RMSE: 9418.762307841782
```

[316]:

Dep. Variable:	Equipment	**No. Observations:**	108
Model:	SARIMAX(1, 0, 1)x(3, 0, [1, 2, 3], 12)	**Log Likelihood**	-1117.233
Date:	Mon, 16 Dec 2024	**AIC**	2254.465
Time:	13:06:51	**BIC**	2281.286
Sample:	04-01-2015 - 03-01-2024	**HQIC**	2265.340
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Print Production Volume	14.9288	2.674	5.582	0.000	9.687	20.171
ar.L1	0.7611	0.381	1.998	0.046	0.014	1.508
ma.L1	-0.6559	0.447	-1.467	0.142	-1.532	0.220
ar.S.L12	0.5870	1.444	0.407	0.684	-2.243	3.417
ar.S.L24	-0.7045	2.007	-0.351	0.726	-4.638	3.229
ar.S.L36	0.4498	1.234	0.365	0.715	-1.968	2.867
ma.S.L12	-0.3539	1.468	-0.241	0.810	-3.231	2.524
ma.S.L24	0.8016	1.894	0.423	0.672	-2.910	4.513
ma.S.L36	-0.1922	1.088	-0.177	0.860	-2.324	1.940
sigma2	6.531e+07	5.56e-07	1.17e+14	0.000	6.53e+07	6.53e+07

Ljung-Box (L1) (Q):	0.64	**Jarque-Bera (JB):**	2.43
Prob(Q):	0.42	**Prob(JB):**	0.30
Heteroskedasticity (H):	0.62	**Skew:**	0.32
Prob(H) (two-sided):	0.15	**Kurtosis:**	2.63

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 6.25e+30. Standard errors may be unstable.

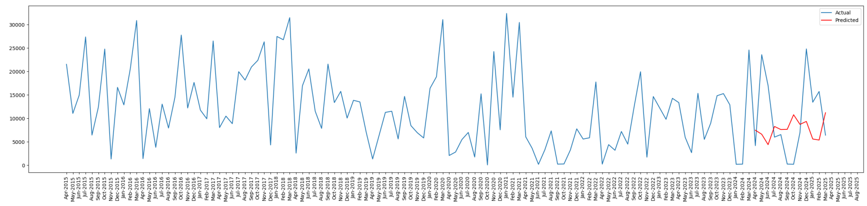
[317]:

```
predictions_sarima_x = predictions_sarima_x.reindex(y.index)
print(predictions_sarima_x.index)
print(y.index)
```

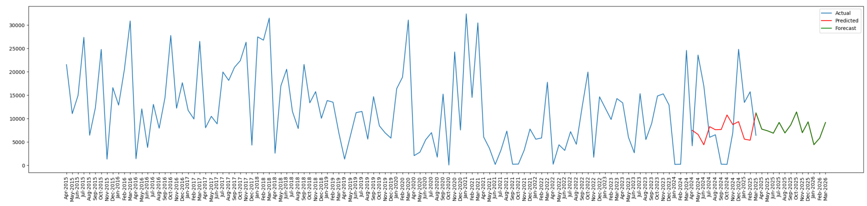
```
Index(['Apr-2015', 'May-2015', 'Jun-2015', 'Jul-2015',␣
↪'Aug-2015', 'Sep-2015',
       'Oct-2015', 'Nov-2015', 'Dec-2015', 'Jan-2016',
       ...
       'Jun-2025', 'Jul-2025', 'Aug-2025', 'Sep-2025',␣
↪'Oct-2025', 'Nov-2025',
       'Dec-2025', 'Jan-2026', 'Feb-2026', 'Mar-2026'],
      dtype='object', name='Month-Year', length=132)
Index(['Apr-2015', 'May-2015', 'Jun-2015', 'Jul-2015',␣
↪'Aug-2015', 'Sep-2015',
       'Oct-2015', 'Nov-2015', 'Dec-2015', 'Jan-2016',
       ...
```

```
       'Jun-2025', 'Jul-2025', 'Aug-2025', 'Sep-2025',␣
↪'Oct-2025', 'Nov-2025',
       'Dec-2025', 'Jan-2026', 'Feb-2026', 'Mar-2026'],
      dtype='object', name='Month-Year', length=132)
```

[318]:
```
plt.figure(figsize=(30, 6))
plt.plot(y, label='Actual')
plt.plot(predictions_sarima_x, label='Predicted', color='red')
plt.legend()
plt.xticks(rotation=90)
plt.show()
```



[319]:
```
# Make predictions
predictions_sarima_x = sarima_x_result.predict(start=y_test.
 ↪index[0], end=exog_future.index[-1], exog=exog_future)

predictions_sarima_x = predictions_sarima_x.reindex(y.index)


plt.figure(figsize=(30, 6))
plt.plot(y, label='Actual')
plt.plot(predictions_sarima_x, label='Predicted', color='red')
plt.plot(predictions_sarima_x[-13:], label='Forecast',␣
 ↪color='green')
plt.legend()
plt.xticks(rotation=90)
plt.show()
```



[320]:

```
predictions_sarima_x_df = pd.DataFrame({'Forecast':
↪predictions_sarima_x[-13:]})
predictions_sarima_x_df['Forecast'] =
↪predictions_sarima_x_df['Forecast'].map(lambda x: '{:.2f}'.
↪format(x))
predictions_sarima_x_df
```

[320]:

```
            Forecast
Month-Year
Mar-2025    11180.25
Apr-2025     7716.19
May-2025     7350.67
Jun-2025     6853.01
Jul-2025     9148.29
Aug-2025     6896.77
Sep-2025     8609.13
Oct-2025    11389.45
Nov-2025     6954.25
Dec-2025     9270.08
Jan-2026     4388.11
Feb-2026     5806.75
Mar-2026     9137.56
```

[328]:

```
#predictions_sarima_x_df.to_csv("Equipments_SARIMAX.csv")
```

[ ]: