Business Case Study: Forecasting Airline Passengers for Strategic Planning Objective: To analyze and forecast the number of international airline passengers using the AirPassenger dataset to aid in strategic business planning for an airline company. Dataset Description: The dataset contains the monthly number of international airline passengers (in thousands) from January 1949 to December 1960. Data Fields: ● Month: Month and year (e.g., 1949-01). ● Passengers: Number of international airline passengers (in thousands). Business Scenario: You are a data analyst for a major international airline. The company's management has tasked you with analyzing historical passenger data and forecasting future passenger numbers. The insights from your analysis will be used to make strategic decisions regarding fleet management, route planning, staffing, and marketing campaigns.

1. Data Exploration and Initial Insights Prepare the AirPassenger dataset for the analysis. Identify and describe any noticeable trends and seasonal patterns in the data. Based on your initial analysis, discuss how observed trends and seasonality could impact the airline's operations and strategic decisions.
2. Time Series Analysis and Model Selection Perform the stationary test, interpret the results, and explain whether differencing is needed. Provide the evidence with a suitable plot. Use relevant plots to identify suitable values for ARIMA model parameters p, d, and q.
3. Model Fitting and Forecasting Fit the ARIMA model to the time series data. Interpret the key parameters and their significance. Comment on the adequacy of the model based on the residual analysis and test results. Forecast the number of passengers for the next 24 months and plot the forecasted values and the original time series to visualize the forecast. Provide a table of the forecasted values.
4. Model Improvement and Advanced Analysis Fit a SARIMA/LSTM model and compare the model's performance with the ARIMA model. Provide a table of the forecasted values for both models.

5. Strategic Business Insights Based on the forecasted values, discuss potential implications for the airline's capacity planning like fleet management, optimize ticket pricing, marketing and promotions, and resource allocation.

In [91]:
```
import pandas as pd

data = pd.read_csv('AirPassengers.csv')
data['date'] = pd.to_datetime(data['date'])
data.head()
```

Out[91]:

	date	value
0	1949-01-01	112
1	1949-02-01	118
2	1949-03-01	132
3	1949-04-01	129
4	1949-05-01	121

In [92]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144 entries, 0 to 143
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   date    144 non-null    datetime64[ns]
```

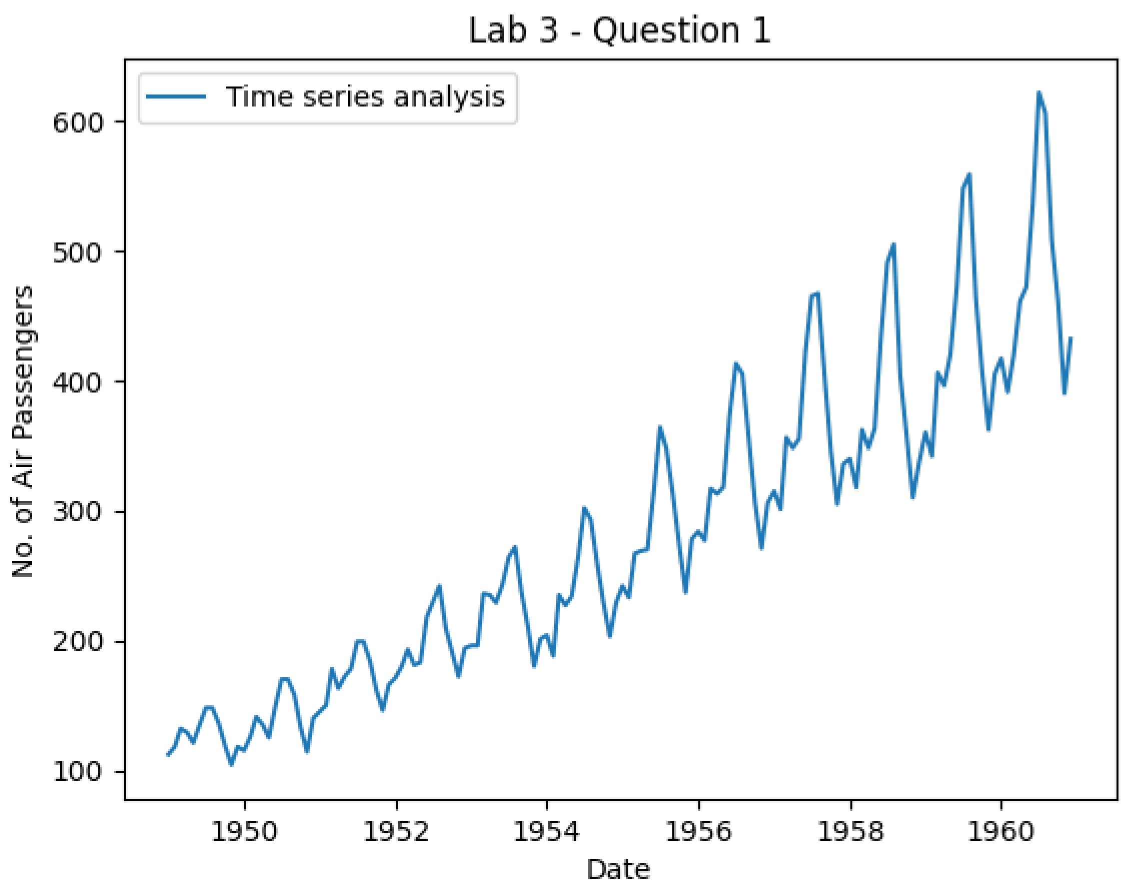
```
 1   value   144 non-null    int64
dtypes: datetime64[ns](1), int64(1)
memory usage: 2.4 KB
```

In [93]:
```
import matplotlib.pyplot as plt
import numpy as np

df = pd.DataFrame(data)
df.set_index('date', inplace=True)
df.head()
```

Out[93]:

	value
date	
1949-01-01	112
1949-02-01	118
1949-03-01	132
1949-04-01	129
1949-05-01	121

In [94]:
```
plt.plot(data['date'], data['value'], label = 'Time series analysis')
# plt.plot(x, y1, label='Line 1')
# plt.plot(x, y2, label='Line 2')
plt.xlabel('Date')
plt.ylabel('No. of Air Passengers')
plt.title('Lab 3 - Question 1')
plt.legend()
plt.show()
```



In [95]:
```
df['SMA'] = df['value'].rolling(window=12).mean()
df['MSTD'] = df['value'].rolling(window=12).std()
df.head()
```

Out[95]:

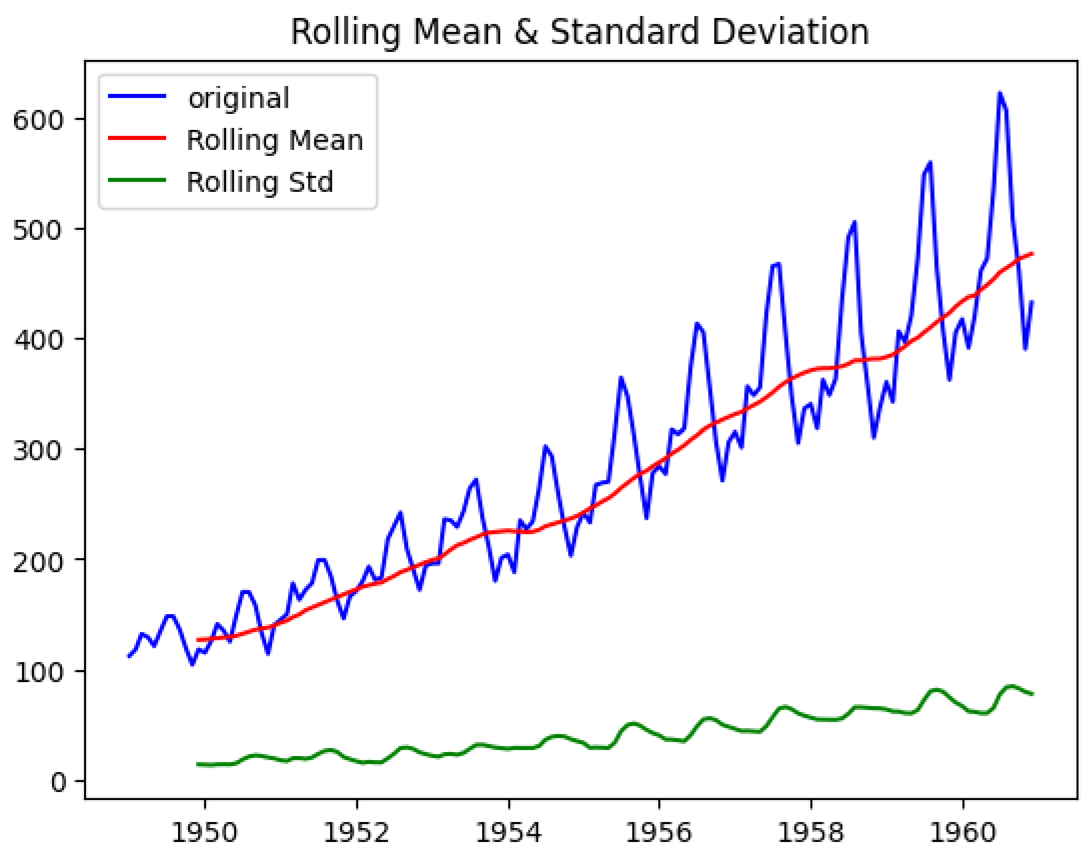
date	value	SMA	MSTD
1949-01-01	112	NaN	NaN
1949-02-01	118	NaN	NaN
1949-03-01	132	NaN	NaN
1949-04-01	129	NaN	NaN
1949-05-01	121	NaN	NaN

In [96]:

