EXP No:3 Implement linear regression model for time series data

Aim:

To analyze, visualize, and forecast electricity production using time series techniques and regression modeling.

Objective:

To explore trends, seasonality, and volatility in electricity production data and build a simple predictive model using linear regression.

Background:

1. **Time Series Analysis:** Understanding patterns in historical data using techniques like rolling mean, autocorrelation, and seasonal decomposition.
2. **Data Visualization:** Using Matplotlib and Seaborn to plot trends, seasonality, and variability in electricity production.
3. **Feature Engineering:** Creating a time-based numeric feature to model the trend in electricity production.
4. **Predictive Modeling:** Applying linear regression to forecast future electricity production values.
5. **Performance Evaluation:** Assessing the regression model's accuracy using mean squared error.

Code:

```
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from statsmodels.graphics.tsaplots import plot_acf

from pandas.plotting import register_matplotlib_converters

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression

from sklearn.metrics import mean_squared_error
```

```
import numpy as np

from statsmodels.tsa.seasonal import seasonal_decompose


# Registering converters to avoid warnings when plotting datetime values

register_matplotlib_converters()


# Load the dataset from the given file path

file_path = r"C:\Users\Lenovo\Downloads\Electric_Production.csv"

df = pd.read_csv(file_path)


# Checking the first few rows of the dataset to understand its structure

print(df.head())


# Convert 'DATE' column to datetime

df['DATE'] = pd.to_datetime(df['DATE'], errors='coerce')


# Ensure the data is sorted by date

df = df.sort_values('DATE')


# Set 'DATE' column as index

df.set_index('DATE', inplace=True)


# If 'IPG2211A2N' is the target column for time-series analysis
```

```
target_column = 'IPG2211A2N'

# Check if the target column exists
if target_column in df.columns:
    # Plot the time-series data
    plt.figure(figsize=(12, 6))
    plt.plot(df.index, df[target_column], label='IPG2211A2N')
    plt.title(f'Time Series of {target_column}')
    plt.xlabel('Date')
    plt.ylabel(target_column)
    plt.xticks(rotation=45)
    plt.grid(True)
    plt.legend()
    plt.show()

    # Rolling Mean (Moving Average) visualization
    rolling_mean = df[target_column].rolling(window=12).mean()
    plt.figure(figsize=(12, 6))
    plt.plot(df.index, df[target_column], label=f'{target_column} Data')
    plt.plot(df.index, rolling_mean, label='12-Month Rolling Mean', color='orange', linewidth=2)
    plt.title(f'{target_column} with Rolling Mean')
    plt.xlabel('Date')
    plt.ylabel(target_column)
```

```
plt.xticks(rotation=45)

plt.legend()

plt.grid(True)

plt.show()


# Plotting Autocorrelation

plt.figure(figsize=(12, 6))

plot_acf(df[target_column], lags=50)

plt.title(f'Autocorrelation of {target_column}')

plt.show()


# Seasonal Decomposition

decomposition = seasonal_decompose(df[target_column], model='additive', period=12)

plt.figure(figsize=(12, 8))

decomposition.plot()

plt.suptitle(f'Seasonal Decomposition of {target_column}')

plt.show()


# Compute and plot the rolling standard deviation (volatility)

rolling_std = df[target_column].rolling(window=12).std()

plt.figure(figsize=(12, 6))

plt.plot(df.index, rolling_std, label=f'Rolling Standard Deviation (12 months)', color='red')

plt.title(f'{target_column} Volatility (Rolling Std Dev)')
```

```
    plt.xlabel('Date')
    plt.ylabel('Standard Deviation')
    plt.xticks(rotation=45)
    plt.legend()
    plt.grid(True)
    plt.show()

    # Seasonal boxplot to observe yearly seasonality
    df['month'] = df.index.month
    plt.figure(figsize=(12, 6))
    sns.boxplot(x='month', y=target_column, data=df)
    plt.title(f'Seasonal Boxplot of {target_column}')
    plt.xlabel('Month')
    plt.ylabel(target_column)
    plt.xticks(ticks=range(12), labels=['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct',
'Nov', 'Dec'])
    plt.grid(True)
    plt.show()

    # ----------- Regression Model for Forecasting -----------

    # Create a new feature: numeric representation of the time (using the number of months)
    df['month_num'] = np.arange(len(df))
```

