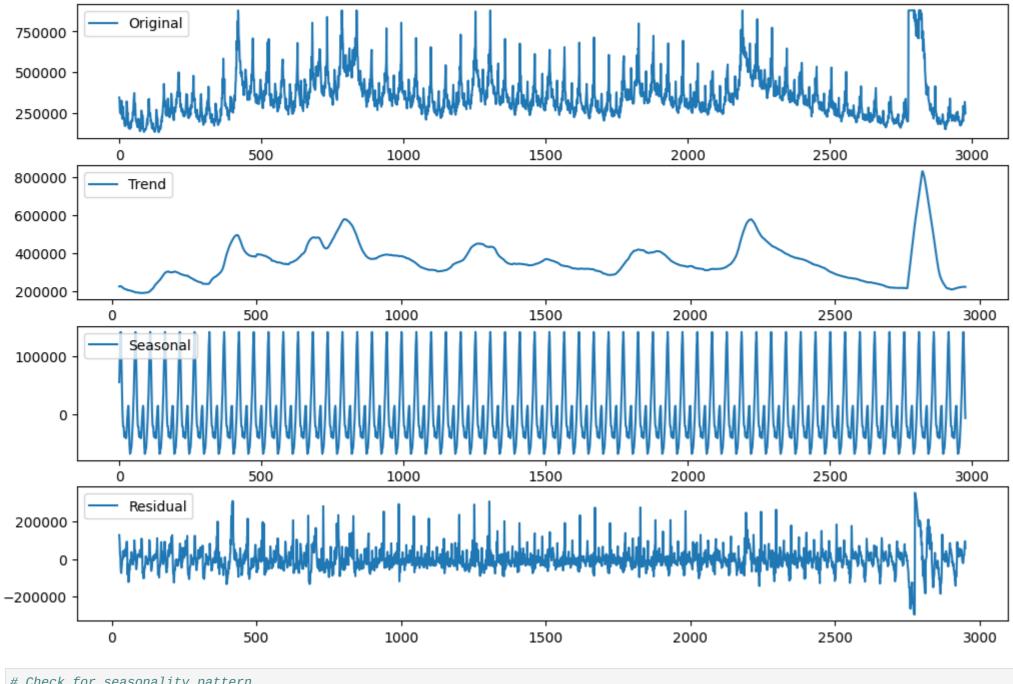
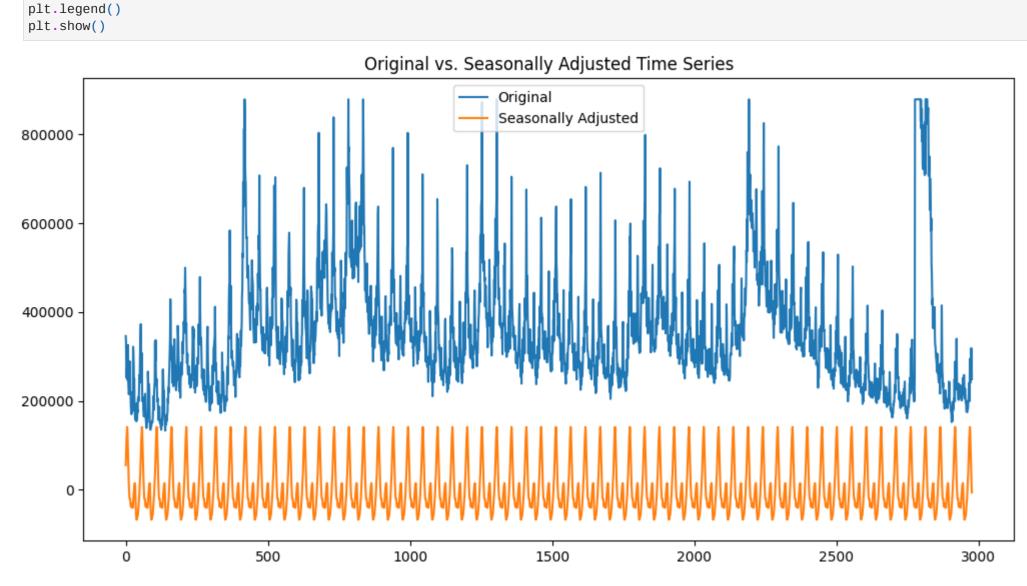
```
In [ ]:
In [ ]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        from fredapi import Fred
        from statsmodels.tsa.statespace.sarimax import SARIMAX
        from statsmodels.tsa.seasonal import seasonal_decompose
        from itertools import product
In [ ]: # fetch FRED data
        def fetch_fred_data(api_key, series_id):
            fred = Fred(api_key=api_key)
            data = fred.get_series(series_id)
            df = pd.DataFrame({'date': data.index, 'value': data.values})
            return df
        # Fetch ICNSA data using FRED API
        FRED_API_KEY = '360481124fc765b815de2697f1bf8d62'
        icnsa = fetch_fred_data(api_key=FRED_API_KEY, series_id='ICNSA')
In [ ]: # Converting 'value' column to numeric
        icnsa['value'] = pd.to_numeric(icnsa['value'], errors='coerce')
In [ ]: # Checking missing values
        missing_values = icnsa['value'].isnull().any()
        print("Missing Values:", missing_values)
       Missing Values: False
In [ ]: # Handling extreme values during COVID years using winsorization
        covid_threshold = np.nanquantile(icnsa['value'], 0.99)
        icnsa['value'] = np.clip(icnsa['value'], a_min=None, a_max=covid_threshold)
In [ ]: # Time series plot
        plt.plot(icnsa['date'], icnsa['value'])
        plt.title("ICNSA Time Series")
        plt.xlabel("Date")
        plt.ylabel("Value")
        plt.show()
                                       ICNSA Time Series
          900000 -
          800000
          700000
          600000 -
       Value
         500000
          400000
          300000
          200000
          100000
                                                   2000
                                               Date
In [ ]: # Grid search for SARIMAX parameters
        p_values = range(0, 3)
        d_values = range(0, 2)
        q_values = range(0, 3)
In [ ]: # Generate all possible combinations of p, d, q
        orders = list(product(p_values, d_values, q_values))
        # Finding optimal parameters using grid search
        best_bic = np.inf
        best_order = None
        for order in orders:
            try:
                arima_model = SARIMAX(icnsa['value'], order=order)
                arima_results = arima_model.fit(disp=False)
                bic = arima_results.bic
               if bic < best_bic:</pre>
                    best_bic = bic
                    best_order = order
            except:
                continue
        print("Best SARIMAX Order:", best_order)
      c:\Users\Lenovo\AppData\Local\Programs\Python\Python311\Lib\site-packages\statsmodels\tsa\statespace\sarimax.py:966: UserWarning: Non-stationary starting autoregressive parameters found. Usin
      g zeros as starting parameters.
        warn('Non-stationary starting autoregressive parameters'
       c:\Users\Lenovo\AppData\Local\Programs\Python\Python311\Lib\site-packages\statsmodels\tsa\statespace\sarimax.py:978: UserWarning: Non-invertible starting MA parameters found. Using zeros as s
       tarting parameters.
        warn('Non-invertible starting MA parameters found.'
       Best SARIMAX Order: (2, 1, 2)
In []: # Fit ARIMA model with the best parameters
        arima_model_best = SARIMAX(icnsa['value'], order=best_order)
        arima_results_best = arima_model_best.fit(disp=False)
In [ ]: # Forecast without seasonal adjustment
        forecast_arima = arima_results_best.get_forecast(steps=1)
        predicted_value = round(forecast_arima.predicted_mean.values[0])
        print("Forecast value:", predicted_value)