```
plt.plot(df["value"], color = 'blue', label='original')
plt.plot(df['SMA'], color = 'red', label='Rolling Mean')
plt.plot(df['MSTD'], color = 'green', label='Rolling Std')
plt.legend(loc = 'best')
plt.title('Rolling Mean & Standard Deviation')
```

Out[96]:

```
Text(0.5, 1.0, 'Rolling Mean & Standard Deviation')
```



In [97]:

```
from statsmodels.tsa.stattools import adfuller
```

ADF Test Null hypothesis: data is non stationary Alternate hypothesis: data is stationary if test static < critical value and p-value <0.05 then reject null hypothesis

In [98]:

```
#Perform Dickey-Fuller test:
print('Results of Dickey Fuller Test:')
airpass_test = adfuller(df['value'], autolag='AIC')
dfoutput = pd.Series(airpass_test[0:4], index=['Test Statistic','p-value','#Lags Used','
for key,value in airpass_test[4].items():
    dfoutput['Critical Value (%s)'%key] = value
print(dfoutput)
```

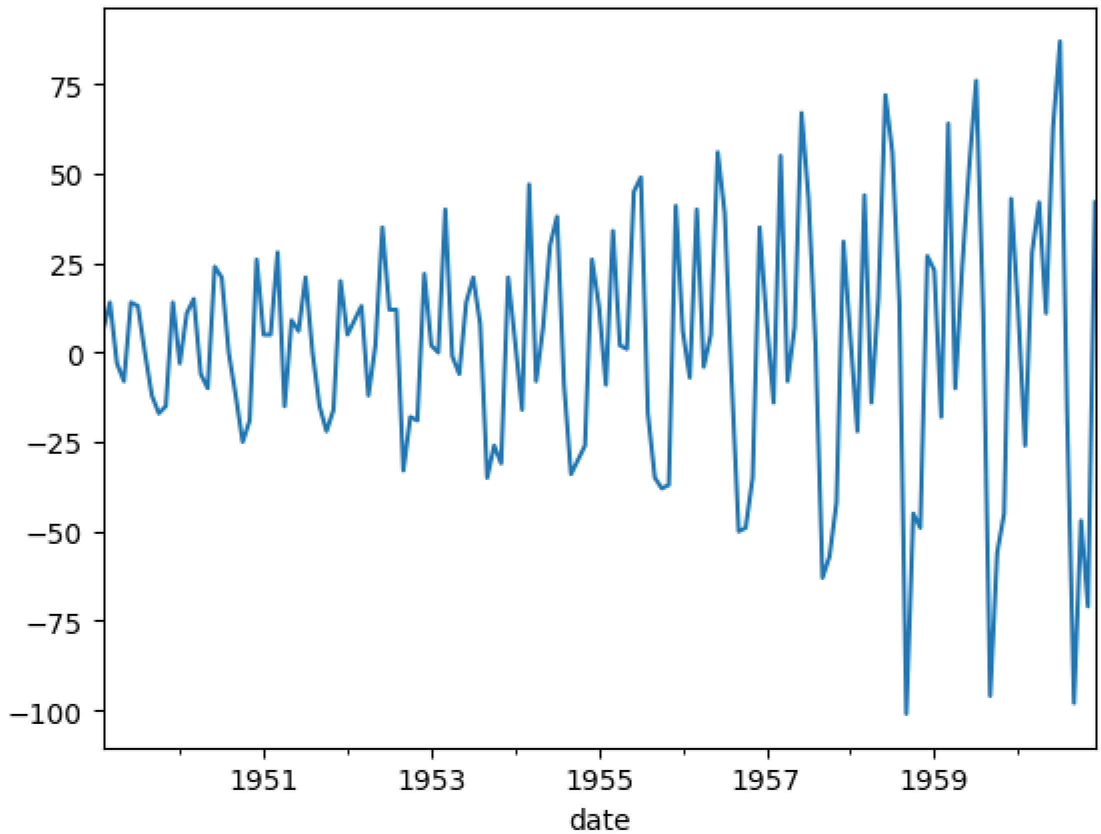
```
Results of Dickey Fuller Test:
Test Statistic                  0.815369
```

```
p-value                          0.991880
#Lags Used                      13.000000
Number of Observations Used    130.000000
Critical Value (1%)             -3.481682
Critical Value (5%)             -2.884042
Critical Value (10%)            -2.578770
dtype: float64
```

In [99]:

```
#single differencing
df["value_diff"] = df["value"] - df['value'].shift(1)
df['value_diff'].dropna().plot()
```

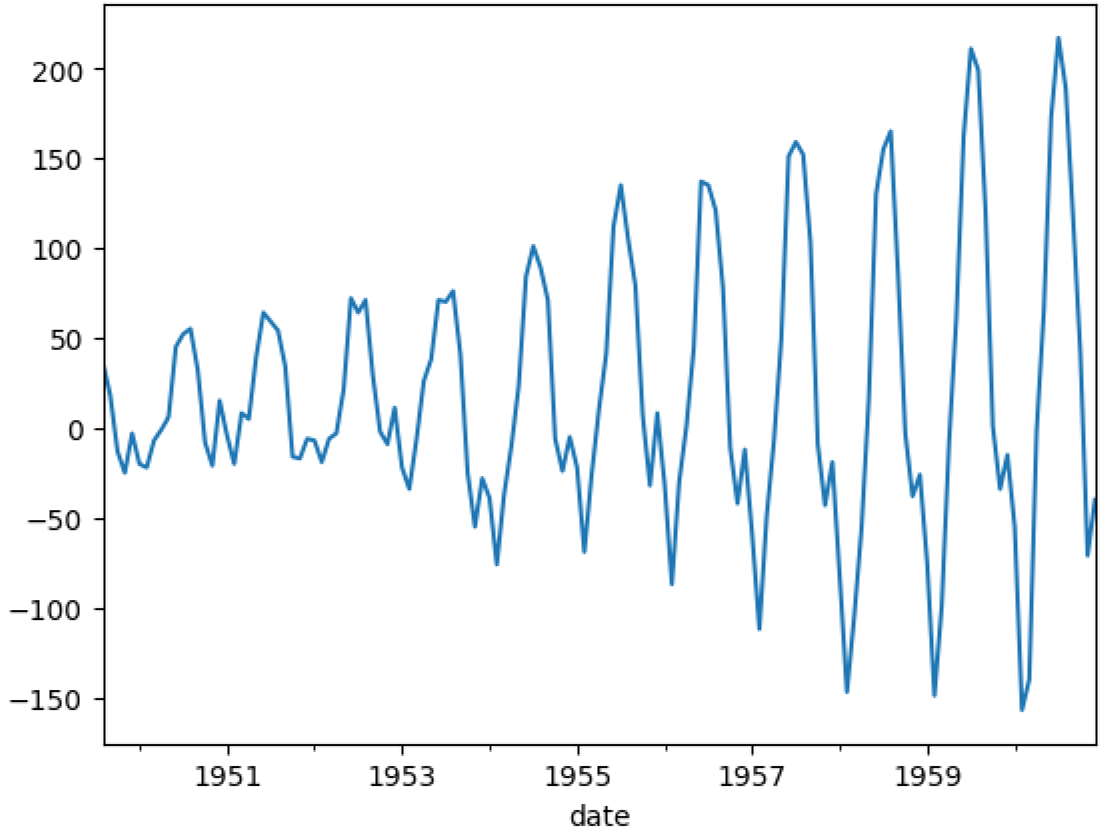
Out[99]: <Axes: xlabel='date'>



In [100…

