| EX:No.8<br><br>DATE:12/04/25 | **Create an ARIMA Model for time series forecasting** |
|---|---|

## AIM:

To Create an ARIMA Model for time series forecasting.

## ALGORITHM:

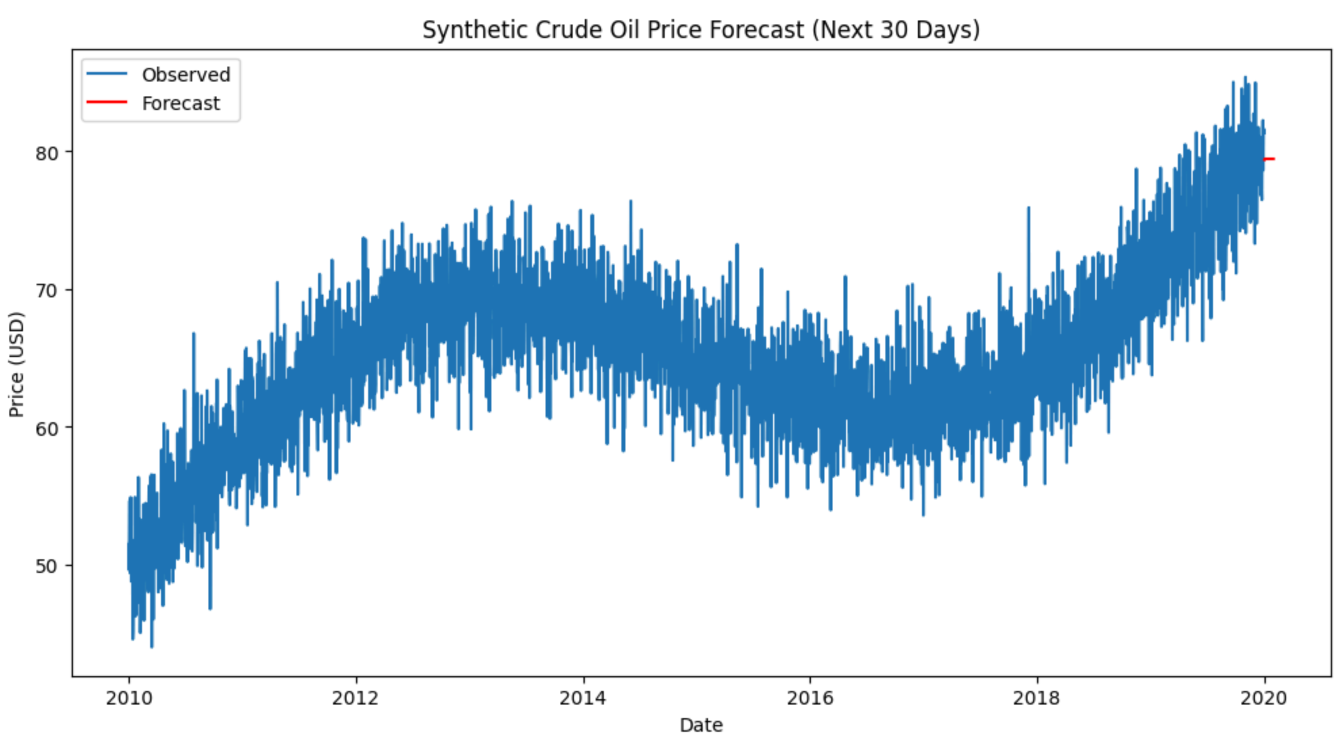
1. ADF Test – Checks if the PM2.5 time series is stationary using statistical significance.
2. Differencing – Transforms non-stationary data to stationary by subtracting consecutive values.
3. ARIMA Model Selection – Chooses ARIMA(p,d,q) model where p = autoregressive lags, d = differencing, q = moving average lags.
4. Model Training – Fits the ARIMA model to historical PM2.5 data using specified parameters.
5. Forecasting – Predicts future PM2.5 values for the next 30 days using the trained model.
6. Visualization – Plots actual vs forecasted PM2.5 levels to visualize model performance.

