Week6_7_Time_Series1

May 15, 2021

Time Series

- This is simple and effective time series Machine Learning algorithm and more on this next week

Importing Python Libraries we need

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import datetime
import seaborn as sns
```

Load the dataset using URL and display

[2]:
```
Df = pd.read_csv("~/Desktop/Analysis/Work/ML_EIT/Data/Electric_Production.csv")
Df.head()
```

[2]:

	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

[3]:
```
pd.set_option('display.max_columns',100)
pd.set_option('display.max_rows',100)
```

Data Shape

[4]:
```
Df.shape
```

[4]:
```
(397, 2)
```

Data Describe

[5]:
```
Df.describe()
```

[5]:

	IPG2211A2N
count	397.000000
mean	88.847218
std	15.387834
min	55.315100
25%	77.105200
50%	89.779500
75%	100.524400
max	129.404800

[9]:
```
###### <span style="font-family: Arial; font-weight:bold;font-size:1.0em;color:
↪#357ec3">rename columns
```

[10]:
```
Df = Df.rename(columns = {'DATE': 'ds', 'IPG2211A2N':'ts'})
Df.head()
```

[10]:

	ds	ts
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

Table columns information

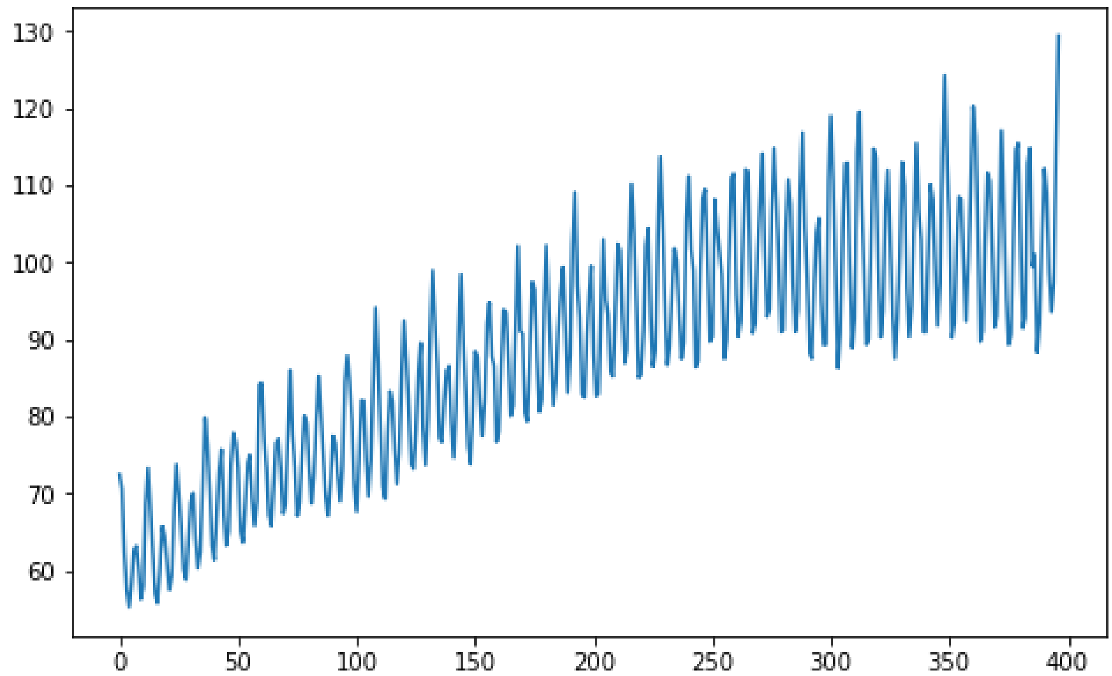
[11]:
```
Df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 397 entries, 0 to 396
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   ds      397 non-null    object
 1   ts      397 non-null    float64
dtypes: float64(1), object(1)
memory usage: 6.3+ KB
```

Data Visualization

[13]:
```
plt.figure(figsize=(8,5))
plt.plot(Df.ts)
```

[13]:
```
[<matplotlib.lines.Line2D at 0x7fce728fd070>]
```

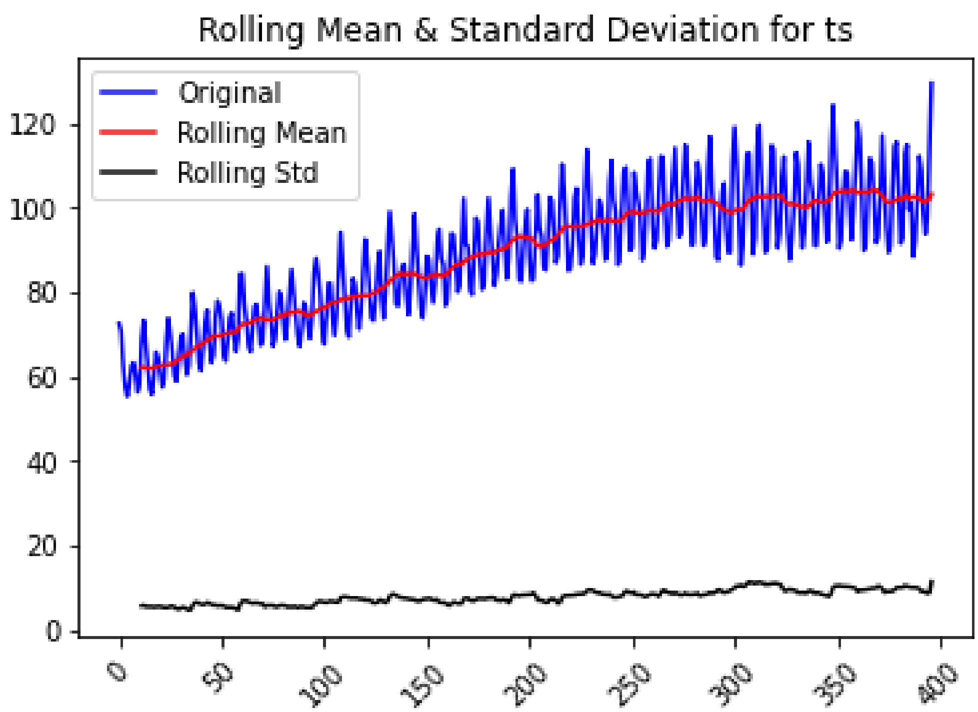


Stationarity Test

[14]:
```
from statsmodels.tsa.stattools import adfuller

