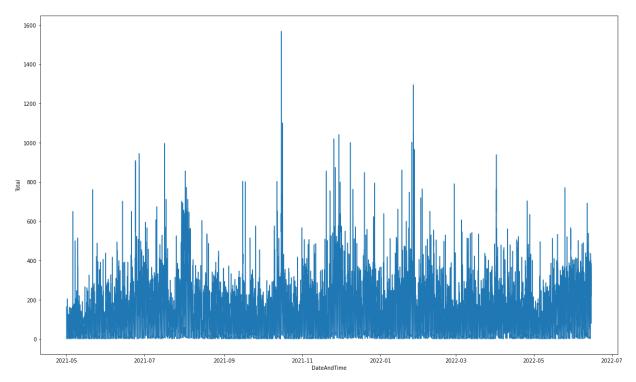
```
In [1]: import numpy as np
         import pandas as pd
         import matplotlib.pylab as plt
         from statsmodels.tsa.arima_model import ARIMA
         %matplotlib inline
         from matplotlib.pylab import rcParams
         rcParams['figure.figsize']=20,12
In [3]: dataset= pd.read_csv('TimeSeries_Gediz_no_null_trainset.csv')
         dataset['DateAndTime']=pd.to_datetime(dataset['DateAndTime'],infer_datetime_formate
         indexedDataset=dataset.set index(['DateAndTime'])
In [4]: from datetime import datetime
         indexedDataset
Out[4]:
                            Total
               DateAndTime
          2021-05-01 00:00:00
                             164
          2021-05-01 00:30:00
                             66
          2021-05-01 01:00:00
                               9
          2021-05-01 01:30:00
                               2
          2021-05-01 02:00:00
                               5
          2022-06-14 21:30:00
                             283
          2022-06-14 22:00:00
                             184
          2022-06-14 22:30:00
                             166
          2022-06-14 23:00:00
                             102
          2022-06-14 23:30:00
                             80
         19487 rows × 1 columns
In [5]: len(indexedDataset)
```

Out[5]: 19487

```
In [98]: # plot graph
    plt.xlabel("DateAndTime")
    plt.ylabel("Total")
    plt.plot(indexedDataset)
```

#### Out[98]: [<matplotlib.lines.Line2D at 0x1d281707c10>]



```
In [6]: rolmean=indexedDataset.rolling(window=12).mean()
rolstd=indexedDataset.rolling(window=12).std()
```

```
In [7]: print(rolmean)
                                   Total
        DateAndTime
        2021-05-01 00:00:00
                                     NaN
        2021-05-01 00:30:00
                                     NaN
        2021-05-01 01:00:00
                                     NaN
        2021-05-01 01:30:00
                                     NaN
        2021-05-01 02:00:00
                                     NaN
         . . .
        2022-06-14 21:30:00
                              299.250000
        2022-06-14 22:00:00 292.166667
        2022-06-14 22:30:00 283.750000
        2022-06-14 23:00:00 261.333333
        2022-06-14 23:30:00 240.333333
        [19487 rows x 1 columns]
In [8]: print(rolstd)
                                  Total
        DateAndTime
        2021-05-01 00:00:00
                                    NaN
        2021-05-01 00:30:00
                                    NaN
        2021-05-01 01:00:00
                                    NaN
        2021-05-01 01:30:00
                                    NaN
```

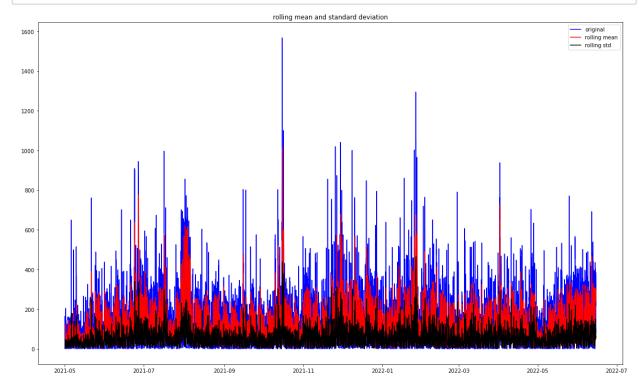
NaN

2021-05-01 02:00:00

2022-06-14 21:30:00 61.430116 2022-06-14 22:00:00 69.593408 2022-06-14 22:30:00 78.456850 2022-06-14 23:00:00 88.984507 2022-06-14 23:30:00 99.862026

[19487 rows x 1 columns]

```
In [9]: orig=plt.plot(indexedDataset, color='blue', label='original')
    mean=plt.plot(rolmean, color='red', label='rolling mean')
    std=plt.plot(rolstd, color='black', label='rolling std')
    plt.legend(loc='best')
    plt.title('rolling mean and standard deviation')
    plt.show(block=False)
```



In [10]: print('Dataset is Stationary according to statistics of mean and standard deviati

Dataset is Stationary according to statistics of mean and standard deviation.

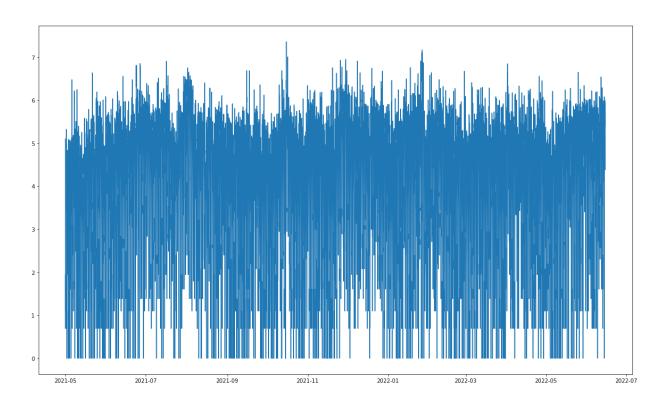
```
In [11]: indexedDataset['Total']=indexedDataset['Total'].fillna(0.0)
In [12]: indexedDataset
Out[12]:
                            Total
                DateAndTime
           2021-05-01 00:00:00
                             164
           2021-05-01 00:30:00
                              66
           2021-05-01 01:00:00
                               9
           2021-05-01 01:30:00
           2021-05-01 02:00:00
                               5
           2022-06-14 21:30:00
                             283
           2022-06-14 22:00:00
                             184
           2022-06-14 22:30:00
                             166
           2022-06-14 23:00:00
                             102
           2022-06-14 23:30:00
                              80
          19487 rows × 1 columns
In [13]: # Perform Dickey-Fuller Test
          from statsmodels.tsa.stattools import adfuller
          print('Results of Dickey-Fuller Test : ')
          dftest=adfuller(indexedDataset['Total'], autolag='AIC')
          dfoutput=pd.Series(dftest[0:4], index=['Test Statistic', 'p-value', 'Lags Used',
          for key,value in dftest[4].items():
              dfoutput['Critical value (%s)' %key]=value
          print(dfoutput)
          Results of Dickey-Fuller Test:
          Test Statistic
                                          -8.020799e+00
          p-value
                                           2.078948e-12
          Lags Used
                                          4.500000e+01
          Number of Observations Used 1.944100e+04
          Critical value (1%)
                                        -3.430686e+00
                                  -2.861689e+00
-2.566849e+00
          Critical value (5%)
          Critical value (10%)
          dtype: float64
```

