EXP No:10 Develop vector auto regression model for multivariate time series data forecasting.

Aim:

To analyze and forecast electric production using a Vector AutoRegression (VAR) model by transforming the univariate time series data into a multivariate format through lagged variables.

Objectives:

- Load and preprocess electric production data.
- Perform EDA and check for stationarity.
- Create lagged features for VAR modeling.
- Train and test the VAR model with optimal lag selection.
- Forecast future values and evaluate model performance using MAE and RMSE.
- Visualize actual vs. forecasted production

Background:

Forecasting electric production is essential for energy planning and management. This project uses time series analysis with a VAR model, applying lagged values to capture trends and dependencies. After ensuring stationarity, the model is trained and evaluated to provide accurate future predictions.

Code:

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from statsmodels.tsa.api import VAR

from statsmodels.tsa.stattools import adfuller

from sklearn.metrics import mean_absolute_error, mean_squared_error



# Step 1: Load and Preprocess Data

# Load the dataset

data = pd.read_csv(r"D:\Downloads\Electric_Production.csv")
```

```
# Convert DATE to datetime and set as index
data['DATE'] = pd.to_datetime(data['DATE'])
data.set_index('DATE', inplace=True)

# Rename column for clarity
data.rename(columns={'IPG2211A2N': 'Electric_Production'}, inplace=True)

# Step 2: Exploratory Data Analysis (EDA)
# Plot the time series
plt.figure(figsize=(10, 6))
plt.plot(data['Electric_Production'], label='Electric Production')
plt.title('Electric Production Over Time')
plt.xlabel('Date')
plt.ylabel('Electric Production')
plt.legend()
plt.show()

# Check for missing values
print("Missing Values:\n", data.isnull().sum())

# Summary statistics
print("Summary Statistics:\n", data.describe())
```

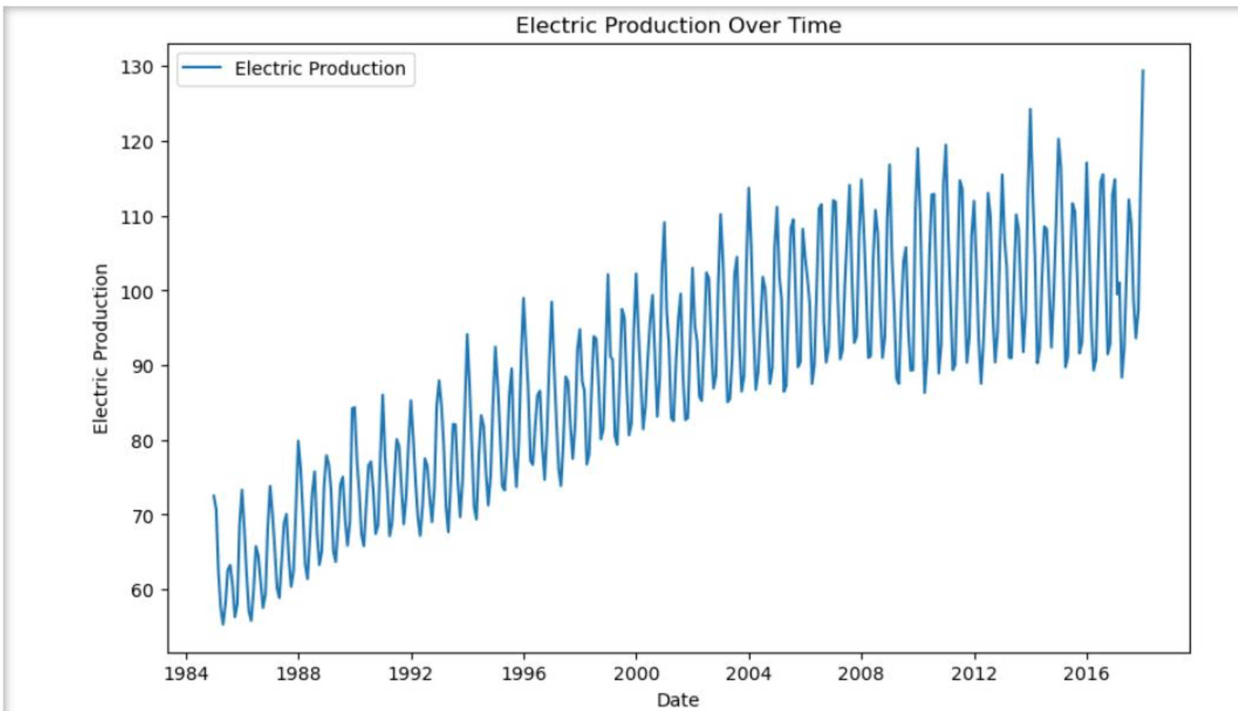
```
# Step 3: Check Stationarity
def adf_test(series, title=''):
    result = adfuller(series.dropna())
    print(f'ADF Test for {title}:')
    print(f'ADF Statistic: {result[0]}')
    print(f'p-value: {result[1]}')
    print('Stationary' if result[1] < 0.05 else 'Non-Stationary')
    print()