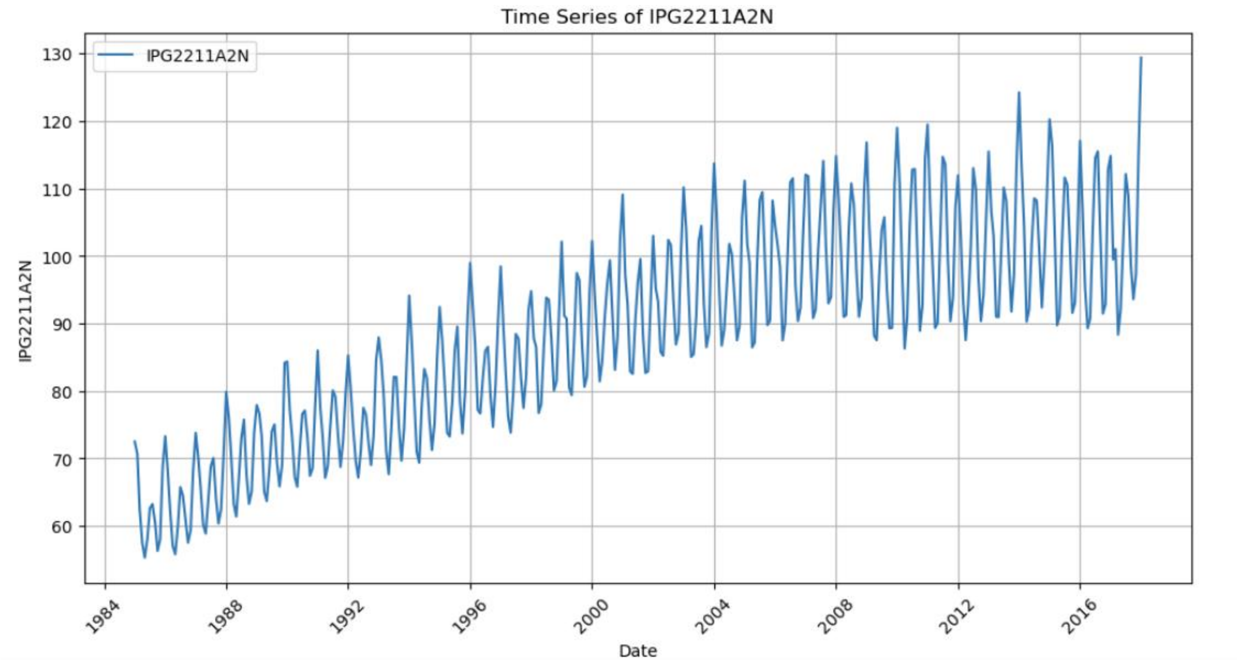
```
    # Prepare the features (X) and the target variable (y)

    X = df[['month_num']]  # Using 'month_num' as feature

    y = df[target_column]  # The target variable is the time series



    # Split data into train and test sets

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, shuffle=False)



    # Create and train the Linear Regression model

    model = LinearRegression()

    model.fit(X_train, y_train)



    # Make predictions on the test set

    y_pred = model.predict(X_test)



    # Plot actual vs predicted values

    plt.figure(figsize=(12, 6))

    plt.plot(df.index[len(X_train):], y_test, label='Actual Data', color='blue')

    plt.plot(df.index[len(X_train):], y_pred, label='Predicted Data', color='orange',
linestyle='dashed')

    plt.title(f'{target_column} - Actual vs Predicted')

    plt.xlabel('Date')

    plt.ylabel(target_column)

    plt.xticks(rotation=45)

    plt.legend()
```