## In [15]: #Estimating Trend (scale has changed) indexedDataset\_logscale=np.log(indexedDataset) plt.plot(indexedDataset\_logscale) indexedDataset\_logscale

#### Out[15]:

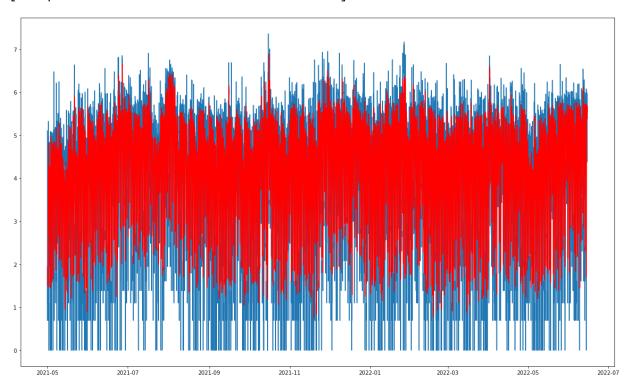
DateAndTime				
2021-05-01 00:00:00	5.099866			
2021-05-01 00:30:00	4.189655			
2021-05-01 01:00:00	2.197225			
2021-05-01 01:30:00	0.693147			
2021-05-01 02:00:00	1.609438			
2022-06-14 21:30:00	5.645447			
2022-06-14 22:00:00	5.214936			
2022-06-14 22:30:00	5.111988			
2022-06-14 23:00:00	4.624973			
2022-06-14 23:30:00	4.382027			

Total



# In [16]: #Taking MA (Moving Average Model) movingAverage=indexedDataset\_logscale.rolling(window=12).mean() movingSTD=indexedDataset\_logscale.rolling(window=12).std() plt.plot(indexedDataset\_logscale) plt.plot(movingAverage, color='red')

Out[16]: [<matplotlib.lines.Line2D at 0x213b90bb7f0>]



In [17]: datasetLogScaleMinusMovingAverage=indexedDataset\_logscale - movingAverage

In [18]: movingAverage

#### Out[18]:

	Total
<b>DateAndTime</b>	
2021-05-01 00:00:00	Nan
2021-05-01 00:30:00	Nan
2021-05-01 01:00:00	Nan
2021-05-01 01:30:00	Nan
2021-05-01 02:00:00	Nan
2022-06-14 21:30:00	5.681851
2022-06-14 22:00:00	5.650203
2022-06-14 22:30:00	5.610598
2022-06-14 23:00:00	5.502995
2022-06-14 23:30:00	5.384403

#### In [19]: #Remove Nan Values

datasetLogScaleMinusMovingAverage = datasetLogScaleMinusMovingAverage.dropna()
datasetLogScaleMinusMovingAverage.head(50)

#### Out[19]:

	Total
<b>DateAndTime</b>	
2021-05-01 05:30:00	-1.242751
2021-05-01 06:00:00	-0.035592
2021-05-01 06:30:00	0.981939
2021-05-01 07:00:00	1.939204
2021-05-01 07:30:00	1.275074
2021-05-01 08:00:00	1.465973
2021-05-01 08:30:00	1.742746
2021-05-01 09:00:00	1.817974
2021-05-01 09:30:00	1.407211
2021-05-01 10:00:00	1.474996
2021-05-01 10:30:00	1.053285
2021-05-01 11:00:00	1.215154
2021-05-01 11:30:00	0.933801
2021-05-01 12:00:00	0.714616
2021-05-01 12:30:00	0.333379
2021-05-01 13:00:00	0.628495
2021-05-01 13:30:00	0.319151
2021-05-01 14:00:00	0.406339
2021-05-01 14:30:00	0.579644
2021-05-01 15:00:00	0.736739
2021-05-01 15:30:00	0.222046
2021-05-01 16:00:00	-0.140846
2021-05-01 16:30:00	0.001303
2021-05-01 17:00:00	0.146088
2021-05-01 17:30:00	-0.068272
2021-05-01 18:00:00	-0.076969
2021-05-01 18:30:00	-0.306747
2021-05-01 19:00:00	-0.063684
2021-05-01 19:30:00	0.017809
2021-05-01 20:00:00	-0.069340