```
# seasonal differencing
n =7
df["value_sdiff"] = df["value"] - df['value'].shift(n)
df['value_sdiff'].dropna().plot()
```

Out[100]: <Axes: xlabel='date'>



In [101…

```
# transformation
df['log_value'] = np.log(df['value'])
df.head()
```

Out[101]:

date	value	SMA	MSTD	value_diff	value_sdiff	log_value
1949-01-01	112	NaN	NaN	NaN	NaN	4.718499
1949-02-01	118	NaN	NaN	6.0	NaN	4.770685
1949-03-01	132	NaN	NaN	14.0	NaN	4.882802
1949-04-01	129	NaN	NaN	-3.0	NaN	4.859812
1949-05-01	121	NaN	NaN	-8.0	NaN	4.795791

In [102…

```
# Differencing logarithmic value
df["log_diff"] = df["log_value"] - df['log_value'].shift(1)
df.head()
```

Out[102]:

date	value	SMA	MSTD	value_diff	value_sdiff	log_value	log_diff
1949-01-01	112	NaN	NaN	NaN	NaN	4.718499	NaN
1949-02-01	118	NaN	NaN	6.0	NaN	4.770685	0.052186
1949-03-01	132	NaN	NaN	14.0	NaN	4.882802	0.112117
1949-04-01	129	NaN	NaN	-3.0	NaN	4.859812	-0.022990
1949-05-01	121	NaN	NaN	-8.0	NaN	4.795791	-0.064022

In [103…

```
df['SMA_log'] = df['log_value'].rolling(window=12).mean()
df['MSTD_log'] = df['log_value'].rolling(window=12).std()
df.head(10)
```

Out[103]:

date	value	SMA	MSTD	value_diff	value_sdiff	log_value	log_diff	SMA_log	MSTD_log
1949-01-01	112	NaN	NaN	NaN	NaN	4.718499	NaN	NaN	NaN
1949-02-01	118	NaN	NaN	6.0	NaN	4.770685	0.052186	NaN	NaN
1949-03-01	132	NaN	NaN	14.0	NaN	4.882802	0.112117	NaN	NaN
1949-04-01	129	NaN	NaN	-3.0	NaN	4.859812	-0.022990	NaN	NaN
1949-05-01	121	NaN	NaN	-8.0	NaN	4.795791	-0.064022	NaN	NaN
1949-06-01	135	NaN	NaN	14.0	NaN	4.905275	0.109484	NaN	NaN
1949-07-01	148	NaN	NaN	13.0	NaN	4.997212	0.091937	NaN	NaN
1949-08-01	148	NaN	NaN	0.0	36.0	4.997212	0.000000	NaN	NaN
1949-09-01	136	NaN	NaN	-12.0	18.0	4.912655	-0.084557	NaN	NaN
1949-10-01	119	NaN	NaN	-17.0	-13.0	4.779123	-0.133531	NaN	NaN

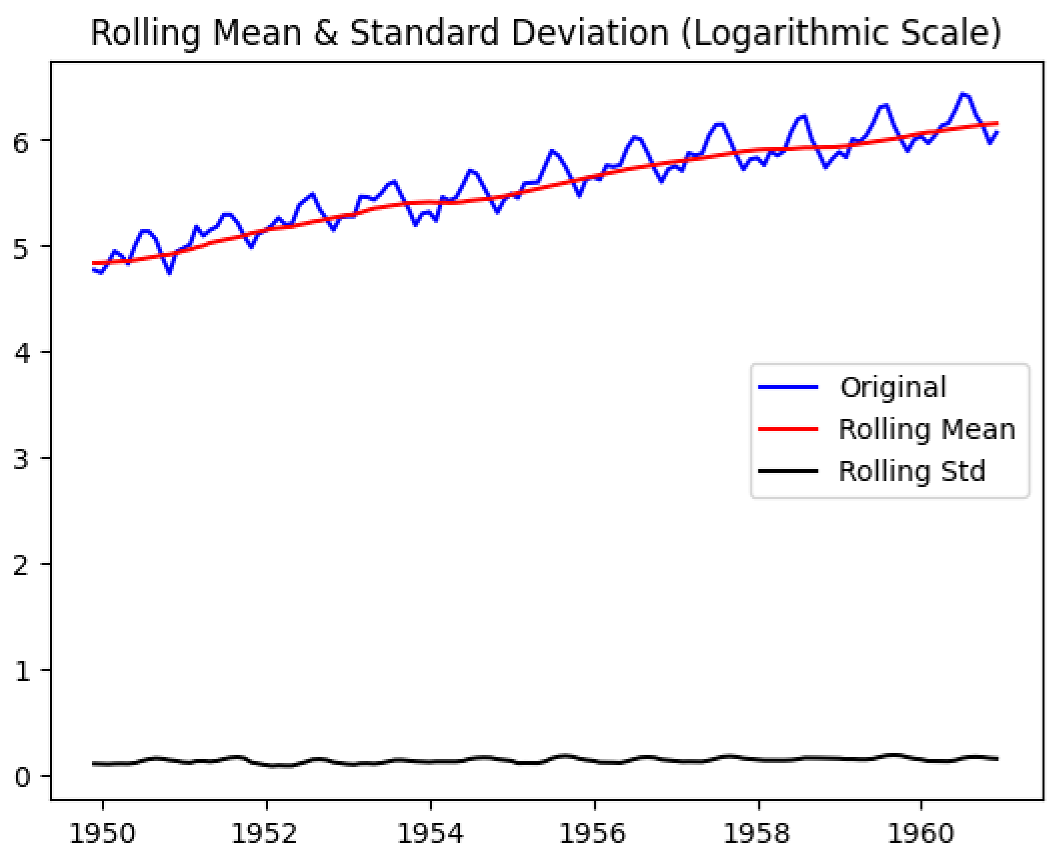
In [108…