def stationarity_test(df, ts):
    """
    Test stationarity using moving average statistics and Dickey-Fuller test
    Source: https://www.analyticsvidhya.com/blog/2016/02/
 ↪time-series-forecasting-codes-python/
    """

    # Determing rolling statistics
    rolmean = df[ts].rolling(window = 12, center = False).mean()
    rolstd = df[ts].rolling(window = 12, center = False).std()

    # Plot rolling statistics:
    orig = plt.plot(df[ts],
                    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 & Standard Deviation for %s' %(ts))
    plt.xticks(rotation = 45)
    plt.show(block = False)
    plt.close()

    # Perform Dickey-Fuller test:
    # Null Hypothesis (H_0): time series is not stationary
    # Alternate Hypothesis (H_1): time series is stationary
    print ('Results of Dickey-Fuller Test:')
    dftest = adfuller(df[ts],
                      autolag='AIC')
    dfoutput = pd.Series(dftest[0:4],
                         index = ['Test Statistic',
                                  'p-value',
                                  '# Lags Used',
                                  'Number of Observations Used'])
    for key, value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput)
```

[15]:
```
stationarity_test(Df,'ts')
```




```
Results of Dickey-Fuller Test:
```

```
Test Statistic                  -2.256990
p-value                          0.186215
# Lags Used                     15.000000
Number of Observations Used    381.000000
Critical Value (1%)             -3.447631
Critical Value (5%)             -2.869156
Critical Value (10%)            -2.570827
dtype: float64
```

[16]:
```
def log_trans(df,ts):return df[ts].apply(lambda x:np.log(x))
```

Decomposition

[18]:
```
def plot_decomposition(df, ts,trend,seasonal, residual):

    f, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2,2, figsize = (15, 5), sharex =␣
 ↪True)

    ax1.plot(df[ts], label = 'Original')
    ax1.legend(loc = 'best')
    ax1.tick_params(axis = 'x', rotation = 45)

    ax2.plot(df[trend], label = 'Trend')
    ax2.legend(loc = 'best')
    ax2.tick_params(axis = 'x', rotation = 45)

    ax3.plot(df[seasonal],label = 'Seasonality')
    ax3.legend(loc = 'best')
    ax3.tick_params(axis = 'x', rotation = 45)

    ax4.plot(df[residual], label = 'Residuals')
    ax4.legend(loc = 'best')
    ax4.tick_params(axis = 'x', rotation = 45)
    plt.tight_layout()