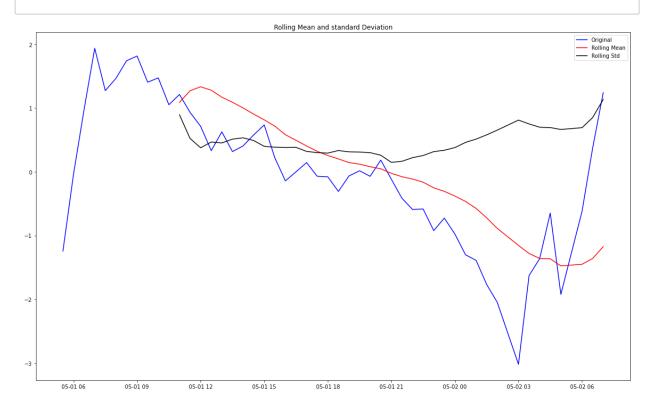
#### Total

_						
п	124	~ /	۱n	<b>~</b> 17	Γin	2

DateAndTime	
2021-05-01 20:30:00	0.185176
2021-05-01 21:00:00	-0.115288
2021-05-01 21:30:00	-0.413083
2021-05-01 22:00:00	-0.589069
2021-05-01 22:30:00	-0.581440
2021-05-01 23:00:00	-0.920316
2021-05-01 23:30:00	-0.724938
2021-05-02 00:00:00	-0.974855
2021-05-02 00:30:00	-1.299527
2021-05-02 01:00:00	-1.387588
2021-05-02 01:30:00	-1.766426
2021-05-02 02:00:00	-2.046884
2021-05-02 03:00:00	-3.017877
2021-05-02 03:30:00	-1.625402
2021-05-02 04:00:00	-1.360564
2021-05-02 04:30:00	-0.645488
2021-05-02 05:00:00	-1.920981
2021-05-02 06:00:00	-0.617641
2021-05-02 06:30:00	0.372794
2021-05-02 07:00:00	1.243077

```
In [20]: #DCF Test (Augmented Dickey-Fuller (ADF) Test)
         from statsmodels.tsa.stattools import adfuller
         def test_stationarity(timeseries):
             #Determing rolling statistics
             movingAverage=timeseries.rolling(window=12).mean()
             movingSTD=timeseries.rolling(window=12).std()
             #plot rolling statistics
             orig = plt.plot(timeseries, color='blue', label='Original')
             mean =plt.plot(movingAverage, color='red', label='Rolling Mean')
             std = plt.plot(movingSTD, color='black', label='Rolling Std')
             plt.legend(loc='best')
             plt.title('Rolling Mean and standard Deviation')
             plt.show(block=False)
             #Perform Dickey-fuller test
             print('Results of Dickey-fuller Test')
             dftest=adfuller(timeseries['Total'], autolag='AIC')
             dfoutput=pd.Series(dftest[0:4], index=['Test Statistic', 'p-value', 'Lags Us€
             for key,value in dftest[4].items():
                 dfoutput['Critical value (%s)' %key]=value
             print(dfoutput)
             movingAverage
             movingSTD
             dftest
             dfoutput
             datasetLogScaleMinusMovingAverage
```

In [115]: test\_stationarity(datasetLogScaleMinusMovingAverage.head(50))

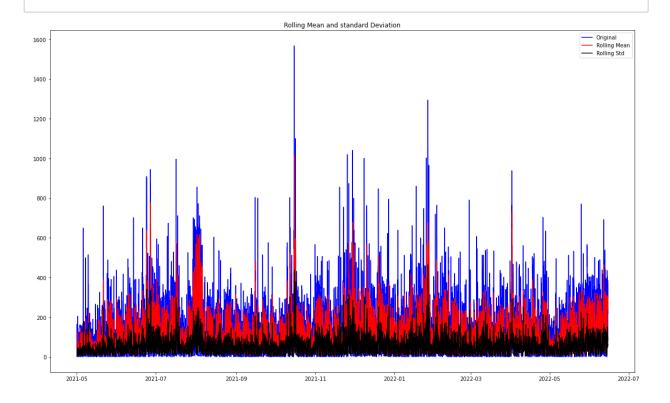


Results of Dickey-fuller Test

Test Statistic -2.417712
p-value 0.136800
Lags Used 4.000000
Number of Observations Used 45.000000
Critical value (1%) -3.584829
Critical value (5%) -2.928299
Critical value (10%) -2.602344

dtype: float64

#### In [21]: test\_stationarity(indexedDataset)



Results of Dickey-fuller Test Test Statistic -8.020799e+00 p-value 2.078948e-12 Lags Used 4.500000e+01 Number of Observations Used 1.944100e+04 Critical value (1%) -3.430686e+00 Critical value (5%) -2.861689e+00 Critical value (10%) -2.566849e+00 dtype: float64

```
In [22]: |datasetLogScaleMinusMovingAverage["Total"]
Out[22]: DateAndTime
         2021-05-01 05:30:00
                               -1.242751
         2021-05-01 06:00:00
                               -0.035592
         2021-05-01 06:30:00
                               0.981939
         2021-05-01 07:00:00
                                1.939204
         2021-05-01 07:30:00
                                1.275074
                                  . . .
         2022-06-14 21:30:00
                               -0.036404
         2022-06-14 22:00:00
                             -0.435267
         2022-06-14 22:30:00
                               -0.498610
         2022-06-14 23:00:00 -0.878022
         2022-06-14 23:30:00 -1.002376
         Name: Total, Length: 19476, dtype: float64
```

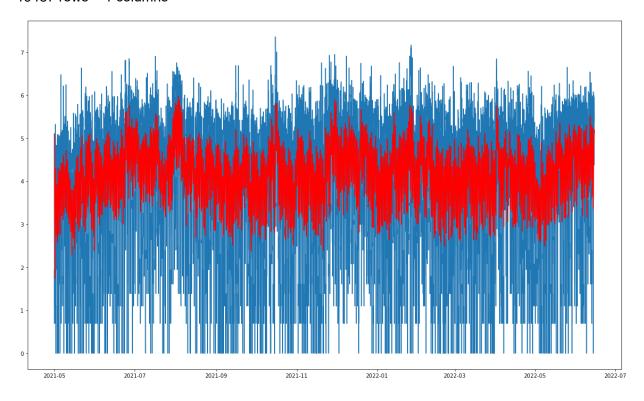
In [23]: datasetLogScaleMinusMovingAverage=datasetLogScaleMinusMovingAverage.dropna()

In [27]: exponentialDecayWeightedAverage=indexedDataset\_logscale.ewm(halflife=12, min\_peri plt.plot(indexedDataset\_logscale) plt.plot(exponentialDecayWeightedAverage, color='red')
exponentialDecayWeightedAverage

#### Out[27]:

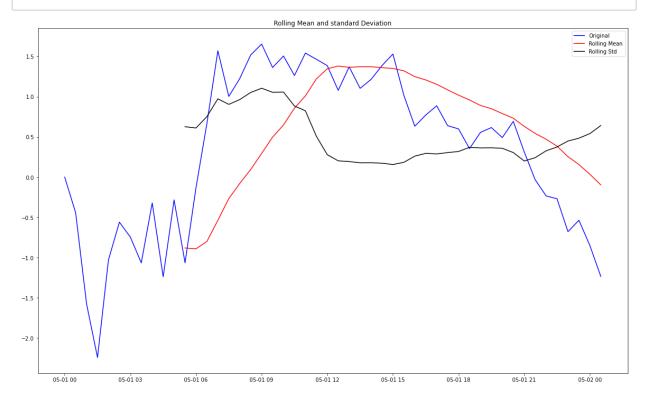
DateAndTime				
2021-05-01 00:00:00	5.099866			
2021-05-01 00:30:00	4.631620			
2021-05-01 01:00:00	3.772858			
2021-05-01 01:30:00	2.934994			
2021-05-01 02:00:00	2.638407			
2022-06-14 21:30:00	5.196527			
2022-06-14 22:00:00	5.197560			
2022-06-14 22:30:00	5.192757			
2022-06-14 23:00:00	5.160890			
2022-06-14 23:30:00	5.117176			