adf_test(data['Electric_Production'], 'Electric Production')

# Apply differencing if non-stationary
data_diff = data.diff().dropna()

# Re-check stationarity after differencing
adf_test(data_diff['Electric_Production'], 'Differenced Electric Production')

# Step 4: Prepare Data for VAR
# Create lagged variables to simulate multivariate data
var_data = pd.DataFrame({
    'Electric_Production': data_diff['Electric_Production'],
    'Lag1': data_diff['Electric_Production'].shift(1),
```

```
    'Lag2': data_diff['Electric_Production'].shift(2)
}).dropna()

# Step 5: Split Data into Training and Testing Sets
# Split data into train and test sets (80% train, 20% test)
train_size = int(len(var_data) * 0.8)
train_data = var_data.iloc[:train_size]
test_data = var_data.iloc[train_size:]

print("Train Data Shape:", train_data.shape)
print("Test Data Shape:", test_data.shape)

# Step 6: Fit the VAR Model
# Fit VAR model
model = VAR(train_data)
model_fitted = model.fit(maxlags=12, ic='aic')  # Select lag based on AIC

# Summary of the model
print("\nVAR Model Summary:\n")
print(model_fitted.summary())

# Step 7: Forecasting
# Forecast for the test period
```

```
forecast_steps = len(test_data)
forecast = model_fitted.forecast(train_data.values[-model_fitted.k_ar:], steps=forecast_steps)

# Convert forecast to DataFrame (only take the first column for Electric_Production)
forecast_index = test_data.index
forecast_df = pd.DataFrame(forecast[:, 0], index=forecast_index, columns=['Forecast'])

# Reverse differencing to get original scale
last_observed = data['Electric_Production'].iloc[len(data) - len(test_data) - 1]
forecast_df['Forecast'] = last_observed + forecast_df['Forecast'].cumsum()

# Plot actual vs forecast
plt.figure(figsize=(10, 6))
plt.plot(data['Electric_Production'], label='Actual')
plt.plot(forecast_df['Forecast'], label='Forecast', linestyle='--')
plt.title('Actual vs Forecasted Electric Production')
plt.xlabel('Date')
plt.ylabel('Electric Production')
plt.legend()
plt.show()

# Step 8: Evaluate Model Performance
# Calculate evaluation metrics
```

```
actual = data['Electric_Production'].iloc[-len(test_data):]

mae = mean_absolute_error(actual, forecast_df['Forecast'])

rmse = np.sqrt(mean_squared_error(actual, forecast_df['Forecast']))


print(f'\nMean Absolute Error (MAE): {mae:.2f}')