#plt.subtitle('Signal Decomposition of %s' %(ts), x =0.5, y= 1.05, fontsize =␣
 ↪18)
plt.show()
```

[19]:
```
Df["ts_log"]=  log_trans(Df,"ts")
```

[20]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
decomposition = seasonal_decompose(Df["ts_log"],  model ="additive" ,freq=48,␣
 ↪extrapolate_trend=4)
```

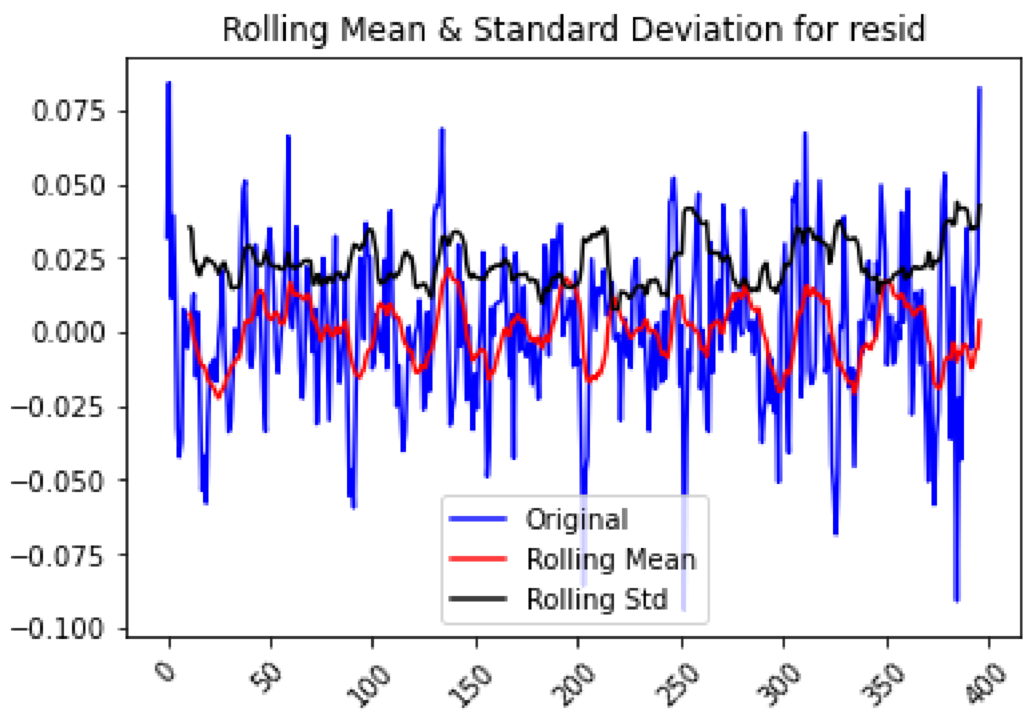
```
<ipython-input-20-6e240d52ead8>:2: FutureWarning: the 'freq'' keyword is
deprecated, use 'period' instead
  decomposition = seasonal_decompose(Df["ts_log"],  model ="additive" ,freq=48,
```

```
extrapolate_trend=4)
```

[21]:
```
New_Df= Df
New_Df.loc[:,"trend"]= decomposition.trend
New_Df.loc[:,"seasonal"]= decomposition.seasonal
New_Df.loc[:,"resid"] = decomposition.resid
New_Df.shape
```