Total



#### In [28]: #Another Transformation

datasetLogScaleMinusMovingExponentialDecayAverage=indexedDataset\_logscale - expor datasetLogScaleMinusMovingExponentialDecayAverage=datasetLogScaleMinusMovingExpor test\_stationarity(datasetLogScaleMinusMovingExponentialDecayAverage.head(50))

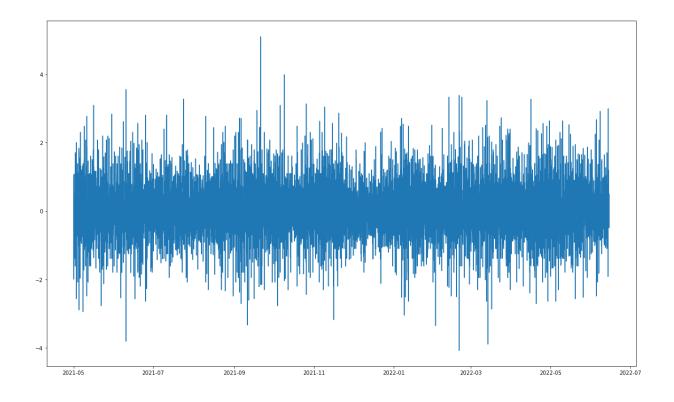


Results of Dickey-fuller Test

Test Statistic	-1.534868
p-value	0.516198
Lags Used	4.000000
Number of Observations Used	45.000000
Critical value (1%)	-3.584829
Critical value (5%)	-2.928299
Critical value (10%)	-2.602344
dtype: float64	

#### Out[29]:

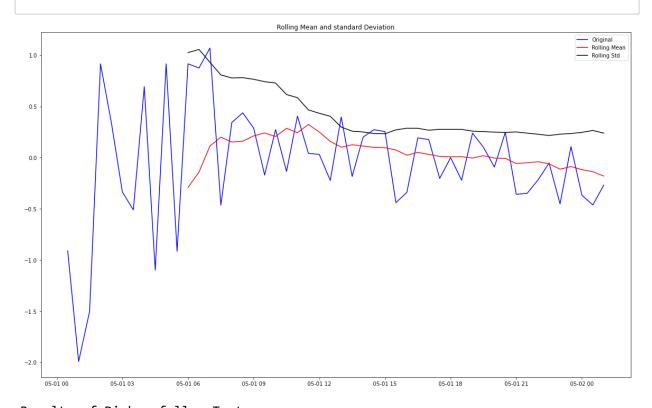
	Total
DateAndTime	
2021-05-01 00:00:00	Nan
2021-05-01 00:30:00	-0.910212
2021-05-01 01:00:00	-1.992430
2021-05-01 01:30:00	-1.504077
2021-05-01 02:00:00	0.916291
2022-06-14 21:30:00	-0.218184
2022-06-14 22:00:00	-0.430511
2022-06-14 22:30:00	-0.102948
2022-06-14 23:00:00	-0.487015
2022-06-14 23:30:00	-0.242946



```
In [30]: # ARIMA (Autoregressive Integrated Moving Average) model is a generalization of a # ARMA (Autoregressive Moving Average) model is used to describe weakly stationar # ARIMA: AR (Auto Regression) model, MA (Moving Average) model, I (Integration) m
```

#### In [31]: #Flat output

datasetLogDiffShifting=datasetLogDiffShifting.dropna()
test\_stationarity(datasetLogDiffShifting.head(50))
datasetLogDiffShifting



Results of Dickey-fuller Test

Test Statistic -2.208965
p-value 0.203008
Lags Used 10.000000
Number of Observations Used 39.000000
Critical value (1%) -3.610400
Critical value (5%) -2.939109
Critical value (10%) -2.608063

dtype: float64

#### Out[31]:

#### Total

DateAndTime		
2021-05-01 00:30:00	-0.910212	
2021-05-01 01:00:00	-1.992430	
2021-05-01 01:30:00	-1.504077	
2021-05-01 02:00:00	0.916291	
2021-05-01 02:30:00	0.336472	
2022-06-14 21:30:00	-0.218184	
2022-06-14 22:00:00	-0.430511	
2022-06-14 22:30:00	-0.102948	

#### Total

#### **DateAndTime**

**2022-06-14 23:00:00** -0.487015 **2022-06-14 23:30:00** -0.242946

19486 rows × 1 columns

In [32]: indexedDataset

#### Out[32]:

#### Total

DateAndTime		
2021-05-01 00:00:00	164	
2021-05-01 00:30:00	66	
2021-05-01 01:00:00	9	
2021-05-01 01:30:00	2	
2021-05-01 02:00:00	5	
2022-06-14 21:30:00	283	
2022-06-14 22:00:00	184	
2022-06-14 22:30:00	166	
2022-06-14 23:00:00	102	
2022-06-14 23:30:00	80	

In [33]: datasetLogDiffShifting.rolling(window=12).mean()
 indexedDataset\_logscale=indexedDataset\_logscale.dropna()
 indexedDataset\_logscale=indexedDataset\_logscale.fillna(0)
 indexedDataset\_logscale

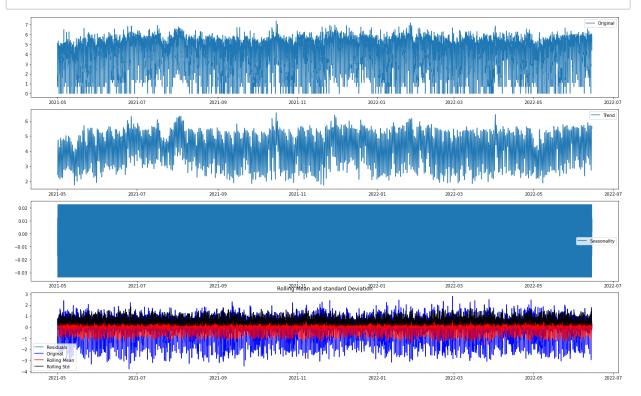
#### Out[33]:

#### Total

DateAndTime			
2021-05-01 00:00:00	5.099866		
2021-05-01 00:30:00	4.189655		
2021-05-01 01:00:00	2.197225		
2021-05-01 01:30:00	0.693147		
2021-05-01 02:00:00	1.609438		
2022-06-14 21:30:00	 5.645447		
 2022-06-14 21:30:00 2022-06-14 22:00:00	 5.645447 5.214936		
2022 00 1121100100	0.0.0		
2022-06-14 22:00:00	5.214936		

```
In [35]: from random import randrange
         from pandas import Series
         from matplotlib import pyplot
         from statsmodels.tsa.seasonal import seasonal decompose
         from statsmodels.tsa.stattools import adfuller
         decomposition=seasonal decompose(indexedDataset logscale, period=20)
         trend=decomposition.trend
         seasonal=decomposition.seasonal
         residual=decomposition.resid
         plt.subplot(411)
         plt.plot(indexedDataset_logscale, label='Original')
         plt.legend(loc='best')
         plt.subplot(412)
         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()
         decomposedLogdata=residual
         decomposedLogdata.dropna(inplace=True)
         decomposedLogdata
         #Testing Stationarity
         #Determing rolling statistics
         movingAverage=decomposedLogdata.rolling(window=12).mean()
         movingSTD=decomposedLogdata.rolling(window=12).std()
         #plot rolling statistics
         orig = plt.plot(decomposedLogdata, color='blue', label='Original')
         mean =plt.plot(movingAverage, color='red', label='Rolling Mean')
         std = plt.plot(movingSTD, color='black', label='Rolling Std')
         plt.legend(loc='best')
         plt.title('Rolling Mean and standard Deviation')
         plt.show(block=False)
         #Perform Dickey-fuller test
         print('Results of Dickey-fuller Test')
         dftest=adfuller(decomposedLogdata, autolag='AIC')
         dfoutput=pd.Series(dftest[0:4], index=['Test Statistic', 'p-value', 'Lags Used',
         for key,value in dftest[4].items():
             dfoutput['Critical value (%s)' %key]=value
```

#### print(dfoutput)



Results of Dickey-fuller Test

Test Statistic -64.737427
p-value 0.000000
Lags Used 45.000000
Number of Observations Used 19421.000000
Critical value (1%) -3.430687
Critical value (5%) -2.861689
Critical value (10%) -2.566849

dtype: float64

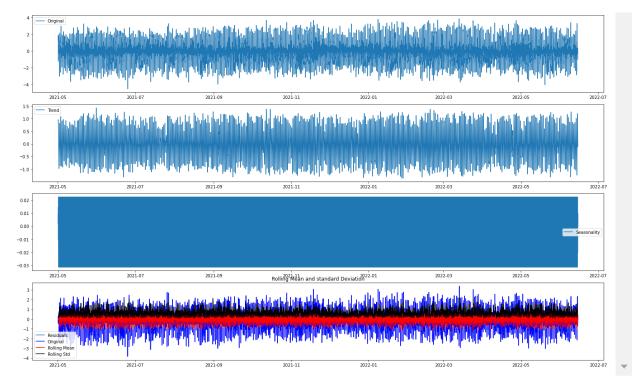
### In [36]: indexedDataset\_logscale

### Out[36]:

7	$\overline{}$	4	_	ı

DateAndTime					
2021-05-01 00:00:00	5.099866				
2021-05-01 00:30:00	4.189655				
2021-05-01 01:00:00	2.197225				
2021-05-01 01:30:00	0.693147				
2021-05-01 02:00:00	1.609438				
2022-06-14 21:30:00	5.645447				
2022-06-14 22:00:00	5.214936				
2022-06-14 22:00:00 2022-06-14 22:30:00	5.214936 5.111988				
	0.2				
2022-06-14 22:30:00	5.111988				

```
In [37]: decomposition=seasonal decompose(datasetLogScaleMinusMovingAverage, period=20)
         trend=decomposition.trend
         seasonal=decomposition.seasonal
         residual=decomposition.resid
         plt.subplot(411)
         plt.plot(datasetLogScaleMinusMovingAverage, label='Original')
         plt.legend(loc='best')
         plt.subplot(412)
         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()
         decomposedLogdata=residual
         decomposedLogdata.dropna(inplace=True)
         decomposedLogdata
         #Testing Stationarity
         #Determing rolling statistics
         movingAverage=decomposedLogdata.rolling(window=12).mean()
         movingSTD=decomposedLogdata.rolling(window=12).std()
         #plot rolling statistics
         orig = plt.plot(decomposedLogdata, color='blue', label='Original')
         mean =plt.plot(movingAverage, color='red', label='Rolling Mean')
         std = plt.plot(movingSTD, color='black', label='Rolling Std')
         plt.legend(loc='best')
         plt.title('Rolling Mean and standard Deviation')
         plt.show(block=False)
         #Perform Dickey-fuller test
         print('Results of Dickey-fuller Test')
         dftest=adfuller(decomposedLogdata, autolag='AIC')
         dfoutput=pd.Series(dftest[0:4], index=['Test Statistic', 'p-value', 'Lags Used',
         for key,value in dftest[4].items():
             dfoutput['Critical value (%s)' %key]=value
         print(dfoutput)
         datasetLogDiffShifting
```



Results of Dickey-fuller Test

Test Statistic	-67.205269
p-value	0.000000
Lags Used	45.000000
Number of Observations Used	19410.000000
Critical value (1%)	-3.430687
Critical value (5%)	-2.861689
Critical value (10%)	-2.566849
dtype: float64	

#### Out[37]:

#### Total

DateAndTime				
2021-05-01 00:30:00	-0.910212			
2021-05-01 01:00:00	-1.992430			
<b>2021-05-01 01:30:00</b> -1.504077				
<b>2021-05-01 02:00:00</b> 0.916291				
2021-05-01 02:30:00	0.336472			
2022-06-14 21:30:00	-0.218184			
2022-06-14 22:00:00	-0.430511			
2022-06-14 22:30:00	-0.102948			
2022-06-14 23:00:00	0.407045			
2022-00-14 23.00.00	-0.487015			

#### In [38]: datasetLogDiffShifting

#### Out[38]:

#### Total

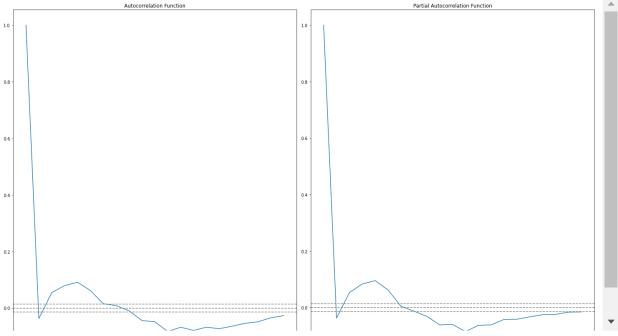
DateAndTime					
2021-05-01 00:30:00	-0.910212				
2021-05-01 01:00:00	-1.992430				
2021-05-01 01:30:00	-1.504077				
2021-05-01 02:00:00	0.916291				
2021-05-01 02:30:00	0.336472				
2022-06-14 21:30:00	-0.218184				
2022-06-14 21:30:00 2022-06-14 22:00:00	-0.218184 -0.430511				
2022 00 1121100100	0.2.0.0.				
2022-06-14 22:00:00	-0.430511				
2022-06-14 22:30:00	-0.430511 -0.102948				