print(f'Root Mean Squared Error (RMSE): {rmse:.2f}')
```

Output:



Missing Values:

 Electric_Production   0

dtype: int64

Summary Statistics:

        Electric_Production

count 397.000000

mean 88.847218

std 15.387834

min 55.315100

25% 77.105200

50% 89.779500

75% 100.524400

max 129.404800

ADF Test for Electric Production:

ADF Statistic: -2.256990350047245

p-value: 0.1862146911658677

Non-Stationary

ADF Test for Differenced Electric Production:

ADF Statistic: -7.104890882267318

p-value: 4.0777865655392766e-10

Stationary

Train Data Shape: (315, 3)

Test Data Shape: (79, 3)

VAR Model Summary:

Summary of Regression Results

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Model:	VAR
Method:	OLS
Date:	Tue, 15, Apr, 2025
Time:	12:41:56

No. of Equations:	3.00000	BIC:	-130.073
Nobs:	314.000	HQIC:	-130.159
Log likelihood:	19119.3	FPE:	2.80387e-57
AIC:	-130.216	Det(Omega_mle):	2.69939e-57

Results for equation Electric_Production

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	coefficient	std. error	t-stat	prob
const	0.190322	0.235740	0.807	0.419
L1.Electric_Production	0.241504	0.046854	5.154	0.000
L1.Lag1	-0.317688	0.045401	-6.997	0.000
L1.Lag2	-0.569448	0.046921	-12.136	0.000

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Results for equation Lag1

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	coefficient	std. error	t-stat	prob
const	0.000000	0.000000	0.483	0.629
L1.Electric_Production	1.000000	0.000000	31738740220841600.000	0.000
L1.Lag1	-0.000000	0.000000	-1.818	0.069
L1.Lag2	0.000000	0.000000	7.037	0.000

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Results for equation Lag2

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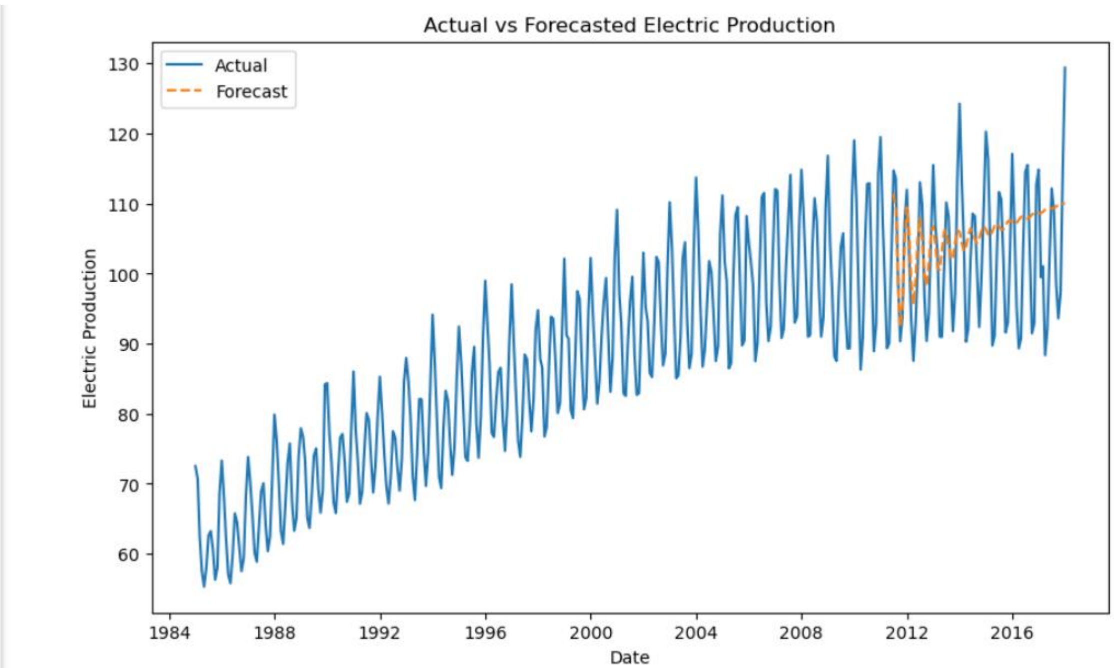
	coefficient	std. error	t-stat	prob
const	0.000000	0.000000	0.198	0.843
L1.Electric_Production	-0.000000	0.000000	-0.996	0.319
L1.Lag1	1.000000	0.000000	18517075836167264.000	0.000
L1.Lag2	0.000000	0.000000	0.995	0.320

==

Correlation matrix of residuals

	Electric_Production	Lag1	Lag2
Electric_Production	1.000000	-0.012320	0.004321
Lag1	-0.012320	1.000000	0.451933
Lag2	0.004321	0.451933	1.000000



Mean Absolute Error (MAE): 7.65

Root Mean Squared Error (RMSE): 9.34

Result:

Thus the program implement program for decomposing time series data into trend and seasonality.