```
df.dropna(inplace=True)
```

In [109…

```
plt.plot(df['log_value'], color='blue', label='Original')
plt.plot(df['SMA_log'], color='red', label='Rolling Mean')
plt.plot(df['MSTD_log'], color='black', label='Rolling Std')
plt.legend(loc='best')
plt.title('Rolling Mean & Standard Deviation (Logarithmic Scale)')
```

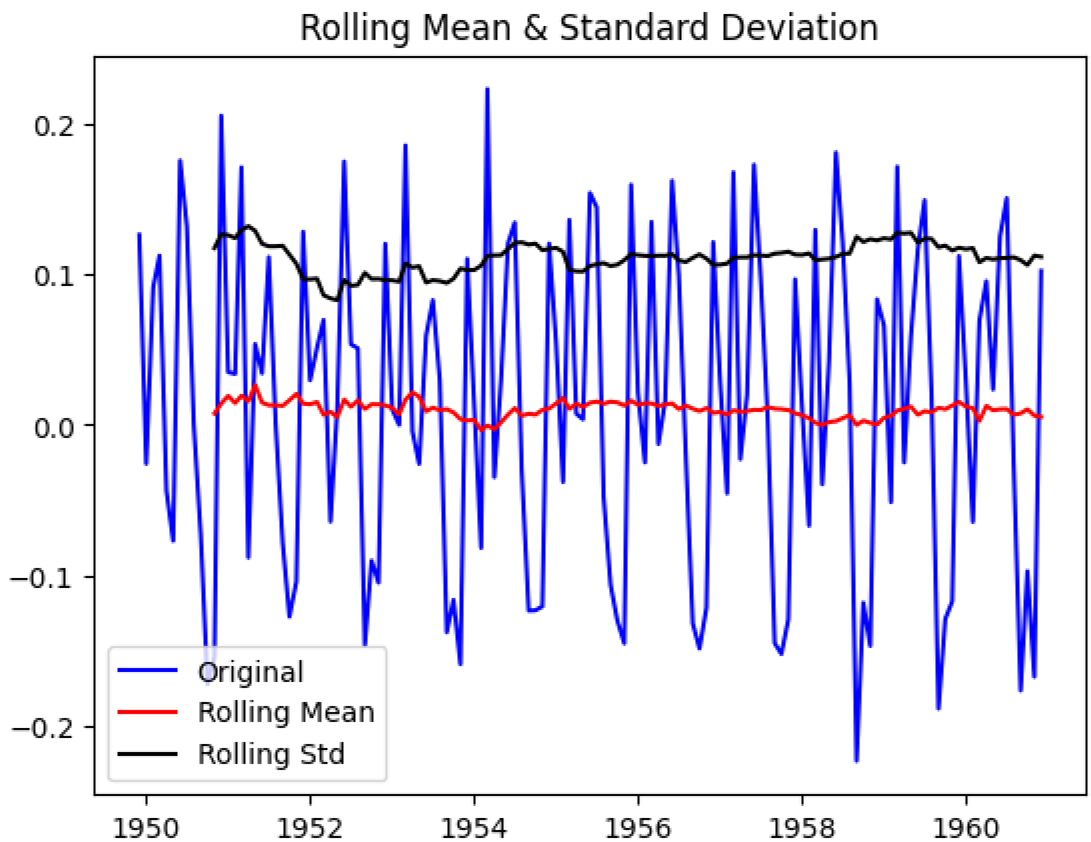
Out[109]: Text(0.5, 1.0, 'Rolling Mean & Standard Deviation (Logarithmic Scale)')



In [110…

```
#Determine rolling statistics
movingAverage = df['log_diff'].rolling(window=12).mean()
movingSTD = df['log_diff'].rolling(window=12).std()

#Plot rolling statistics
plt.plot(df['log_diff'], color='blue', label='Original')
```

```
plt.plot(movingAverage, color='red', label='Rolling Mean')
plt.plot(movingSTD, color='black', label='Rolling Std')
plt.legend(loc='best')
plt.title('Rolling Mean & Standard Deviation')
plt.show(block=False)
```

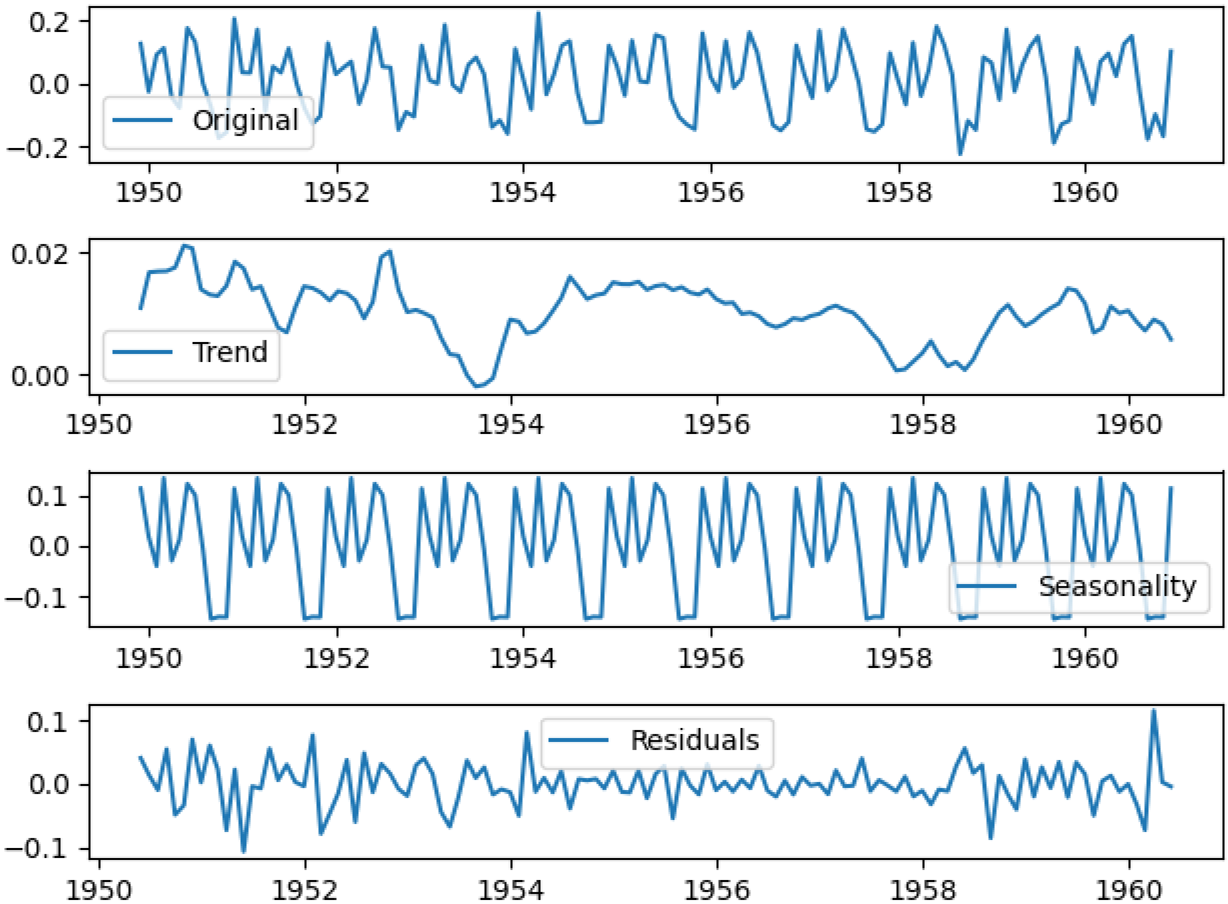


In [111…
```
#Perform Dickey-Fuller test:
print('Results of Dickey Fuller Test:')
airpass_test_log = adfuller(df['log_diff'], autolag='AIC')
dfoutput_log = pd.Series(airpass_test_log[0:4], index=['Test Statistic','p-value','#Lags
for key,value in airpass_test_log[4].items():
    dfoutput_log['Critical Value (%s)'%key] = value
print(dfoutput_log)
```

```
Results of Dickey Fuller Test:
Test Statistic                 -3.122207
p-value                         0.024953
#Lags Used                     13.000000
Number of Observations Used   119.000000
Critical Value (1%)            -3.486535
Critical Value (5%)            -2.886151
Critical Value (10%)           -2.579896
dtype: float64
```

In [113…
```
from statsmodels.tsa.seasonal import seasonal_decompose
decomposition = seasonal_decompose(df['log_diff'])

trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid

plt.subplot(411)
plt.plot(df['log_diff'], label='Original')
plt.legend(loc='best')