19486 rows × 1 columns

In [39]: #Autocorrelation Function (ACF) is a calculated value used to represent how simil #Partial Autocorrelation Function (PACF)

4

```
In [40]: #ACF and PACF Plot
                                 from statsmodels.tsa.stattools import acf, pacf
                                 lag acf=acf(datasetLogDiffShifting, nlags=20)
                                 lag_pacf=pacf(datasetLogDiffShifting, nlags=20, method='ols')
                                 #PLot ACF
                                 plt.subplot(121)
                                 plt.plot(lag_acf)
                                 plt.axhline(y=0,linestyle='--',color='gray')
                                plt.axhline(y=-1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',color='gr
                                 plt.axhline(y=1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',color='grange'
                                 plt.title('Autocorrelation Function')
                                 #PLot PACF
                                 plt.subplot(122)
                                 plt.plot(lag pacf)
                                 plt.axhline(y=0,linestyle='--',color='gray')
                                 plt.axhline(y=-1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',color='gr
                                 plt.axhline(y=1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='--',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='---',color='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle='grainestyle=
                                 plt.title('Partial Autocorrelation Function')
                                 plt.tight_layout()
                                                                                          Autocorrelation Function
                                                                                                                                                                                                                               Partial Autocorrelation Function
                                   1.0
                                                                                                                                                                           1.0
```



```
0.06200139, 0.01546686, 0.00877073, -0.00951371, -0.04392857,

-0.04834585, -0.08304124, -0.06759946, -0.07888219, -0.06742184,

-0.07277546, -0.06387453, -0.05377011, -0.04831648, -0.03414877,

-0.02658755])
```

#### In [43]: pip install statsmodels

Requirement already satisfied: statsmodels in c:\users\bita\anaconda3\lib\site-packages (0.13.2)Note: you may need to restart the kernel to use updated packages.

Requirement already satisfied: numpy>=1.17 in c:\users\bita\anaconda3\lib\site-packages (from statsmodels) (1.21.5)

Requirement already satisfied: scipy>=1.3 in c:\users\bita\anaconda3\lib\site-p ackages (from statsmodels) (1.7.3)

Requirement already satisfied: pandas>=0.25 in c:\users\bita\anaconda3\lib\site -packages (from statsmodels) (1.4.2)

Requirement already satisfied: patsy>=0.5.2 in c:\users\bita\anaconda3\lib\site -packages (from statsmodels) (0.5.2)

Requirement already satisfied: packaging>=21.3 in c:\users\bita\anaconda3\lib\s ite-packages (from statsmodels) (21.3)

Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in c:\users\bita\anacon da3\lib\site-packages (from packaging>=21.3->statsmodels) (3.0.4)

Requirement already satisfied: pytz>=2020.1 in c:\users\bita\anaconda3\lib\site -packages (from pandas>=0.25->statsmodels) (2021.3)

Requirement already satisfied: python-dateutil>=2.8.1 in c:\users\bita\anaconda 3\lib\site-packages (from pandas>=0.25->statsmodels) (2.8.2)

Requirement already satisfied: six in c:\users\bita\anaconda3\lib\site-packages (from patsy>=0.5.2->statsmodels) (1.16.0)

```
In [44]: from statsmodels.tsa.arima.model import ARIMA

#AR Model
    cclone_indexedDataset_logscale.index = pd.DatetimeIndex(clone_indexedDataset_logs
    model = ARIMA(clone_indexedDataset_logscale, order=(2, 1, 0))
    results_AR = model.fit()
    plt.plot(datasetLogDiffShifting, color='gray')
    plt.plot(results_AR.fittedvalues, color='red')
    print(results_AR.fittedvalues)
    print('Plotting AR model')
```

```
NameError Traceback (most recent call last)

Input In [44], in <cell line: 4>()

1 from statsmodels.tsa.arima.model import ARIMA

3 #AR Model

----> 4 cclone_indexedDataset_logscale.index = pd.DatetimeIndex(clone_indexedDataset_logscale.index)

5 model = ARIMA(clone_indexedDataset_logscale, order=(2, 1, 0))

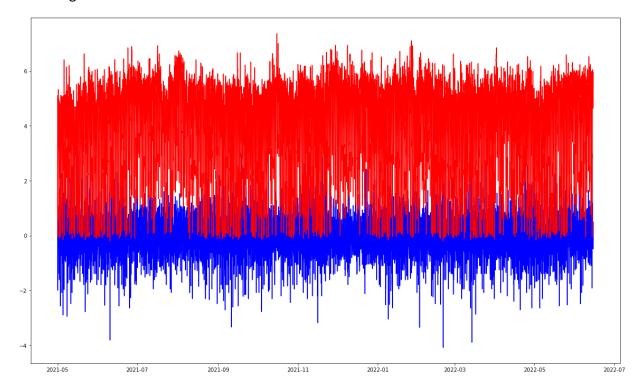
6 results_AR = model.fit()

NameError: name 'clone_indexedDataset_logscale' is not defined
```

```
In [155]: #MA Model

clone_indexedDataset_logscale = indexedDataset_logscale.copy().resample('30min').
    clone_indexedDataset_logscale.index = pd.DatetimeIndex(clone_indexedDataset_logsc
    model = ARIMA(clone_indexedDataset_logscale, order=(0, 1, 2))
    results_MA = model.fit()
    plt.plot(datasetLogDiffShifting, color='blue')
    plt.plot(results_MA.fittedvalues, color='red')
    print(results_MA.fittedvalues)
    print('Plotting MA model')
```

```
DateAndTime
2021-05-01 00:00:00
                       0.000000
2021-05-01 00:30:00
                       5,099866
2021-05-01 01:00:00
                       4.243494
2021-05-01 01:30:00
                       2.258168
2021-05-01 02:00:00
                       0.660707
2022-06-14 21:30:00
                       5.869480
2022-06-14 22:00:00
                       5.652071
2022-06-14 22:30:00
                       5.226284
2022-06-14 23:00:00
                       5.092600
2022-06-14 23:30:00
                       4.644515
Freq: 30T, Length: 19680, dtype: float64
Plotting MA model
```