[21]:
```
(397, 6)
```

[23]:
```
stationarity_test(New_Df, "resid")
```

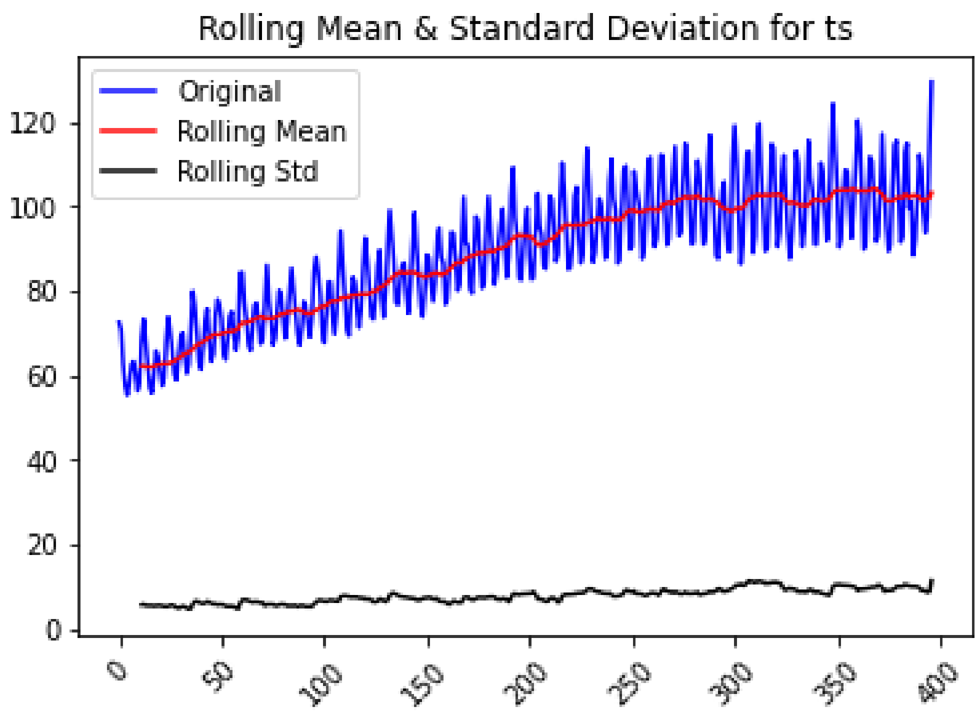



```
Results of Dickey-Fuller Test:
Test Statistic                 -5.710560e+00
p-value                         7.316325e-07
# Lags Used                     1.500000e+01
Number of Observations Used     3.810000e+02
Critical Value (1%)            -3.447631e+00
Critical Value (5%)            -2.869156e+00
Critical Value (10%)           -2.570827e+00
dtype: float64
```

[24]:
```
decomposition.seasonal
```

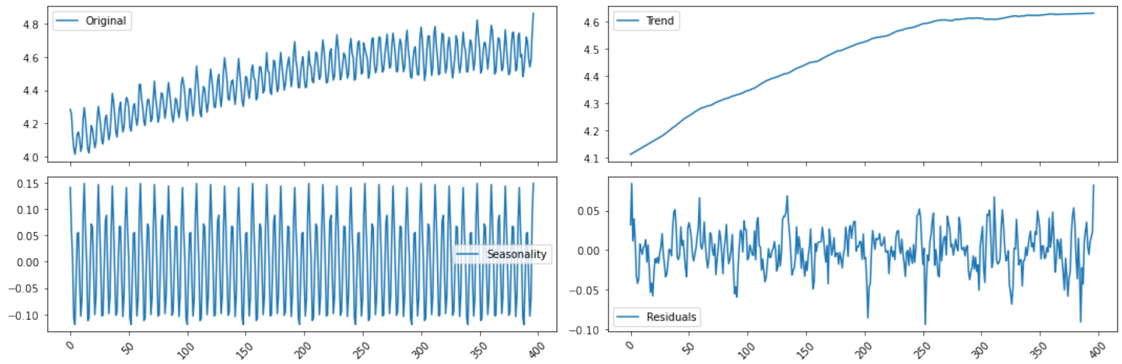
[24]:
```
0       0.140710
1       0.060143
2       0.006784
3      -0.106743
4      -0.119370
          …
392    -0.035025
393    -0.103407
394    -0.070384
395     0.087688
396     0.148382
Name: seasonal, Length: 397, dtype: float64
```

[25]:
```
stationarity_test(New_Df, "ts")
```




```
Results of Dickey-Fuller Test:
Test Statistic                  -2.256990
p-value                          0.186215
# Lags Used                     15.000000
Number of Observations Used    381.000000
Critical Value (1%)             -3.447631
Critical Value (5%)             -2.869156
Critical Value (10%)            -2.570827
dtype: float64
```

[26]:
```
plot_decomposition(New_Df, ts = "ts_log",trend ="trend",seasonal="seasonal",residual= "resid")
```