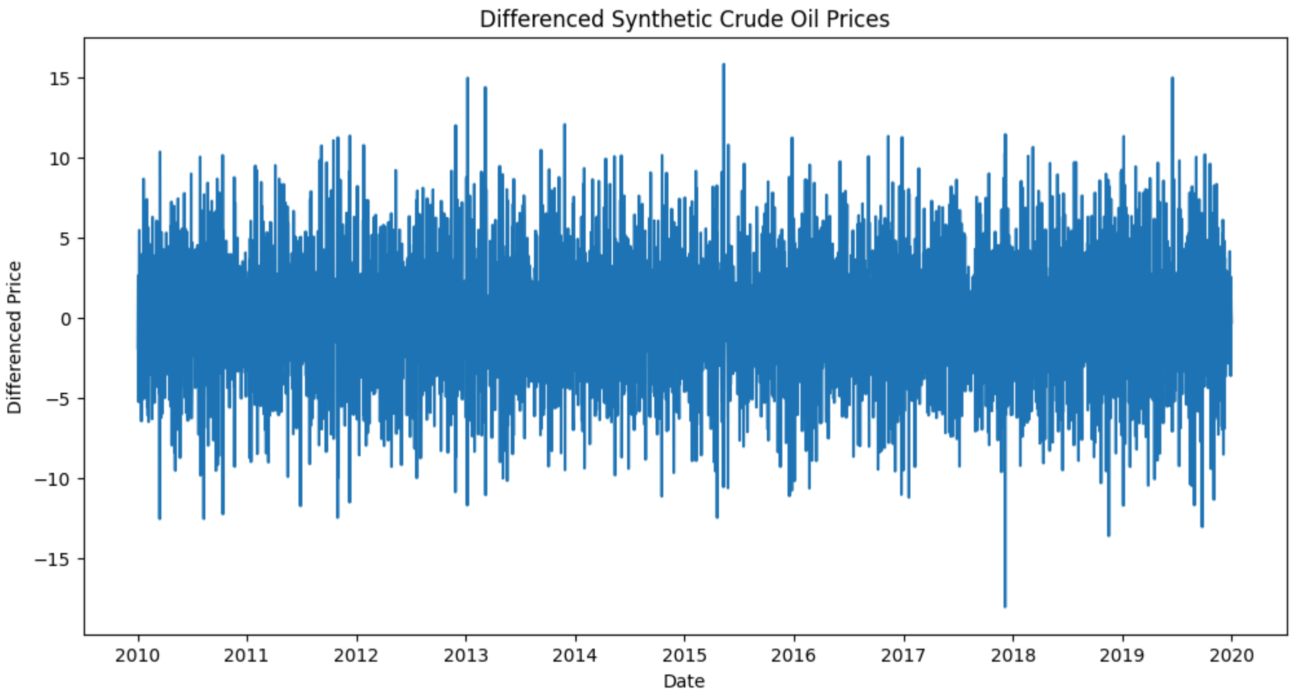
## Code:

```
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.arima.model import ARIMA
from pandas.plotting import register_matplotlib_converters
from statsmodels.tsa.stattools import adfuller
import seaborn as sns

register_matplotlib_converters()

# Step 1: Load the dataset
df = pd.read_csv('/content/us_air_pollution_2012_2021_updated.csv', parse_dates=['Date'])
df.set_index('Date', inplace=True)

# Step 2: Handle encoding issues
df.columns = [col.encode('utf-8').decode('utf-8').replace("Â", "") for col in df.columns]
df = df.apply(pd.to_numeric, errors='coerce')  # convert all to numeric, force errors to NaN

# Step 3: Drop missing values
df = df.dropna()

# Step 4: Visualize the PM2.5 levels
plt.figure(figsize=(10, 4))
plt.plot(df['PM2.5 (µg/m³)'], label='PM2.5')
plt.title('PM2.5 over time')
plt.legend()
plt.show()
```

```
# Step 5: Check stationarity using ADF test
result = adfuller(df['PM2.5 (µg/m³)'])
print('ADF Statistic:', result[0])
print('p-value:', result[1])

# Step 6: Differencing (if p-value > 0.05)
df['PM2.5_diff'] = df['PM2.5 (µg/m³)'].diff().dropna()

# Step 7: Fit ARIMA model (you can tune p,d,q manually or use auto_arima)
model = ARIMA(df['PM2.5 (µg/m³)'], order=(1,1,1))  # Example (p=1, d=1, q=1)
model_fit = model.fit()

# Step 8: Summary
print(model_fit.summary())

# Step 9: Forecast
forecast = model_fit.forecast(steps=30)  # Forecasting next 30 time points

# Step 10: Plot forecast
plt.figure(figsize=(10, 4))
plt.plot(df['PM2.5 (µg/m³)'], label='Historical')
plt.plot(pd.date_range(start=df.index[-1], periods=31, freq='D')[1:], forecast, label='Forecast', color='red')
plt.legend()
plt.title('PM2.5 Forecast')
plt.show()
```

## OUTPUT:






```
ADF Statistic: -9.886813891901397
p-value: 3.6455466907399357e-17
                               SARIMAX Results
==============================================================================
Dep. Variable:           PM2.5 (µg/m³)   No. Observations:                  120
Model:                  ARIMA(1, 1, 1)   Log Likelihood                -432.639
Date:                 Sat, 12 Apr 2025   AIC                            871.278
Time:                         04:33:41   BIC                            879.615
Sample:                     01-01-2012   HQIC                           874.663
                          - 12-01-2021
Covariance Type:                   opg

==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.0723      0.097      0.742      0.458      -0.119       0.263
ma.L1         -0.9665      0.042    -22.821      0.000      -1.050      -0.884
sigma2        82.4100     16.919      4.871      0.000      49.250     115.570
==================================================================================
=
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):
6.85
Prob(Q):                              0.91   Prob(JB):
0.03
Heteroskedasticity (H):               0.71   Skew:
0.06
Prob(H) (two-sided):                  0.29   Kurtosis:
1.83
==================================================================================
```

## RESULT:

Thus, the program using the time series data implementation has been done successfully.