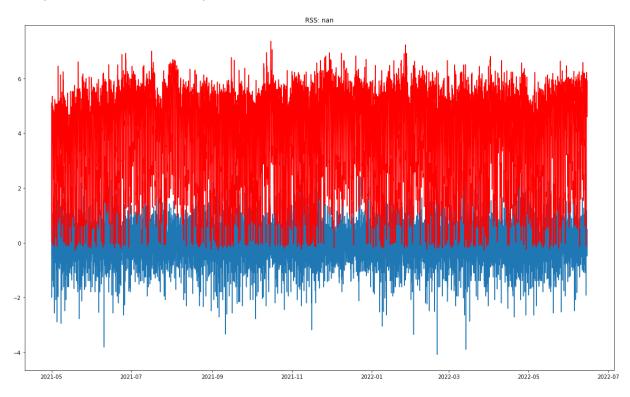
```
In [45]: model=ARIMA(indexedDataset_logscale, order=(2,1,2))
    results_ARIMA=model.fit()
    plt.plot(datasetLogDiffShifting)
    plt.plot(results_ARIMA.fittedvalues, color='red')
    plt.title('RSS: %.4f' % sum((results_ARIMA.fittedvalues-datasetLogDiffShifting["]
```

C:\Users\BITA\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa\_model.py:47
1: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.
 self. init dates(dates, freq)

C:\Users\BITA\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa\_model.py:47
1: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.
 self.\_init\_dates(dates, freq)

C:\Users\BITA\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa\_model.py:47
1: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.
 self. init dates(dates, freq)

Out[45]: Text(0.5, 1.0, 'RSS: nan')



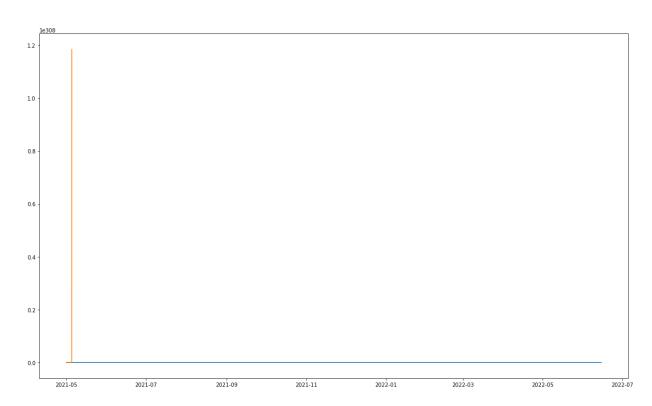
```
In [47]: | predictions_ARIMA_diff=pd.Series(results_ARIMA.fittedvalues, copy=True)
          print(predictions_ARIMA_diff.head())
          DateAndTime
          2021-05-01 00:00:00
                                 0.000000
          2021-05-01 00:30:00
                                 5.099866
          2021-05-01 01:00:00
                                 4.193625
          2021-05-01 01:30:00
                                 2.160300
          2021-05-01 02:00:00
                                 0.532114
          dtype: float64
In [48]: #Convert to cumulative sum
          predictions ARIMA diff cumsum=predictions ARIMA diff.cumsum()
          print(predictions_ARIMA_diff_cumsum.head())
          DateAndTime
          2021-05-01 00:00:00
                                  0.000000
          2021-05-01 00:30:00
                                  5.099866
          2021-05-01 01:00:00
                                  9.293492
          2021-05-01 01:30:00
                                 11.453792
          2021-05-01 02:00:00
                                 11.985906
          dtype: float64
In [49]: predictions_ARIMA_log=pd.Series(indexedDataset_logscale['Total'], indexedDataset_
          predictions ARIMA log=predictions ARIMA log.add(predictions ARIMA diff cumsum, fi
          predictions ARIMA log.head()
Out[49]: DateAndTime
          2021-05-01 00:00:00
                                  5.099866
          2021-05-01 00:30:00
                                  9.289521
          2021-05-01 01:00:00
                                 11.490716
          2021-05-01 01:30:00
                                 12.146939
          2021-05-01 02:00:00
                                 13.595344
          dtype: float64
In [105]: predictions_ARIMA_log
Out[105]: DateAndTime
                                     5.099866
          2021-05-01 00:00:00
          2021-05-01 00:30:00
                                     9.289521
          2021-05-01 01:00:00
                                    11.490716
          2021-05-01 01:30:00
                                    12.146939
          2021-05-01 02:00:00
                                    13.595344
          2022-06-14 21:30:00
                                 81747.994553
          2022-06-14 22:00:00
                                 81753.243180
          2022-06-14 22:30:00
                                 81758.395071
          2022-06-14 23:00:00
                                 81763.024469
          2022-06-14 23:30:00
                                 81767.389419
          Length: 19487, dtype: float64
```

### In [50]: predictions\_ARIMA=np.exp(predictions\_ARIMA\_log) plt.plot(indexedDataset) plt.plot(predictions\_ARIMA)

C:\Users\BITA\anaconda3\lib\site-packages\pandas\core\arraylike.py:397: Runtime
Warning: overflow encountered in exp
 result = getattr(ufunc, method)(\*inputs, \*\*kwargs)

#### Out[50]: [<matplotlib.lines.Line2D at 0x213baed98e0>]

C:\Users\BITA\anaconda3\lib\site-packages\matplotlib\ticker.py:2072: RuntimeWar
ning: overflow encountered in multiply
 steps = self.\_extended\_steps \* scale



```
In [51]: predictions_ARIMA
Out[51]: DateAndTime
         2021-05-01 00:00:00
                                 1.640000e+02
                                 1.082400e+04
         2021-05-01 00:30:00
         2021-05-01 01:00:00
                                 9.780356e+04
         2021-05-01 01:30:00
                                 1.885162e+05
         2021-05-01 02:00:00
                                 8.023854e+05
                                     . . .
         2022-06-14 21:30:00
                                          inf
         2022-06-14 22:00:00
                                          inf
         2022-06-14 22:30:00
                                          inf
         2022-06-14 23:00:00
                                          inf
         2022-06-14 23:30:00
                                          inf
         Length: 19487, dtype: float64
In [61]: |indexedDataset_logscale
```

#### Out[61]:

#### **Total**

DateAndTime	
2021-05-01 00:00:00	5.099866
2021-05-01 00:30:00	4.189655
2021-05-01 01:00:00	2.197225
2021-05-01 01:30:00	0.693147
2021-05-01 02:00:00	1.609438
2022-06-14 21:30:00	5.645447
2022-06-14 22:00:00	5.214936
2022-06-14 22:30:00	5.111988
2022-06-14 23:00:00	4.624973
2022-06-14 23:00:00 2022-06-14 23:30:00	4.624973 4.382027

**DateAndTime** 

19487 rows × 1 columns

```
In [75]: x=results_ARIMA.forecast(steps=96)
```

C:\Users\BITA\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa\_model.py:83
4: ValueWarning: No supported index is available. Prediction results will be gi
ven with an integer index beginning at `start`.
 return get\_prediction\_index(

```
In [80]: x
Out[80]: 19487
                   4.319302
         19488
                   4.215320
                   4.098493
         19489
         19490
                   3.991250
         19491
                   3.908125
         19578
                   3.952334
         19579
                   3.952334
         19580
                   3.952334
         19581
                   3.952334
                   3.952334
         19582
         Name: predicted_mean, Length: 96, dtype: float64
In [83]: results_ARIMA
Out[83]: <statsmodels.tsa.arima.model.ARIMAResultsWrapper at 0x213b6be0190>
In [98]: | td = pd.read_csv('TimeSeries_Gediz_no_null_testset_LN.csv',
                  header=0,
                  usecols=["Total"])
         td
Out[98]:
                 Total
           0 4.158883
           1 3.610918
           2 3.044522
           3 2.944439
           4 2.639057
           91 5.303305
          92 5.153292
          93 5.680173
          94 4.663439
          95 4.248495
         96 rows × 1 columns
```

```
In [97]: |td['Total']
Out[97]: 0
               4.158883
               3.610918
         1
         2
               3.044522
         3
               2.944439
         4
               2.639057
         91
               5.303305
         92
              5.153292
         93
               5.680173
         94
               4.663439
         95
               4.248495
         Name: Total, Length: 96, dtype: float64
In [68]: #Measuring Time Series Forecasting Performance
         #Evaluation Metrics to Measure Performance:
         #R-Squared
         #Mean Absolute Error
         #Mean Absolute Percentage Error
         #Mean Squared Error
         #Root Mean Squared Error
         #Normalized Root Mean Squared Error
         #Weighted Absolute Percentage Error
         #Weighted Mean Absolute Percentage Error
In [99]: x
Out[99]: 19487
                  4.319302
         19488
                 4.215320
         19489
                 4.098493
         19490
                  3.991250
         19491
                 3.908125
                   . . .
         19578
                  3.952334
         19579
                 3.952334
         19580
                  3.952334
         19581
                  3.952334
         19582
                  3.952334
         Name: predicted_mean, Length: 96, dtype: float64
```

```
In [100]: # RMSE (Root Mean Square Error)
          from sklearn.metrics import mean_squared_error
          y_actual = td['Total']
          y_predicted = x
          RMSE = mean_squared_error(y_actual, y_predicted, squared=False)
          print("Root Mean Square Error (RMSE):\n")
          print(RMSE)
          Root Mean Square Error (RMSE):
          1.6507808512623035
In [101]: # Mean Absolute Percentage Error (MAPE)
          import numpy as np
          def mean_absolute_percentage_error(y_true, y_pred):
              y_true, y_pred = np.array(y_true), np.array(y_pred)
              return np.mean(np.abs((y_true - y_pred) / y_true))*100
In [102]: MAPE=mean_absolute_percentage_error(y_actual, y_predicted)
In [104]: | print("Mean Absolute Percentage Error (MAPE):\n")
          print(MAPE)
          Mean Absolute Percentage Error (MAPE):
          44.69302551428012
```

```
In [96]: df = pd.DataFrame(x)

# show the dataframe
print(df)

# iterating over and calling
# tolist() method for
# each column
for i in list(df):

# show the list of values
print(df[i].tolist())
```

```
predicted mean
19487
             4.319302
19488
             4.215320
             4.098493
19489
19490
             3.991250
19491
             3.908125
19578
              3.952334
19579
             3.952334
19580
             3.952334
19581
             3.952334
19582
             3.952334
```

```
[96 rows x 1 columns]
```

[4.3193018257111975, 4.215320340571137, 4.098493289824193, 3.991250134427406, 3.9081254346501395, 3.8556573882417324, 3.8336012674644753, 3.8368901222039122, 3.857815712285781, 3.8880164989660897, 3.9200075938213588, 3.948136329271842, 3.968972453111979, 3.981230336148755, 3.9853682678832856, 3.9830207591707834, 3.9764024646445293, 3.9677876388111843, 3.95912745587539, 3.951827693246658, 3. 946677111945268, 3.943895366813619, 3.9432588823430432, 3.9442623632323714, 3.9 462798679003135, 3.948699661208688, 3.9510185836198635, 3.952892225601334, 3.95 41453557411597, 3.9547521838712862, 3.954798178311759, 3.9544348036673953, 3.95 38364646174773, 3.953165956114501, 3.9525515675478475, 3.9520762223891617, 3.95 17769909447393, 3.951652116285359, 3.951672295089676, 3.9517931937044866, 3.951 9668364124647, 3.95215035364463, 3.95231143087463, 3.95243051634773, 3.95250035 0643569, 3.952523652360084, 3.9525098544596005, 3.952471685123538, 3.9524221871 05892, 3.9523725307917745, 3.9523307478892242, 3.9523013286512625, 3.9522855028 07481, 3.952281965350834, 3.9522878044316694, 3.9522994248646017, 3.95231331995 1366, 3.9523266104435844, 3.9523373299173326, 3.95234448249074, 3.9523479280875 673, 3.9523481625508574, 3.9523460577587395, 3.9523426148727747, 3.952338766687 1677, 3.952335246961208, 3.952332528778143, 3.9523308222925024, 3.9523301154057 56, 3.9523302386679684, 3.952330937104197, 3.952331935451341, 3.952332988179126 7, 3.9523339105597644, 3.952334591157122, 3.952334988989752, 3.952335120165382 7, 3.9523350391189482, 3.952334819000498, 3.952334534608258, 3.952334249890997 2, 3.95233401073555, 3.9523338427024877, 3.9523337526725264, 3.952333733031091 3, 3.952333766999023, 3.9523338339273586, 3.95233339137147393, 3.95233398988545 6, 3.952334051212446, 3.9523340920363474, 3.952334111598655, 3.952334112775496 5, 3.952334100585476, 3.9523340807755876, 3.9523340586905262