EXPERIMENT 7

Implement program for decomposing time series data into trend and seasonality

AIM:

To Implement program for decomposing time series data into trend and seasonality.

PROCEDURE:

1️⃣ Upload Dataset 📂

- Load the dataset (`Crop_recommendation.csv`) into Google Colab using `files.upload()`.

2️⃣ Prepare Time Series Data 📊

- Add a **date index** (assuming daily records).
- Select a column for decomposition (**e.g., "rainfall"**).

3️⃣ Define Decomposition Parameters ⚙️

- Set a **seasonal period** (must be an **odd** number, e.g., `29`).

4️⃣ Plot the Original Time Series 📈

- Visualize the raw data before decomposition.

5️⃣ Apply STL Decomposition 🔄

- Use `STL(time_series, seasonal=29, robust=True)`.
- Decompose into **Trend, Seasonality, and Residuals**.

6️⃣ Visualize Decomposed Components 🎨

- Plot the **trend, seasonal, and residual components** separately.

7️⃣ Analyze & Interpret 📌

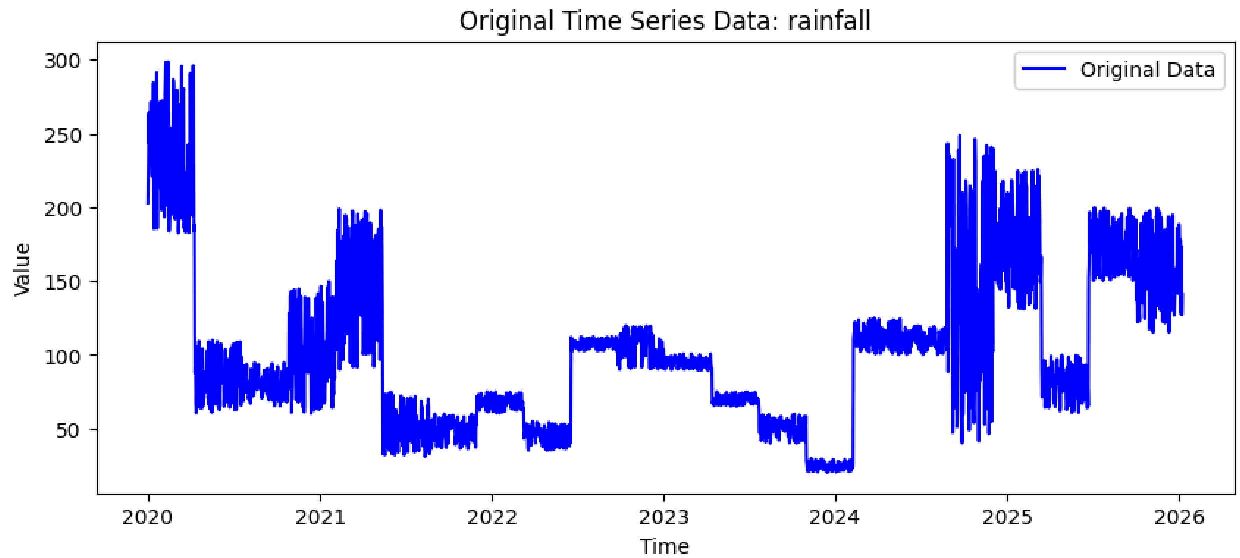
- Observe patterns in trend, seasonality, and noise for insights.

CODE:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.seasonal import STL
from google.colab import files

# Step 1: Upload the CSV File
uploaded = files.upload()

# Get the uploaded file name dynamically
file_name = list(uploaded.keys())[0]

# Step 2: Load the Dataset
df = pd.read_csv(file_name)

# Step 3: Create a Fake Time Index (Simulating Daily Data)
df['Date'] = pd.date_range(start="2020-01-01", periods=len(df), freq='D')
df.set_index('Date', inplace=True)

# Step 4: Select a Time Series Column (Rainfall)
column_name = "rainfall"
if column_name not in df.columns:
    raise ValueError(f"Column '{column_name}' not found in dataset. Available columns:
{df.columns}")

time_series = df[column_name]

# Step 5: Define an Odd Seasonal Period (e.g., 29)
period = 29  # Must be an odd number ≥ 3

# Step 6: Plot Original Data
plt.figure(figsize=(10, 4))
plt.plot(time_series, label="Original Data", color='blue')
plt.title(f"Original Time Series Data: {column_name}")
plt.xlabel("Time")
plt.ylabel("Value")
```

```
plt.legend()
plt.show()

# Step 7: Apply Time Series Decomposition
stl = STL(time_series, seasonal=period, robust=True)
result = stl.fit()

# Step 8: Plot the Decomposed Components
plt.figure(figsize=(12, 8))

plt.subplot(3, 1, 1)
plt.plot(result.trend, label="Trend", color="red")
plt.title("Trend Component")
plt.legend()

plt.subplot(3, 1, 2)
plt.plot(result.seasonal, label="Seasonality", color="green")
plt.title("Seasonality Component")
plt.legend()

plt.subplot(3, 1, 3)
plt.plot(result.resid, label="Residuals", color="purple")
plt.title("Residual Component")
plt.legend()

plt.tight_layout()
plt.show()

# Step 9: Display Sample Values
print("\nTrend Sample:\n", result.trend.tail())
print("\nSeasonality Sample:\n", result.seasonal.tail())
print("\nResidual Sample:\n", result.resid.tail())
```

OUTPUT:



Trend Sample:
Date
2026-01-04   153.517953
2026-01-05   146.999499
2026-01-06   140.188421
2026-01-07   133.042420
2026-01-08   125.576507
Name: trend, dtype: float64

Seasonality Sample:
Date
2026-01-04   11.513146
2026-01-05   -19.794404
2026-01-06   -15.592670
2026-01-07   1.761364
2026-01-08   17.800543
Name: season, dtype: float64

Residual Sample:
Date
2026-01-04   12.743409
2026-01-05   0.719515
2026-01-06   48.727088
2026-01-07   -7.628491
2026-01-08   -2.440009

Name: resid, dtype: float64
RESULT:
The STL decomposition successfully splits the time series data into **Trend, Seasonality, and Residuals**. The **trend component** shows the overall direction of data, the **seasonal component** captures repeating patterns, and the **residual component** represents random variations. 📈✅