ARIMA Model

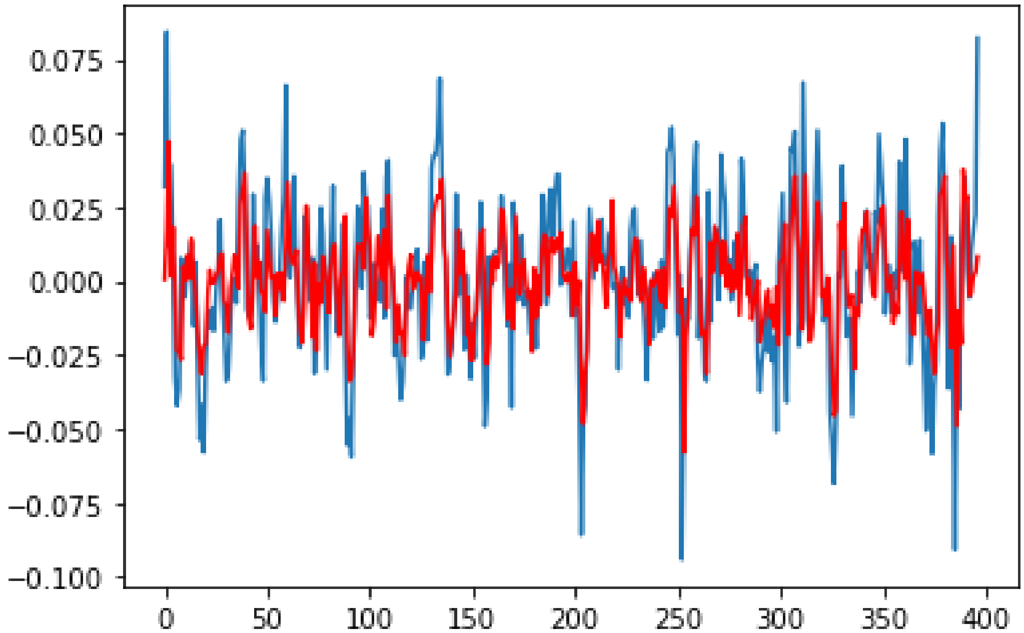
[28]:
```
from statsmodels.tsa.arima_model import ARIMA
```

[29]:
```
def run_arima(df,ts,p,d,q):
    model = ARIMA(df[ts], order=(p,d,q))
    results_arima = model.fit(disp=-1)

    len_results = len(results_arima.fittedvalues)
    ts_modified = df[ts][-len_results:]

    rss = sum((results_arima.fittedvalues - ts_modified)**2)
    rmse = np.sqrt(rss/len(df[ts]))

    print('rmse ',rmse/100)
    plt.figure()
    plt.plot(df[ts])
    plt.plot(results_arima.fittedvalues,color='red')

    plt.show()

    return results_arima
```

[30]:
```
New_Df = New_Df.fillna(value=0)
# New_Df = New_Df.fillna(0)
```

[31]:
```
model_Ar = run_arima(df=New_Df, ts='resid',p=15, d=0, q=0)
```

```
rmse  0.0002077953831303392
```



[32]:
```
model_Ar.summary()
```

[32]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                              ARMA Model Results
==============================================================================
Dep. Variable:                  resid   No. Observations:                  397
Model:                   ARMA(15, 0)   Log Likelihood                 975.445
Method:                       css-mle   S.D. of innovations              0.021
Date:                Sat, 15 May 2021   AIC                          -1916.890
Time:                        16:59:52   BIC                          -1849.164
Sample:                             0   HQIC                         -1890.062

================================================================================
                   coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const            0.0005      0.001      0.396      0.692      -0.002       0.003
ar.L1.resid      0.5515      0.050     10.979      0.000       0.453       0.650
ar.L2.resid     -0.0538      0.058     -0.925      0.355      -0.168       0.060
ar.L3.resid      0.0362      0.058      0.625      0.532      -0.077       0.150
ar.L4.resid     -0.0838      0.058     -1.451      0.147      -0.197       0.029
ar.L5.resid     -0.0244      0.058     -0.423      0.672      -0.138       0.089
ar.L6.resid      0.0276      0.057      0.480      0.631      -0.085       0.140
ar.L7.resid     -0.0504      0.057     -0.881      0.379      -0.163       0.062
ar.L8.resid     -0.0643      0.057     -1.123      0.262      -0.177       0.048
ar.L9.resid     -0.1052      0.058     -1.826      0.068      -0.218       0.008
```