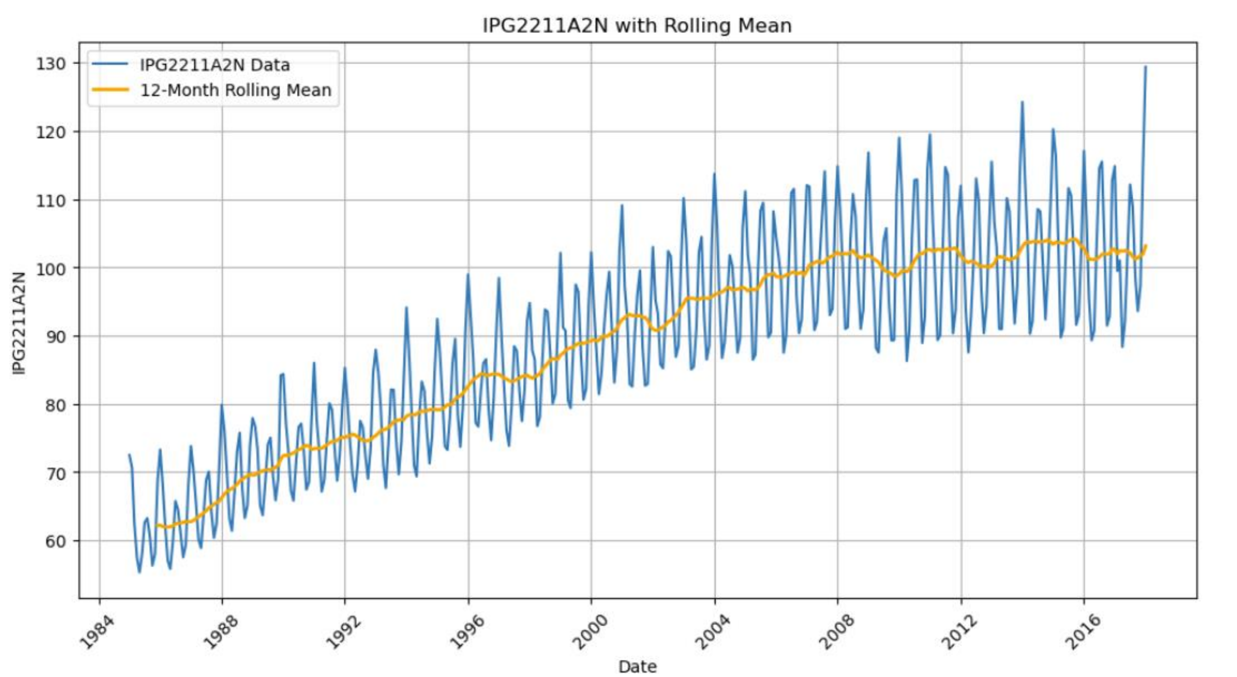
```
    plt.grid(True)

    plt.show()


    # Calculate and print the performance metrics (Mean Squared Error)

    mse = mean_squared_error(y_test, y_pred)

    print(f'Mean Squared Error of the Regression Model: {mse}')


else:

    print(f"Column '{target_column}' is not found in the dataset.")
```

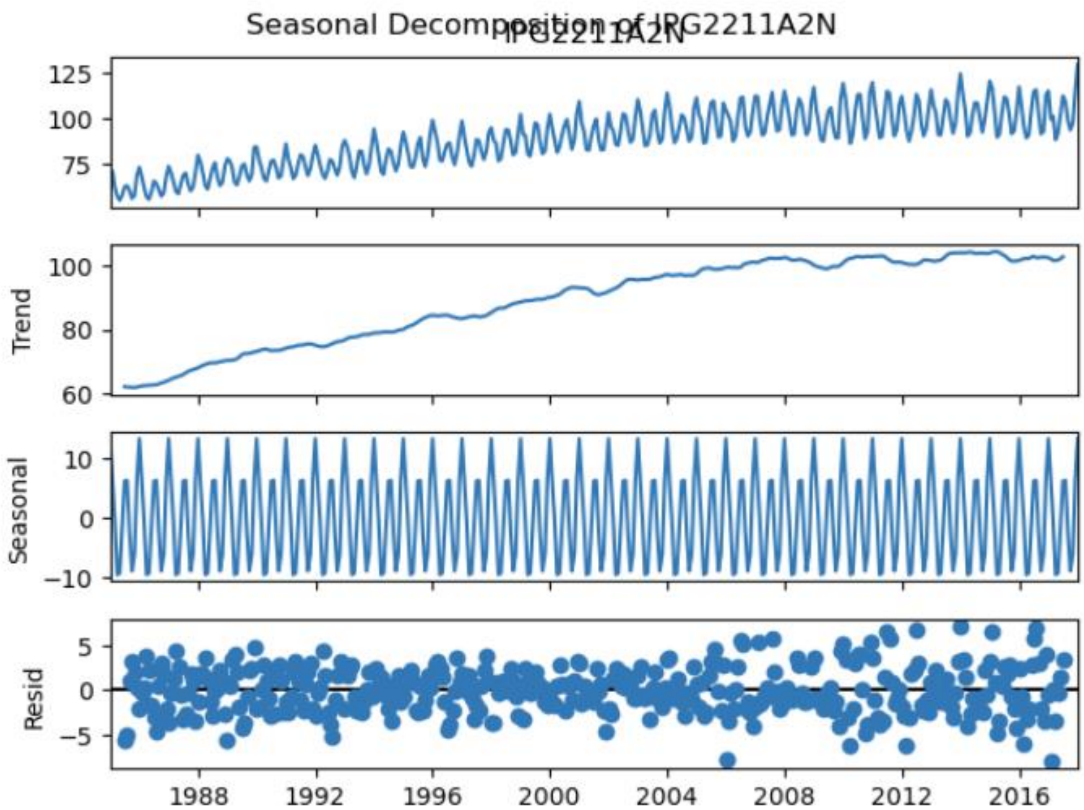
Output:

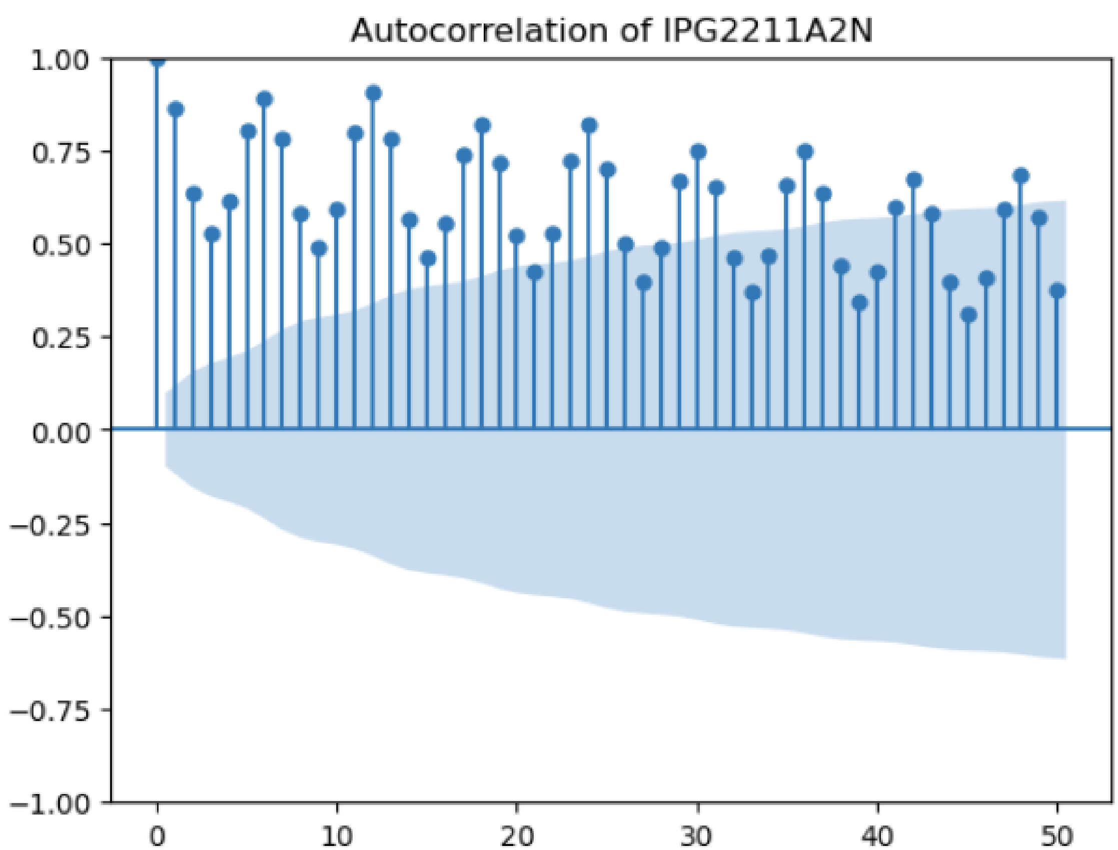
```
DATE  IPG2211A2N
0  1/1/1985     72.5052
1  2/1/1985     70.6720
2  3/1/1985     62.4502
3  4/1/1985     57.4714
4  5/1/1985     55.3151
```