       Forecast value: 252678
In [ ]: # Time series decomposition
        result = seasonal_decompose(icnsa['value'], model='additive', period=52)
        # Plot the decomposition
        plt.figure(figsize=(12, 8))
        plt.subplot(4, 1, 1)
        plt.plot(icnsa['value'], label='Original')
        plt.legend(loc='upper left')
        plt.subplot(4, 1, 2)
        plt.plot(result.trend, label='Trend')
        plt.legend(loc='upper left')
        plt.subplot(4, 1, 3)
        plt.plot(result.seasonal, label='Seasonal')
        plt.legend(loc='upper left')
        plt.subplot(4, 1, 4)
        plt.plot(result.resid, label='Residual')
        plt.legend(loc='upper left')
        plt.suptitle('ICNSA Decomposition')
        plt.show()
                                                              ICNSA Decomposition
                       Original
        750000
        500000
        250000
                                                        1000
                                                                          1500
                                                                                                              2500
                                                                                                                                3000
                                      500
                                                                                            2000
        800000
                       Trend
        600000
        400000
        200000
                                      500
                                                       1000
                                                                          1500
                                                                                            2000
                                                                                                               2500
                                                                                                                                 3000
                    0
                       Seasonal
        100000
```



```
In [ ]: # Check for seasonality pattern
        seasonal_pattern = 52
        if seasonal_pattern > 1:
            # Applying seasonal adjustment
            seasonal_adj = result.seasonal
        else:
            seasonal_adj = icnsa['value']
In [ ]: # Visualizing original and seasonally adjusted time series
        plt.figure(figsize=(12, 6))
        plt.plot(icnsa['value'], label='Original')
        plt.plot(seasonal_adj, label='Seasonally Adjusted')
```



```
In [ ]: # Fit ARIMA model with seasonality adjustment using the best parameters
        arima_model_adj = SARIMAX(seasonal_adj, order=best_order)
        arima_results_adj = arima_model_adj.fit(disp=False)
        forecast_arima_adj = arima_results_adj.get_forecast(steps=1)
        predicted_value_adj = round(forecast_arima_adj.predicted_mean.values[0])
        print("Forecast value with seasonality adjustment:", predicted_value_adj)
       Forecast value with seasonality adjustment: -34692989
```

In [ ]: # Refit model on full data with best parameters model = SARIMAX(icnsa['value'], order=best\_params) results = model.fit() # Make forecast for future dates

plt.title('Original vs. Seasonally Adjusted Time Series')

```
future_dates = pd.date_range(start=icnsa['date'].max() + pd.DateOffset(days=1), periods=52, freq='D')
forecast = results.get_forecast(steps=52)
pred = forecast.predicted_mean
```

# Evaluate forecast RMSE
mse = mean\_squared\_error(test['value'], pred)
print('Test RMSE: %.3f' % np.sqrt(mse))

Test RMSE: 225783.146