plt.subplot(412)
```

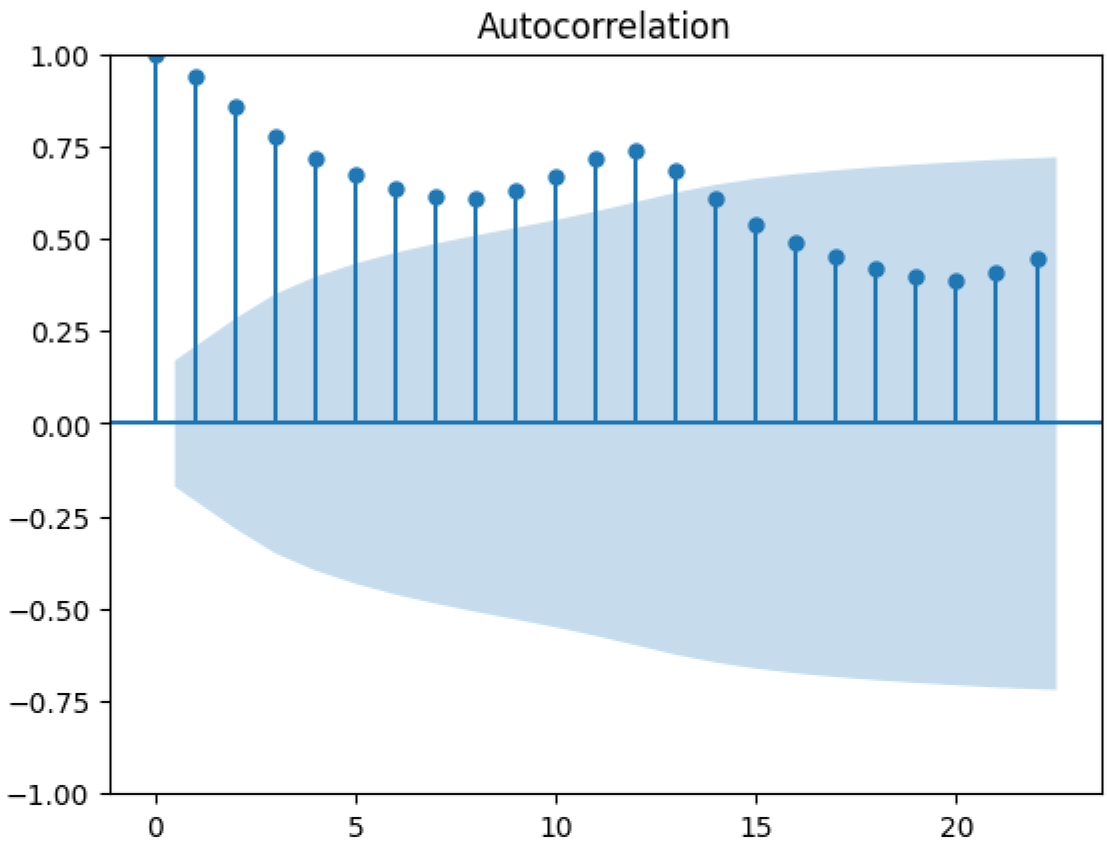
```python
plt.plot(trend, label='Trend')
plt.legend(loc='best')

plt.subplot(413)
plt.plot(seasonal,label='Seasonality')
plt.legend(loc='best')

plt.subplot(414)
plt.plot(residual, label='Residuals')
plt.legend(loc='best')
plt.tight_layout()
```

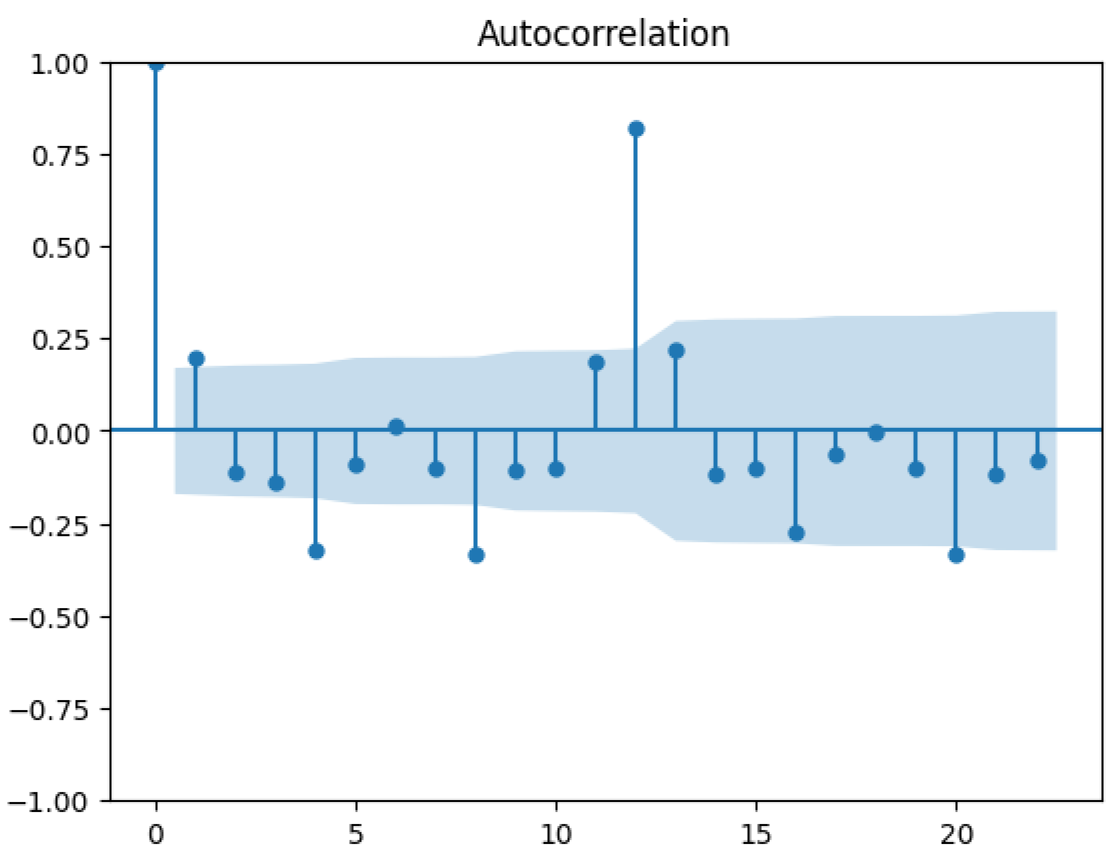


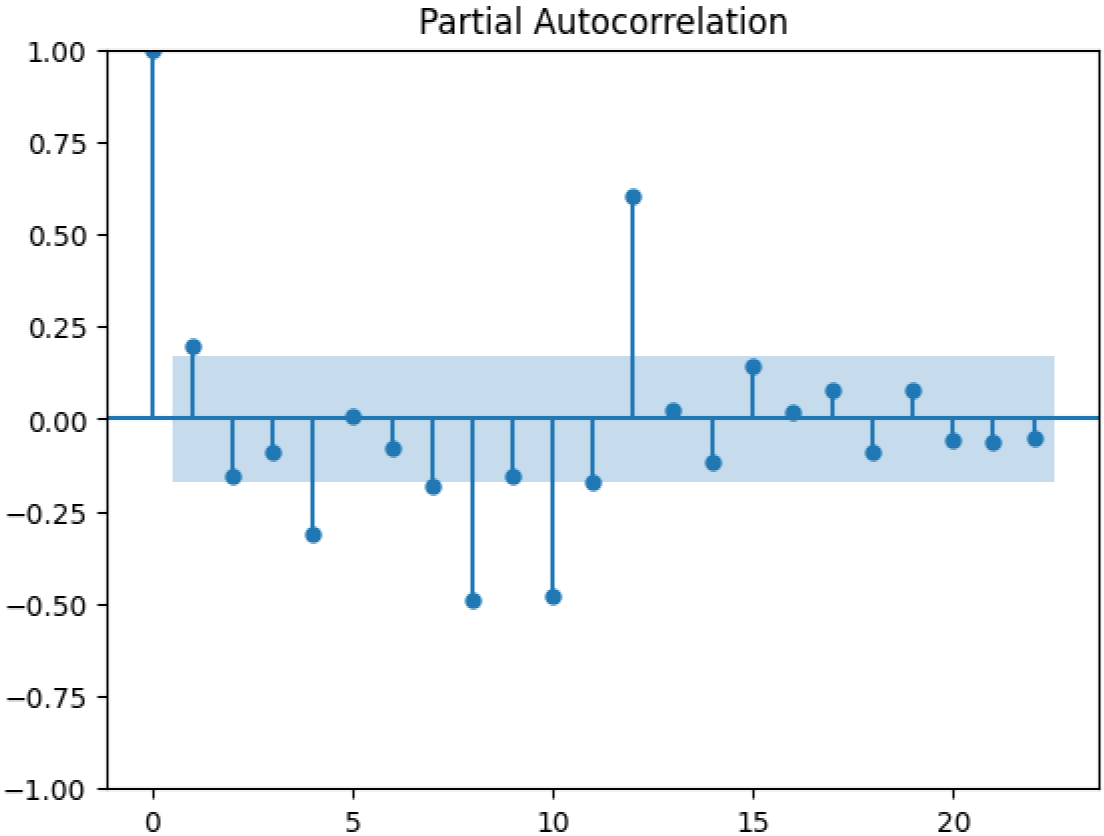
In [114…
```python
from statsmodels.tsa.stattools import acf, pacf
```

In [115…
```python
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf
```

In [116…
```python
plot_acf(df['value'])
plt.show()