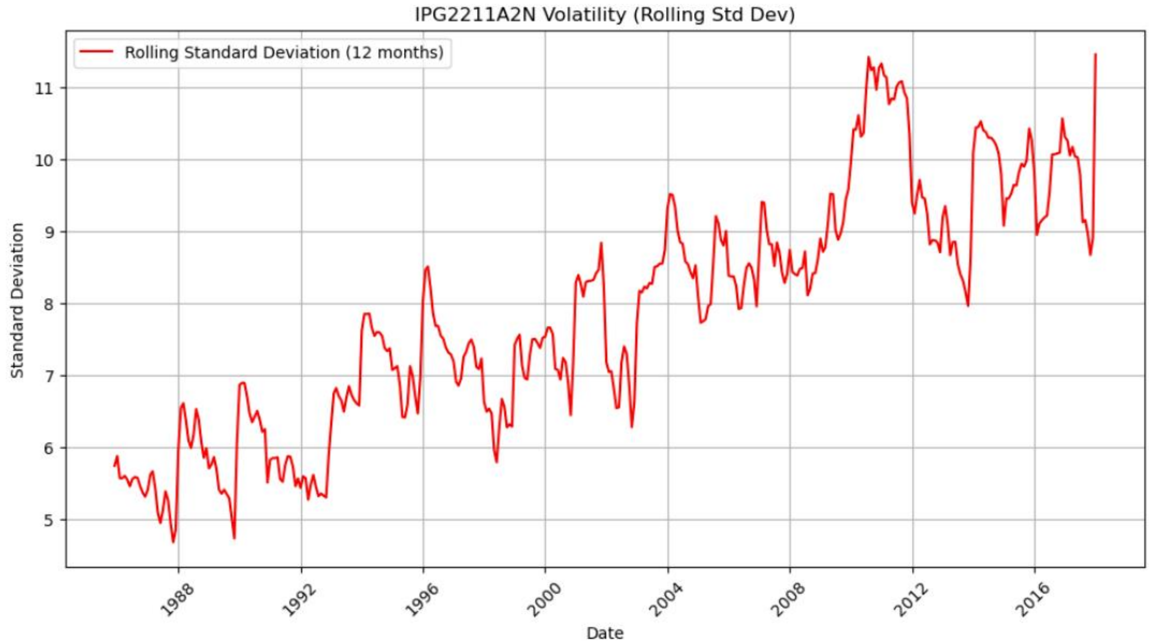
Mean Squared Error of the Regression Model: 190.4708993603595

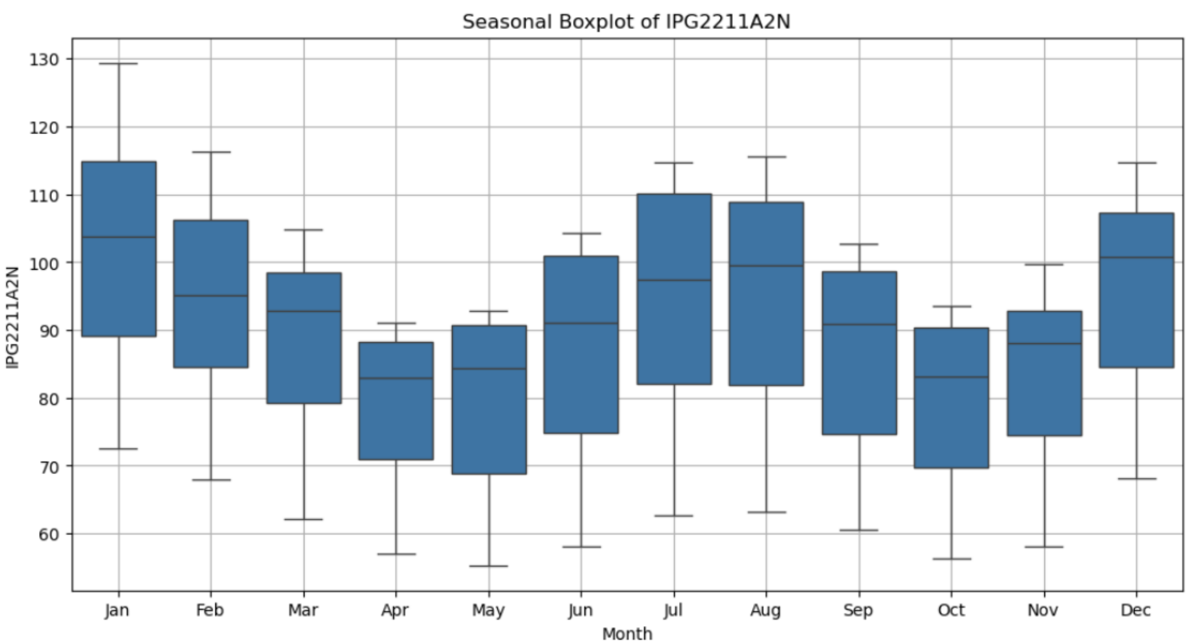

Time Series of IPG2211A2N
IPG2211A2N
60
70
80
90
100
110
120
130
1984
1988
1992
1996
2000
2004
2008
2012
2016
Date