```
ar.L10.resid      0.1360      0.058      2.344      0.019      0.022      0.250
ar.L11.resid     -0.0168      0.059     -0.286      0.775     -0.132      0.098
ar.L12.resid      0.1372      0.059      2.306      0.021      0.021      0.254
ar.L13.resid     -0.1676      0.060     -2.804      0.005     -0.285     -0.050
ar.L14.resid      0.0525      0.061      0.864      0.387     -0.067      0.172
ar.L15.resid     -0.1720      0.053     -3.258      0.001     -0.276     -0.069
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            1.0590           -0.2360j            1.0850           -0.0349
AR.2            1.0590           +0.2360j            1.0850            0.0349
AR.3            0.8931           -0.5689j            1.0589           -0.0903
AR.4            0.8931           +0.5689j            1.0589            0.0903
AR.5            0.5331           -0.9340j            1.0754           -0.1675
AR.6            0.5331           +0.9340j            1.0754            0.1675
AR.7           -1.0670           -0.0000j            1.0670           -0.5000
AR.8           -0.9715           -0.5396j            1.1113           -0.4193
AR.9           -0.9715           +0.5396j            1.1113            0.4193
AR.10          -0.6987           -0.9318j            1.1647           -0.3524
AR.11          -0.6987           +0.9318j            1.1647            0.3524
AR.12          -0.2819           -1.1291j            1.1637           -0.2889
AR.13          -0.2819           +1.1291j            1.1637            0.2889
AR.14           0.1529           -1.2447j            1.2541           -0.2305
AR.15           0.1529           +1.2447j            1.2541            0.2305
-----------------------------------------------------------------------------
"""
```

[33]:
```python
model_Ar.forecast(50)
```

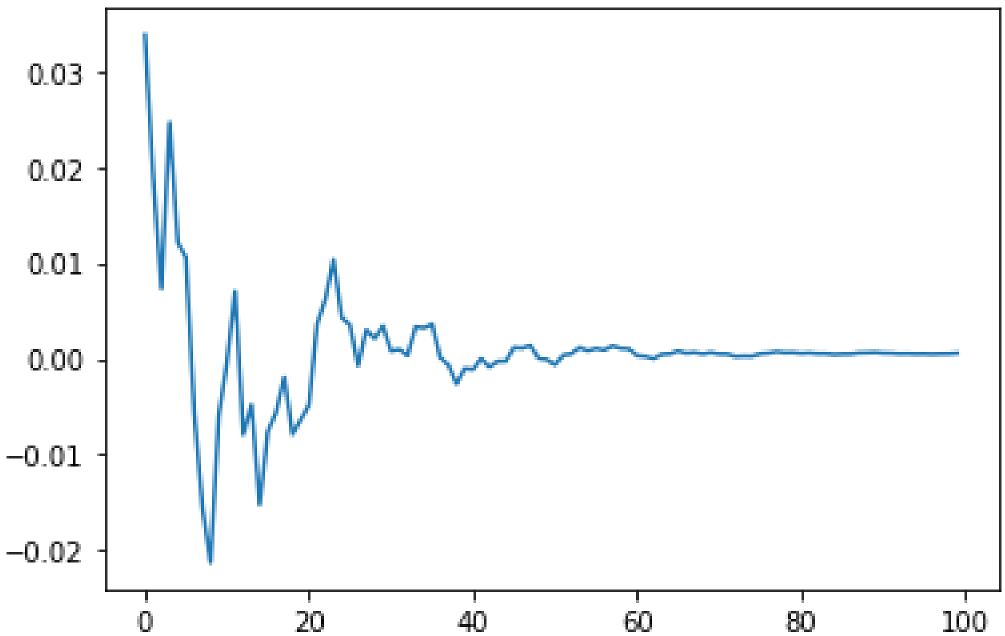
[33]:
```
(array([ 3.37853299e-02,  1.89863006e-02,  7.31208658e-03,  2.46505479e-02,
         1.21581475e-02,  1.05445230e-02, -5.43682558e-03, -1.54285724e-02,
        -2.12913012e-02, -6.00017660e-03, -4.13043687e-04,  7.02535661e-03,
        -7.92453084e-03, -4.83664612e-03, -1.52737855e-02, -7.57207397e-03,
        -5.60161107e-03, -1.94360234e-03, -7.89934080e-03, -6.37636564e-03,
        -4.88780693e-03,  3.61624744e-03,  6.16000949e-03,  1.03472614e-02,
         4.27387121e-03,  3.52298220e-03, -7.46053037e-04,  2.99949686e-03,
         2.08840273e-03,  3.40314881e-03,  7.77576346e-04,  9.56638974e-04,
         3.09712519e-04,  3.31429212e-03,  3.18349963e-03,  3.60371630e-03,
         9.45330449e-05, -6.77297083e-04, -2.64335676e-03, -1.03618912e-03,
        -1.14735524e-03,  9.61178789e-06, -8.93816595e-04, -2.92680598e-04,
        -2.85295155e-04,  1.16270770e-03,  1.08300793e-03,  1.37651722e-03,
         4.64462779e-06, -1.14286889e-04]),
 array([0.02068879, 0.02362665, 0.02418785, 0.02437222, 0.02437228,
        0.02441286, 0.02442641, 0.02447098, 0.02461536, 0.02500394,
        0.02502805, 0.02502827, 0.02524459, 0.02525455, 0.02525871,
        0.02544393, 0.0257149 , 0.0258375 , 0.02587871, 0.02591126,
```