plot_acf(df['log_diff'])
plt.show()
plot_pacf(df['log_diff'])
plt.show()
```


Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20


Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20



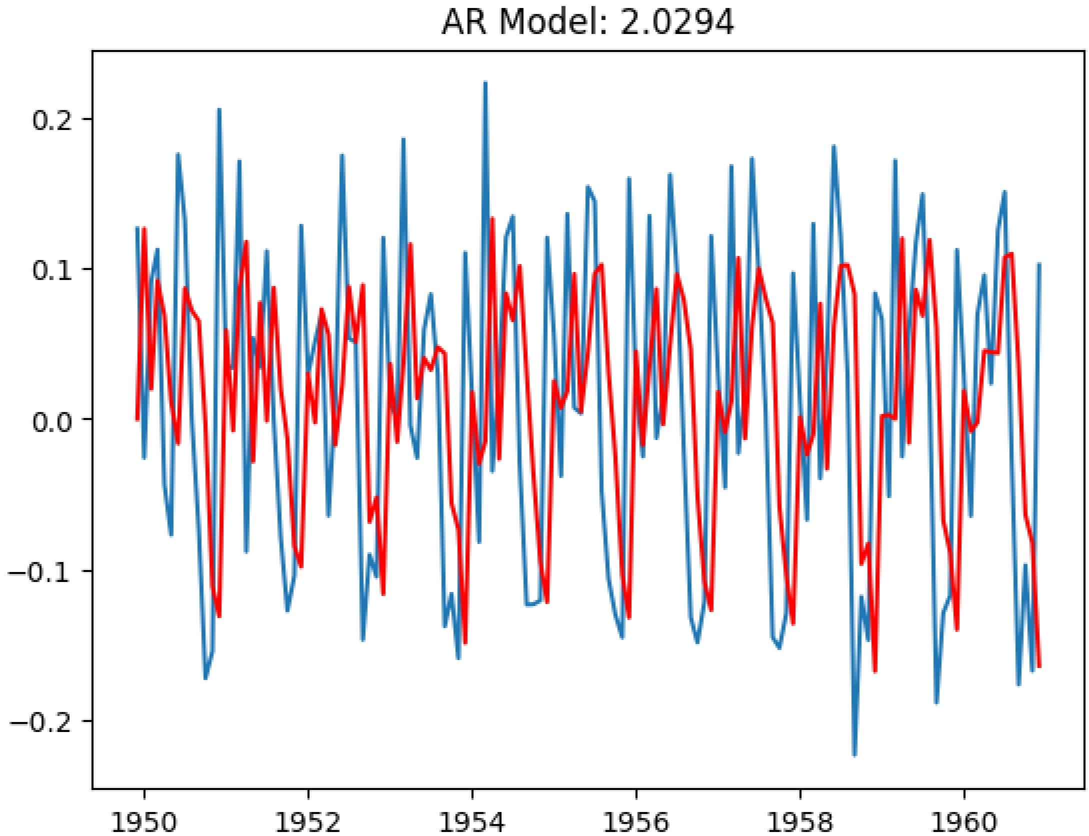
In [ ]:
```
from statsmodels.tsa.arima_model import ARIMA
import warnings
warnings.filterwarnings('ignore')
```

In [133…
```
from statsmodels.tsa.arima.model import ARIMA
ts_log = df['log_diff'].dropna()
```

AR MODEL (2,1,0)

In [134…
```
model1 = ARIMA(ts_log, order=(2,1,0))
results_AR1 = model1.fit()
plt.plot(ts_log)
plt.plot(results_AR1.fittedvalues, color='red')
plt.title('AR Model: %.4f'%sum((results_AR1.fittedvalues - ts_log)**2))
print('Plotting AR model')
```

```
Plotting AR model
```

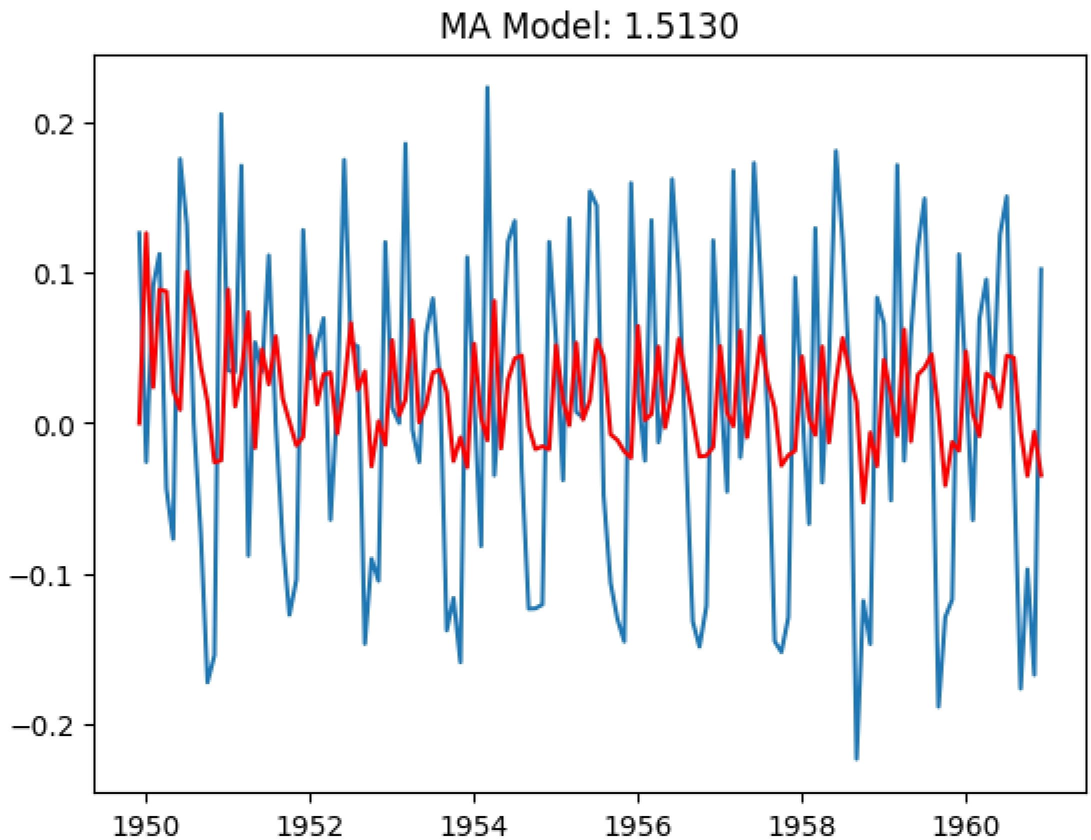


MA MODEL (0,1,2)

In [137…

```
model2 = ARIMA(ts_log, order=(0,1,2))
results_AR2 = model2.fit()
plt.plot(ts_log)
plt.plot(results_AR2.fittedvalues, color='red')
plt.title('MA Model: %.4f'%sum((results_AR2.fittedvalues - ts_log)**2))
print('Plotting MA model')
```

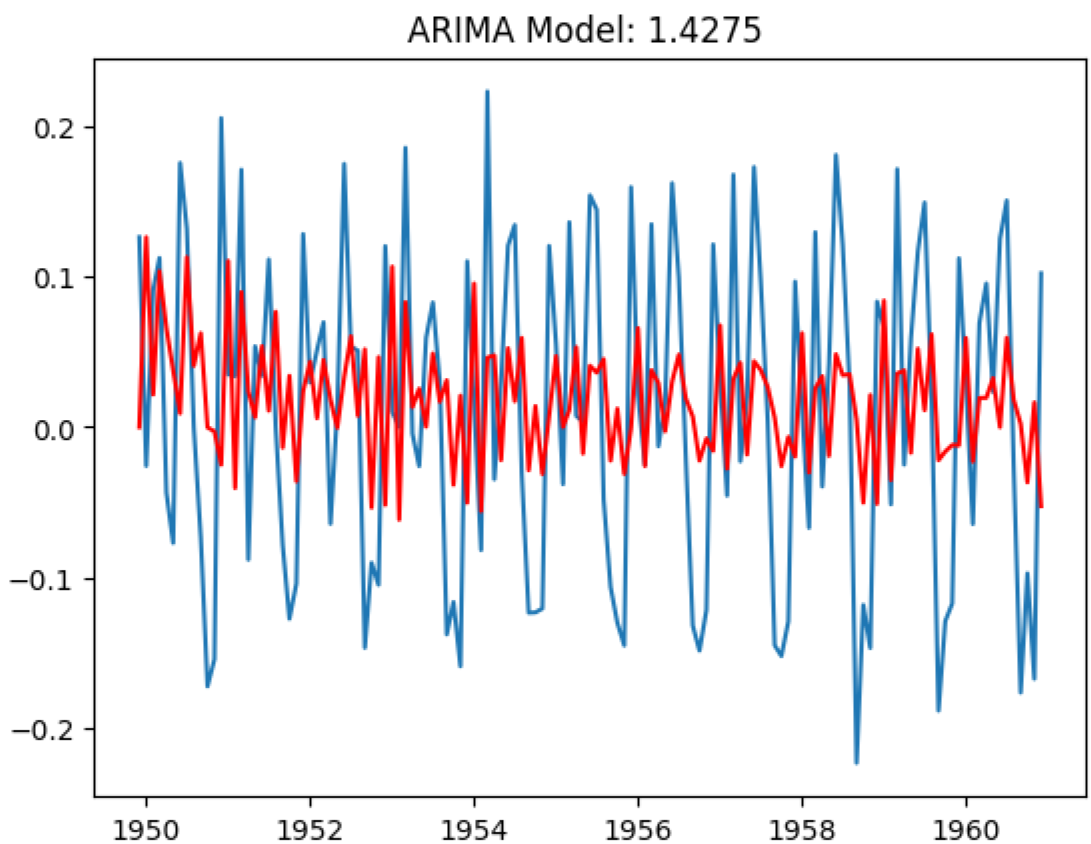
```
Plotting MA model
```



ARIMA MODEL (2,1,2)

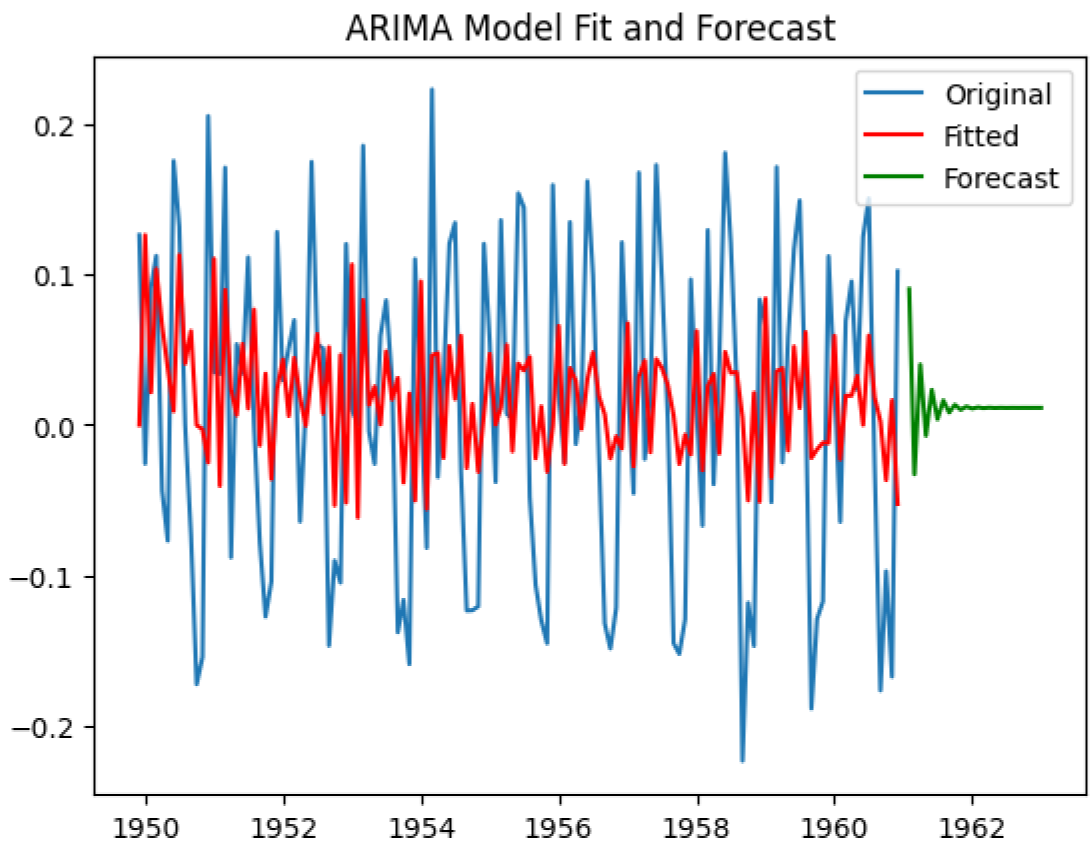
In [135…

```
model3 = ARIMA(ts_log, order=(2,1,2))
result_AR3 = model3.fit()
plt.plot(ts_log)
plt.plot(result_AR3.fittedvalues, color='red')
plt.title('ARIMA Model: %.4f '%sum((result_AR3.fittedvalues - ts_log)**2))
plt.show()
```



In [142…

```python
forecast_periods = 24
forecast = result_AR3.forecast(steps=forecast_periods)
# Assuming airpass_log_diff is your time series data
plt.plot(df['log_diff'], label='Original')
plt.plot(result_AR3.fittedvalues, color='red', label='Fitted')

# Plotting forecasted values
forecast_index = pd.date_range(start=df['log_value'].index[-1], periods=forecast_periods
plt.plot(forecast_index, forecast, color='green', label='Forecast')

plt.title('ARIMA Model Fit and Forecast')
plt.legend()
plt.show()


pd.DataFrame(forecast)
```



Out[142]:

	predicted_mean
1961-01-01	0.090420
1961-02-01	-0.032819
1961-03-01	0.040221
1961-04-01	-0.007137
1961-05-01	0.023355
1961-06-01	0.003712
1961-07-01	0.016365
1961-08-01	0.008215
1961-09-01	0.013465
1961-10-01	0.010083
1961-11-01	0.012262
1961-12-01	0.010858

1962-01-01	0.011762
1962-02-01	0.011180
1962-03-01	0.011555
1962-04-01	0.011313
1962-05-01	0.011469
1962-06-01	0.011369
1962-07-01	0.011433
1962-08-01	0.011392
1962-09-01	0.011419
1962-10-01	0.011401
1962-11-01	0.011412
1962-12-01	0.011405

In [143…
```
from statsmodels.tsa.statespace.sarimax import SARIMAX
```

In [144…
```
# Fit a SARIMA model
sarima_model = SARIMAX(df['log_diff'], order=(1, 1, 1), seasonal_order=(1, 1, 1, 12))
fit_sarima = sarima_model.fit()
```

In [145…
```
# Forecast with the SARIMA model
forecast_steps = 24  # Assuming you want to forecast the next 24 months
sarima_forecast = fit_sarima.get_forecast(steps=forecast_steps)
sarima_forecast_values = sarima_forecast.predicted_mean
sarima_forecast_conf_int = sarima_forecast.conf_int()
```

In [146…
```
# Table of SARIMA forecasted values
forecast_index = pd.date_range(start=df.index[-1], periods=forecast_steps+1, freq='M')[1
sarima_forecast_table = pd.DataFrame({
    'Date': forecast_index,
    'SARIMA Forecasted Passengers (Thousands)': sarima_forecast_values
})
print(sarima_forecast_table)
```

```
                 Date  SARIMA Forecasted Passengers (Thousands)
1961-01-01 1961-01-31                                  0.036420
1961-02-01 1961-02-28                                 -0.058247
1961-03-01 1961-03-31                                  0.119414
1961-04-01 1961-04-30                                  0.023263
1961-05-01 1961-05-31                                  0.034161
1961-06-01 1961-06-30                                  0.134774
1961-07-01 1961-07-31                                  0.138131
1961-08-01 1961-08-31                                 -0.003555
1961-09-01 1961-09-30                                 -0.181645
1961-10-01 1961-10-31                                 -0.117429
1961-11-01 1961-11-30                                 -0.145355
1961-12-01 1961-12-31                                  0.102986
1962-01-01 1962-01-31                                  0.035098
1962-02-01 1962-02-28                                 -0.059252
1962-03-01 1962-03-31                                  0.114853
1962-04-01 1962-04-30                                  0.028383
1962-05-01 1962-05-31                                  0.032744
1962-06-01 1962-06-30                                  0.133447
1962-07-01 1962-07-31                                  0.138538
1962-08-01 1962-08-31                                 -0.005909
1962-09-01 1962-09-30                                 -0.181813
1962-10-01 1962-10-31                                 -0.116407
```

```
1962-11-01 1962-11-30                                        -0.147661
1962-12-01 1962-12-31                                         0.102349
```

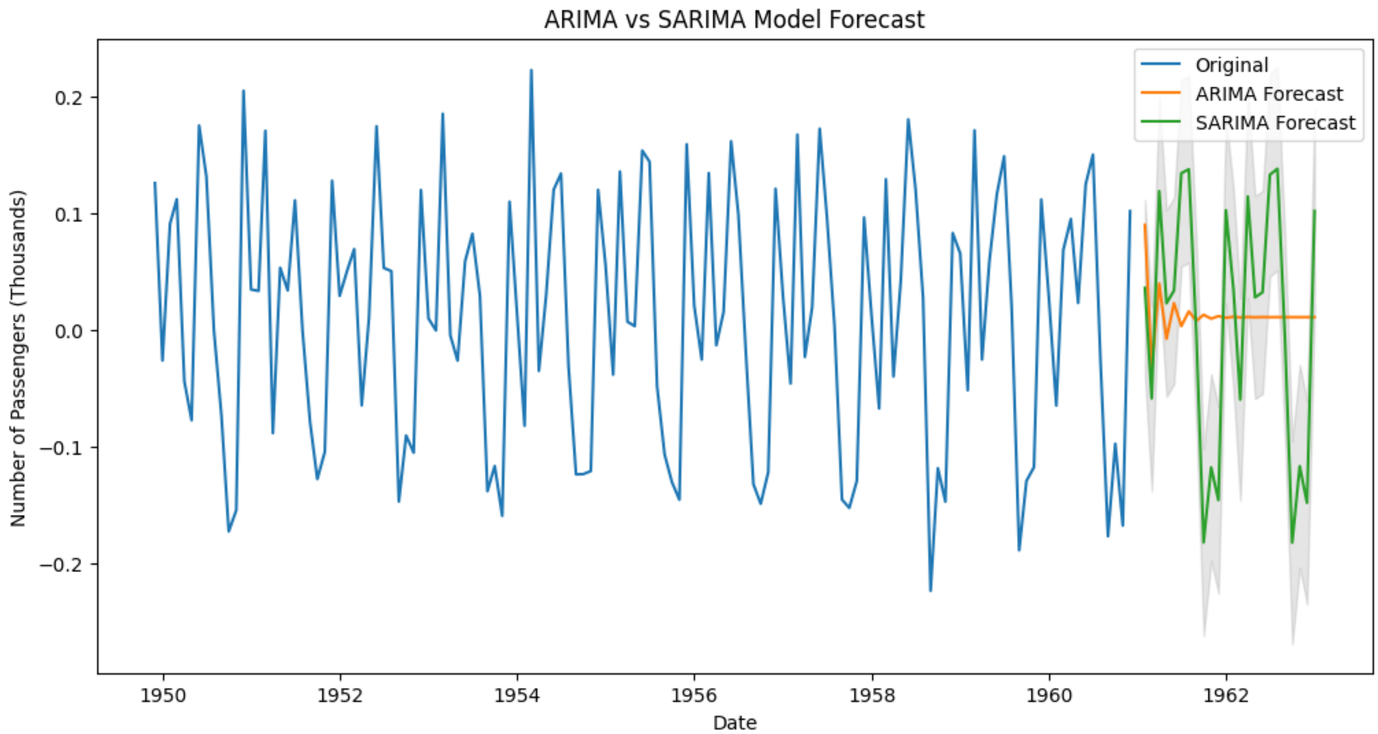
In [148…

```
comparison_table = pd.DataFrame({
    'Date': forecast_index,
    'ARIMA Forecast': forecast,
    'SARIMA Forecast': sarima_forecast_values
})
print(comparison_table)
```

```
                                Date  ARIMA Forecast  SARIMA Forecast
1961-01-01 1961-01-31        0.090420         0.036420
1961-02-01 1961-02-28       -0.032819        -0.058247
1961-03-01 1961-03-31        0.040221         0.119414
1961-04-01 1961-04-30       -0.007137         0.023263
1961-05-01 1961-05-31        0.023355         0.034161
1961-06-01 1961-06-30        0.003712         0.134774
1961-07-01 1961-07-31        0.016365         0.138131
1961-08-01 1961-08-31        0.008215        -0.003555
1961-09-01 1961-09-30        0.013465        -0.181645
1961-10-01 1961-10-31        0.010083        -0.117429
1961-11-01 1961-11-30        0.012262        -0.145355
1961-12-01 1961-12-31        0.010858         0.102986
1962-01-01 1962-01-31        0.011762         0.035098
1962-02-01 1962-02-28        0.011180        -0.059252
1962-03-01 1962-03-31        0.011555         0.114853
1962-04-01 1962-04-30        0.011313         0.028383
1962-05-01 1962-05-31        0.011469         0.032744
1962-06-01 1962-06-30        0.011369         0.133447
1962-07-01 1962-07-31        0.011433         0.138538
1962-08-01 1962-08-31        0.011392        -0.005909
1962-09-01 1962-09-30        0.011419        -0.181813
1962-10-01 1962-10-31        0.011401        -0.116407
1962-11-01 1962-11-30        0.011412        -0.147661
1962-12-01 1962-12-31        0.011405         0.102349
```

In [149…

```
# Plot comparison
plt.figure(figsize=(12, 6))
plt.plot(df['log_diff'], label='Original')
plt.plot(forecast_index, forecast, label='ARIMA Forecast')
plt.plot(forecast_index, sarima_forecast_values, label='SARIMA Forecast')
plt.fill_between(forecast_index, sarima_forecast_conf_int.iloc[:, 0], sarima_forecast_co
plt.title('ARIMA vs SARIMA Model Forecast')
plt.xlabel('Date')
plt.ylabel('Number of Passengers (Thousands)')
plt.legend()
plt.show()
```



In [150…

```
# Calculate average and peak forecasted values
avg_forecasted_passengers = forecast.mean()
peak_forecasted_passengers = forecast.max()

print(f'Average Forecasted Passengers (Thousands): {avg_forecasted_passengers:.2f}')
print(f'Peak Forecasted Passengers (Thousands): {peak_forecasted_passengers:.2f}')
```

```
Average Forecasted Passengers (Thousands): 0.01
Peak Forecasted Passengers (Thousands): 0.09
```

Strategic Business Insights:

1. Fleet Management: The average forecasted passenger number indicates the need for maintaining or increasing the current fleet size to accommodate the expected passenger volume.
2. Optimize Ticket Pricing: Monitoring peak periods as indicated by peak forecasted values can help in dynamic pricing strategies to maximize revenue.
3. Marketing and Promotions: Plan targeted marketing campaigns during low demand periods to boost ticket sales and optimize resource allocation.
4. Resource Allocation: Ensuring adequate staffing and resources during peak periods to maintain service quality and customer satisfaction.