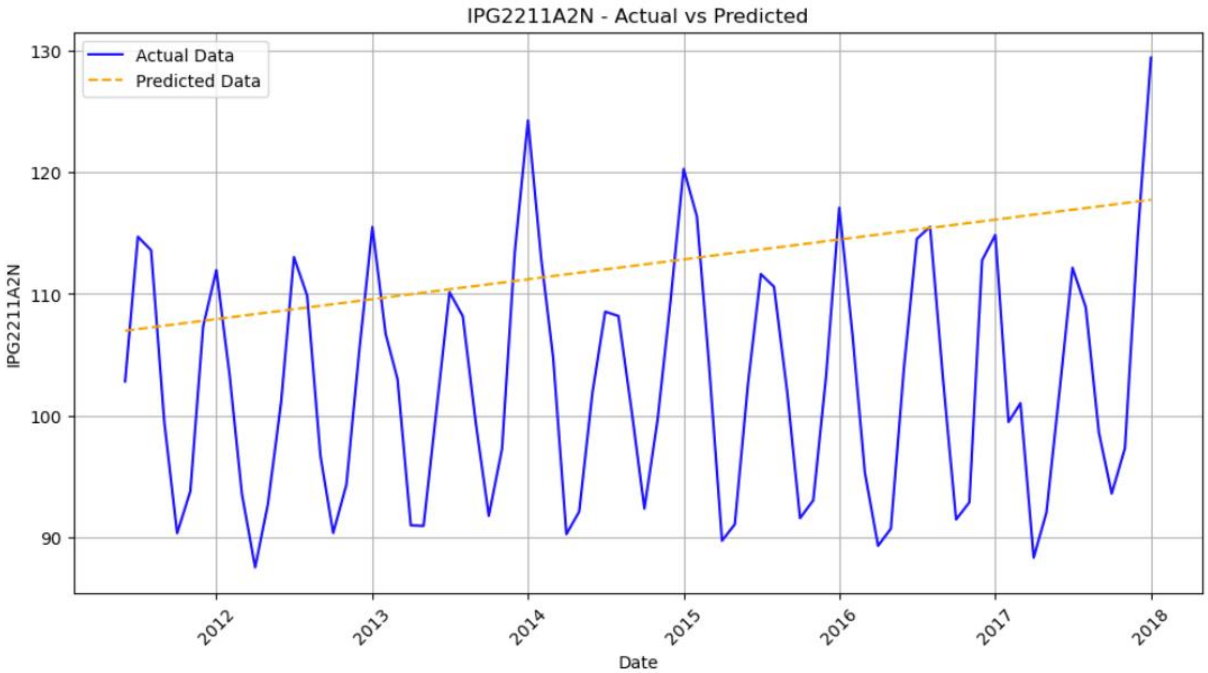

IPG2211A2N with Rolling Mean
IPG2211A2N Data
12-Month Rolling Mean
IPG2211A2N
60
70
80
90
100
110
120
130
1984
1988
1992
1996
2000
2004
2008
2012
2016
Date


Seasonal Decomposition of IPG2211A2N
IPG2211A2N
Trend
Seasonal
Resid
1988
1992
1996
2000
2004
2008
2012
2016


Autocorrelation of IPG2211A2N


IPG2211A2N Volatility (Rolling Std Dev)
Rolling Standard Deviation (12 months)
Standard Deviation
Date
5
6
7
8
9
10
11
1988
1992
1996
2000
2004
2008
2012
2016


Seasonal Boxplot of IPG2211A2N
IPG2211A2N
Month
60
70
80
90
100
110
120
130
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec


IPG2211A2N - Actual vs Predicted
Actual Data
Predicted Data
130
120
110
100
90
IPG2211A2N
2012
2013
2014
2015
2016
2017
2018
Date