```
       0.02591779, 0.02592391, 0.02594137, 0.02597981, 0.02611156,
       0.02614748, 0.02615561, 0.02616837, 0.02617807, 0.0261834 ,
       0.0261837 , 0.02618599, 0.02619094, 0.02619253, 0.02620278,
       0.0262103 , 0.0262214 , 0.02622141, 0.02622384, 0.0262412 ,
       0.02625296, 0.02625916, 0.02625933, 0.02625935, 0.02625991,
       0.02626006, 0.02626101, 0.02626132, 0.02626182, 0.02626218]),
array([[-0.00676395,  0.07433461],
       [-0.02732109,  0.06529369],
       [-0.04009522,  0.05471939],
       [-0.02311813,  0.07241923],
       [-0.03561063,  0.05992693],
       [-0.03730381,  0.05839285],
       [-0.05331171,  0.04243806],
       [-0.06339082,  0.03253367],
       [-0.06953653,  0.02695393],
       [-0.05500701,  0.04300665],
       [-0.04946712,  0.04864103],
       [-0.04202914,  0.05607986],
       [-0.05740302,  0.04155396],
       [-0.05433465,  0.04466135],
       [-0.06477995,  0.03423238],
       [-0.05744127,  0.04229712],
       [-0.05600189,  0.04479867],
       [-0.05258417,  0.04869697],
       [-0.05862068,  0.042822  ],
       [-0.0571615 ,  0.04440877],
       [-0.05568575,  0.04591013],
       [-0.04719369,  0.05442618],
       [-0.04468415,  0.05700417],
       [-0.04057224,  0.06126676],
       [-0.04690384,  0.05545158],
       [-0.04772515,  0.05477111],
       [-0.05201011,  0.05051801],
       [-0.04828956,  0.05428855],
       [-0.04921967,  0.05339647],
       [-0.04791538,  0.05472168],
       [-0.05054152,  0.05209668],
       [-0.05036696,  0.05228023],
       [-0.05102359,  0.05164302],
       [-0.04802213,  0.05465072],
       [-0.04817301,  0.05454001],
       [-0.04776752,  0.05497496],
       [-0.05129846,  0.05148753],
       [-0.05207032,  0.05071573],
       [-0.05404114,  0.04875443],
       [-0.052468  ,  0.05039562],
       [-0.05260221,  0.0503075 ],
```

```
[-0.05145739,  0.05147662],
[-0.05236115,  0.05057351],
[-0.05176006,  0.0511747 ],
[-0.05175377,  0.05118318],
[-0.05030607,  0.05263149],
[-0.05038762,  0.05255364],
[-0.05009472,  0.05284776],
[-0.05146759,  0.05147688],
[-0.05158722,  0.05135864]]))
```

[25]:
```
plt.figure()
plt.plot(model_Ar.forecast(100)[0])
```

[25]:
```
[<matplotlib.lines.Line2D at 0x1a2c701dd0>]
```



[ ]: