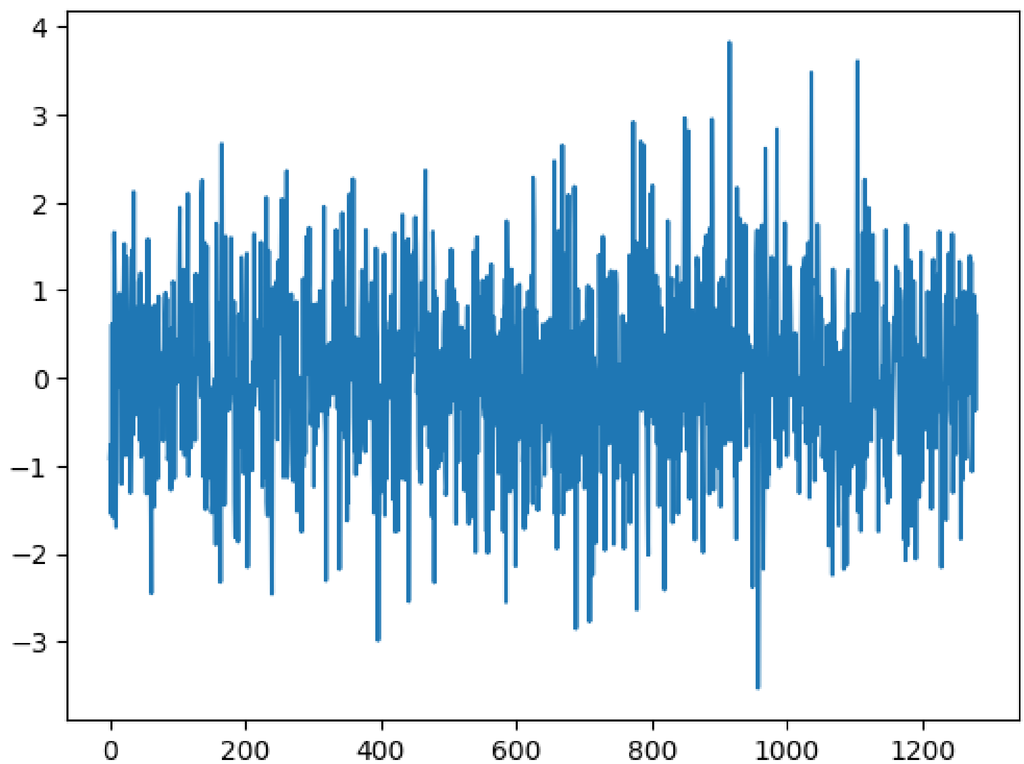
order1

October 13, 2024

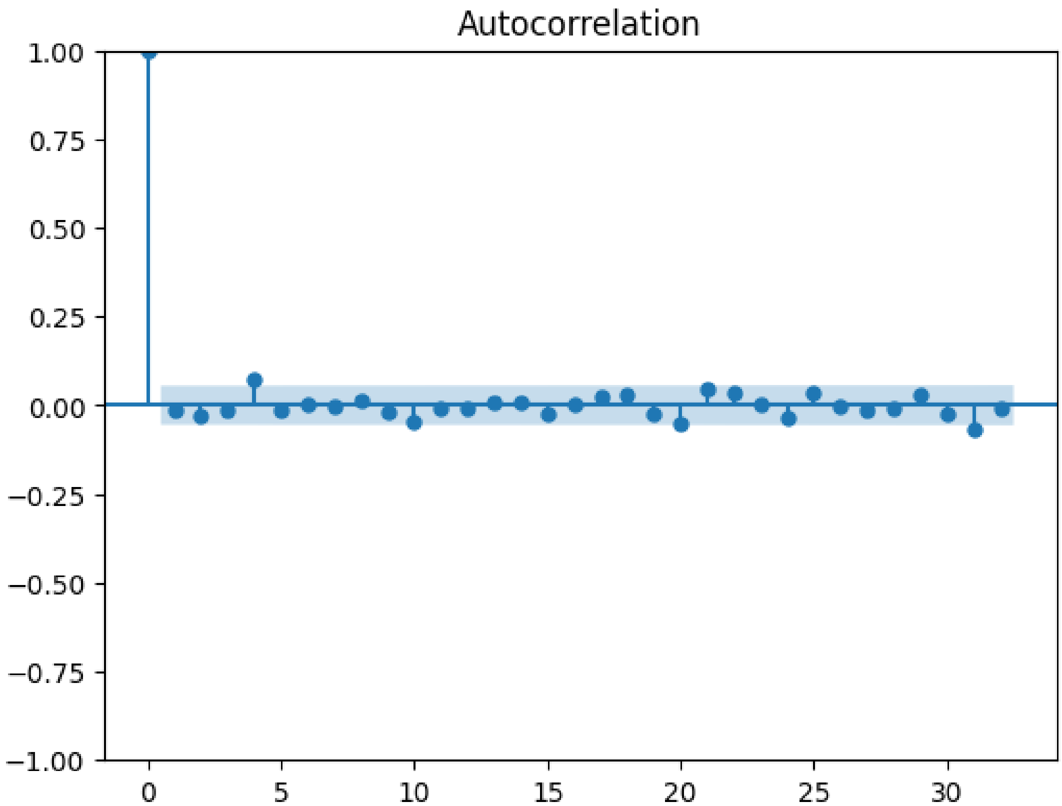
[1]:
```
import numpy as np
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
from statsmodels.stats.diagnostic import acorr_ljungbox
```

[4]:
```
# Gerar uma série de ruído branco com média 0 e desvio padrão 1
ruido_branco = np.random.normal(0, 1, 1280)
```

[5]:
```
plt.plot(ruido_branco)
plt.show()
```



[6]:
```python
sm.graphics.tsa.plot_acf(ruido_branco)
plt.show()
```



[7]:
```python
# Realizar o teste de Ljung-Box para autocorrelação
ljung_box_result = acorr_ljungbox(ruido_branco, lags=[10], return_df=True)
print(ljung_box_result)
```

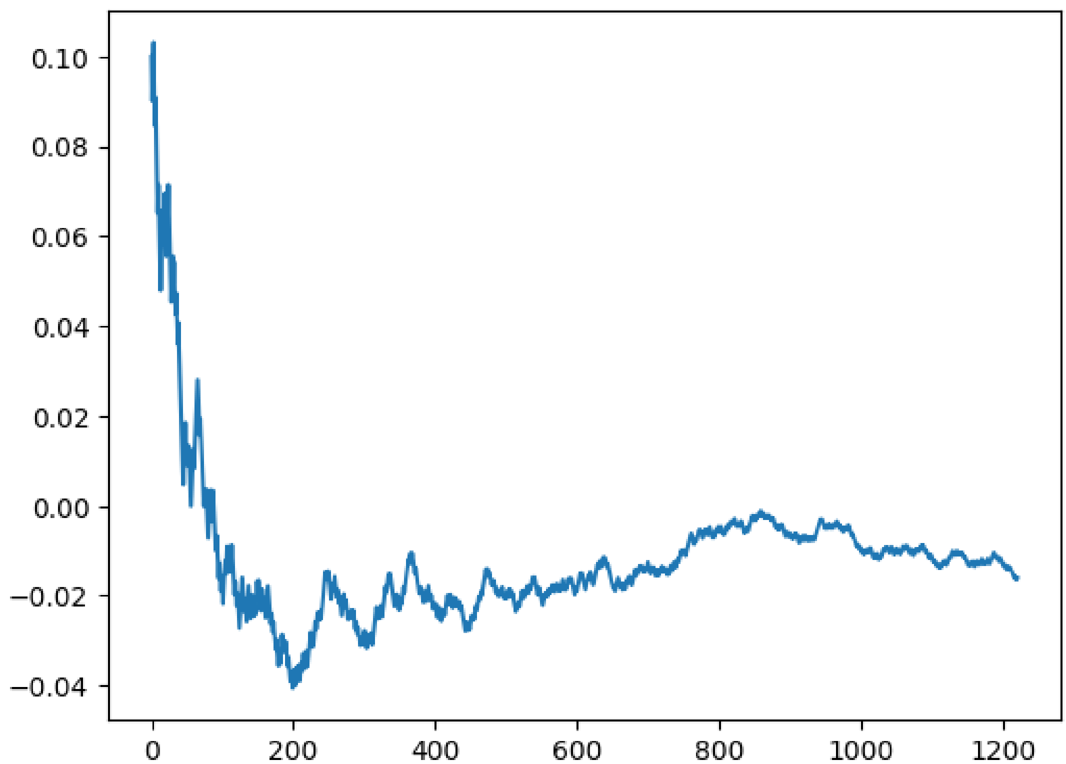
```
      lb_stat  lb_pvalue
10  11.583225   0.313917
```

[8]:
```python
data = pd.read_csv('/home/darkcover/Documentos/Out/dados/odds_200k_1.csv')

array1, array2, array3 = [], [], []
for i in range(0, len(data)):
    if data['Odd'][i] >= 2:
        array1.append(1)
    else:
        array1.append(0)

for j in range(60, 1280):
    array = array1[j - 60: j]
```

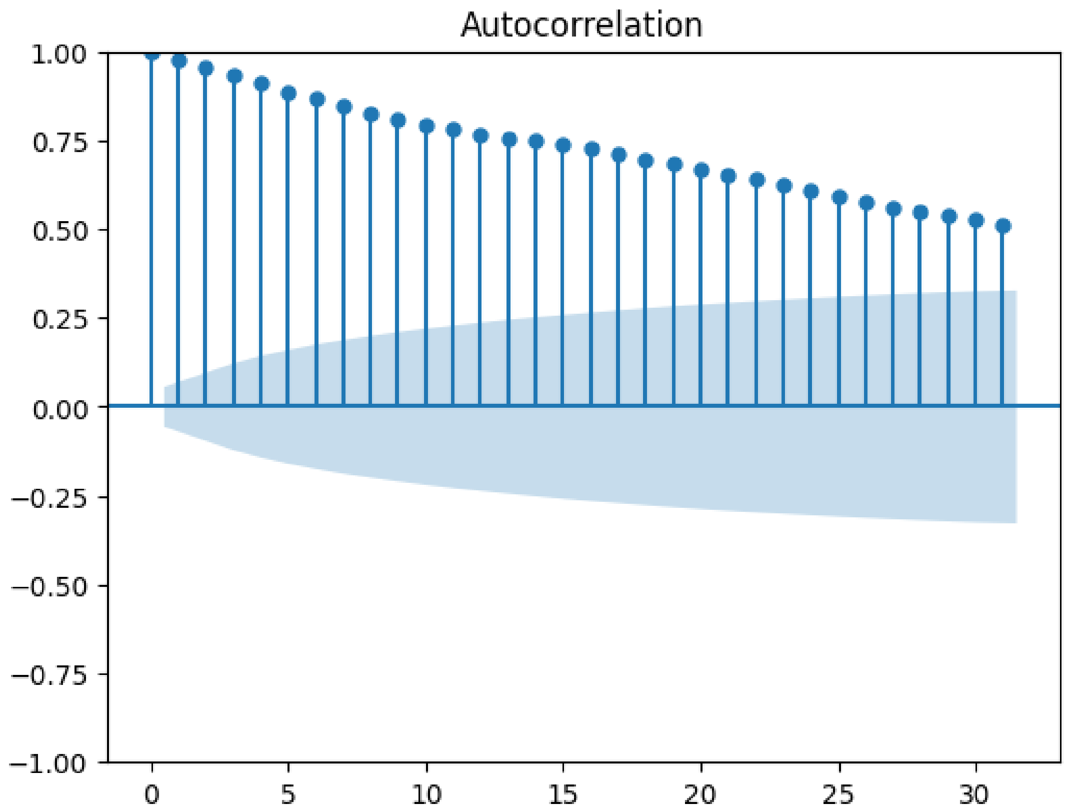
```
    media = sum(array)/60 - 0.5
    array2.append(media)

for k in range(60,1280):
    media = sum(array1[0:k]) / len(array1[0:k]) - 0.5
    array3.append(media)
```

[9]:
```
plt.plot(array3)
```

[9]: [<matplotlib.lines.Line2D at 0x7859f00fa870>]

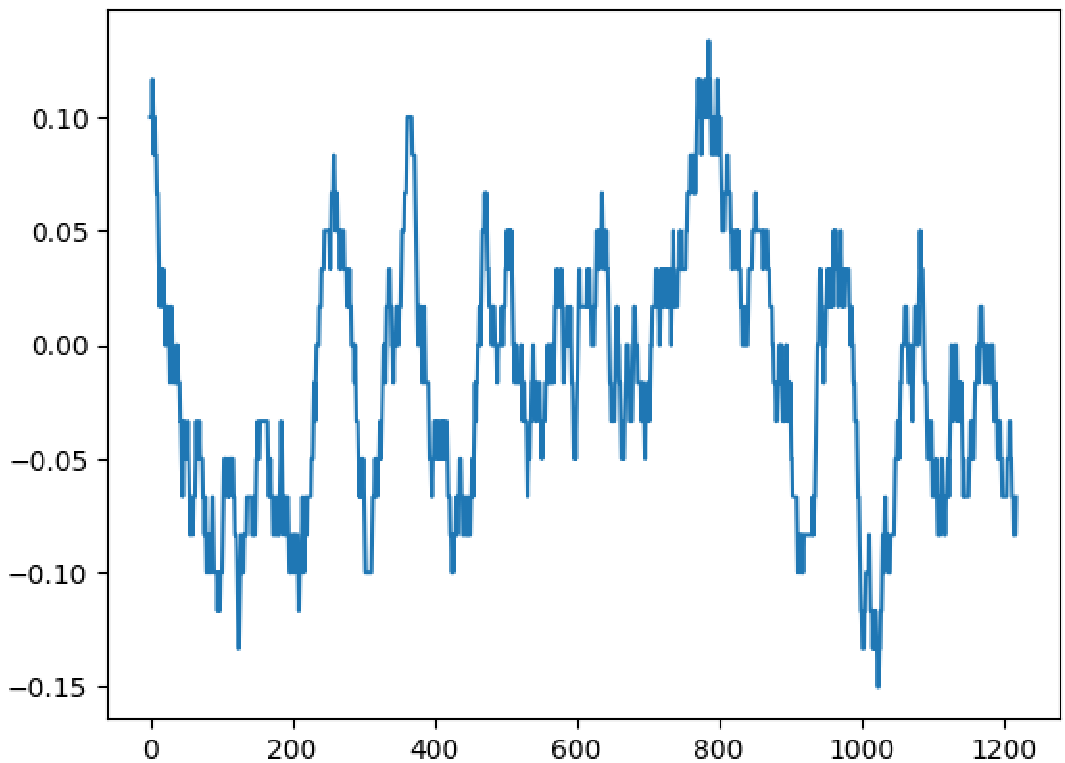


[10]:
```
sm.graphics.tsa.plot_acf(np.array(array3))
plt.show()
```

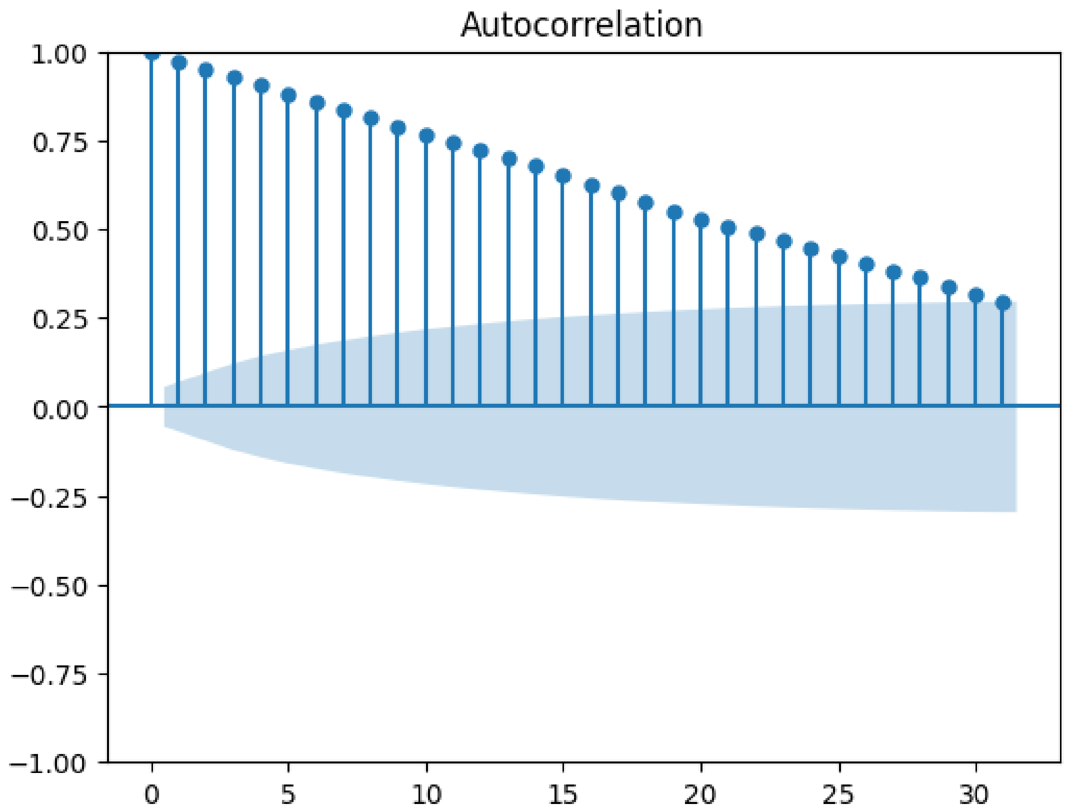


[11]:
```
plt.plot(array2)
```

[11]: [<matplotlib.lines.Line2D at 0x7859f0231820>]



[12]:
```
sm.graphics.tsa.plot_acf(np.array(array2))
plt.show()
```



[13]:

```python
# Realizar o teste de Ljung-Box para autocorrelação
ljung_box_result = acorr_ljungbox(array2, lags=range(60,120), return_df=True)
print(ljung_box_result)
```

```
         lb_stat  lb_pvalue
60  17258.192397        0.0
61  17266.552189        0.0
62  17272.654486        0.0
63  17276.979578        0.0
64  17279.617582        0.0
65  17281.095918        0.0
66  17281.855783        0.0
67  17282.133870        0.0
68  17282.174848        0.0
69  17282.221264        0.0
70  17282.526297        0.0
71  17283.388777        0.0
72  17285.020283        0.0
73  17287.547238        0.0
74  17291.091216        0.0
75  17296.431336        0.0
```

```
76   17303.675919        0.0
77   17313.984608        0.0
78   17327.733539        0.0
79   17344.809364        0.0
80   17365.342923        0.0
81   17389.880508        0.0
82   17418.268552        0.0
83   17450.792484        0.0
84   17488.600381        0.0
85   17533.070316        0.0
86   17584.791363        0.0
87   17641.855838        0.0
88   17705.115740        0.0
89   17775.846112        0.0
90   17852.668176        0.0
91   17936.201749        0.0
92   18027.493572        0.0
93   18125.933653        0.0
94   18229.702949        0.0
95   18339.658520        0.0
96   18456.348949        0.0
97   18578.975653        0.0
98   18707.624575        0.0
99   18840.664841        0.0
100  18976.445981        0.0
101  19113.658196        0.0
102  19250.971376        0.0
103  19387.123477        0.0
104  19519.876751        0.0
105  19649.991004        0.0
106  19775.563684        0.0
107  19896.355177        0.0
108  20012.451934        0.0
109  20123.822250        0.0
110  20228.734092        0.0
111  20326.243473        0.0
112  20418.582824        0.0
113  20504.612663        0.0
114  20584.450297        0.0
115  20657.828045        0.0
116  20724.778092        0.0
117  20785.768731        0.0
118  20840.051336        0.0
119  20888.449561        0.0
```

[14]:
```
from statsmodels.tsa.ar_model import AutoReg
```

```python
# Ajustar o modelo AR ao array2
model_ar = AutoReg(array2, lags=60)  # Ajuste o lag conforme sua análise de ACF
model_ar_fit = model_ar.fit()

# Exibir sumário do modelo AR
print(model_ar_fit.summary())
```

```
                            AutoReg Model Results
==============================================================================
Dep. Variable:                      y   No. Observations:                 1220
Model:                     AutoReg(60)   Log Likelihood                3558.778
Method:               Conditional MLE   S.D. of innovations              0.011
Date:                Sun, 13 Oct 2024   AIC                          -6993.556
Time:                        18:02:24   BIC                          -6680.073
Sample:                            60   HQIC                         -6875.272
                                 1220
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0006      0.000     -1.728      0.084      -0.001    8.41e-05
y.L1           0.9328      0.029     31.812      0.000       0.875       0.990
y.L2           0.0283      0.040      0.706      0.480      -0.050       0.107
y.L3           0.0610      0.040      1.520      0.128      -0.018       0.140
y.L4          -0.0150      0.040     -0.374      0.708      -0.094       0.064
y.L5          -0.0636      0.040     -1.586      0.113      -0.142       0.015
y.L6           0.0613      0.040      1.529      0.126      -0.017       0.140
y.L7          -0.0097      0.040     -0.242      0.809      -0.088       0.069
y.L8           0.0539      0.040      1.348      0.178      -0.024       0.132
y.L9          -0.1323      0.040     -3.322      0.001      -0.210      -0.054
y.L10          0.0351      0.040      0.876      0.381      -0.043       0.114
y.L11          0.0469      0.040      1.172      0.241      -0.032       0.125
y.L12         -0.0164      0.040     -0.411      0.681      -0.095       0.062
y.L13          0.0378      0.040      0.947      0.344      -0.041       0.116
y.L14          0.0183      0.040      0.459      0.647      -0.060       0.097
y.L15         -0.0845      0.040     -2.119      0.034      -0.163      -0.006
y.L16          0.0507      0.040      1.270      0.204      -0.028       0.129
y.L17         -0.0249      0.040     -0.623      0.533      -0.103       0.053
y.L18         -0.0206      0.040     -0.515      0.606      -0.099       0.058
y.L19         -0.0203      0.040     -0.509      0.610      -0.099       0.058
y.L20          0.0396      0.040      0.992      0.321      -0.039       0.118
y.L21         -0.0296      0.040     -0.741      0.459      -0.108       0.049
y.L22          0.0125      0.040      0.314      0.753      -0.066       0.091
y.L23          0.0308      0.040      0.773      0.440      -0.047       0.109
y.L24          0.0090      0.040      0.226      0.821      -0.069       0.087
y.L25          0.0178      0.040      0.448      0.654      -0.060       0.096
y.L26         -0.1005      0.040     -2.522      0.012      -0.179      -0.022
y.L27          0.1177      0.040      2.957      0.003       0.040       0.196
y.L28         -0.0260      0.040     -0.650      0.515      -0.104       0.052
```

y.L29	-0.0272	0.040	-0.683	0.495	-0.105	0.051
y.L30	-0.0068	0.040	-0.170	0.865	-0.085	0.071
y.L31	-0.0014	0.040	-0.034	0.973	-0.080	0.077
y.L32	-0.0501	0.040	-1.257	0.209	-0.128	0.028
y.L33	-0.0192	0.040	-0.483	0.629	-0.097	0.059
y.L34	0.1172	0.040	2.951	0.003	0.039	0.195
y.L35	-0.0432	0.040	-1.087	0.277	-0.121	0.035
y.L36	-0.0298	0.040	-0.749	0.454	-0.108	0.048
y.L37	0.0274	0.040	0.688	0.492	-0.051	0.105
y.L38	-0.0470	0.040	-1.180	0.238	-0.125	0.031
y.L39	0.0513	0.040	1.290	0.197	-0.027	0.129
y.L40	-0.0130	0.040	-0.326	0.744	-0.091	0.065
y.L41	0.0035	0.040	0.088	0.930	-0.075	0.082
y.L42	0.0163	0.040	0.409	0.683	-0.062	0.094
y.L43	-0.0344	0.040	-0.865	0.387	-0.112	0.044
y.L44	0.0374	0.040	0.941	0.347	-0.041	0.115
y.L45	-0.0243	0.040	-0.611	0.542	-0.102	0.054
y.L46	0.0164	0.040	0.413	0.680	-0.061	0.094
y.L47	-0.0715	0.040	-1.804	0.071	-0.149	0.006
y.L48	0.0207	0.040	0.521	0.602	-0.057	0.098
y.L49	0.0209	0.040	0.527	0.598	-0.057	0.099
y.L50	0.0482	0.040	1.214	0.225	-0.030	0.126
y.L51	0.0442	0.040	1.114	0.265	-0.034	0.122
y.L52	-0.1304	0.039	-3.302	0.001	-0.208	-0.053
y.L53	0.0548	0.040	1.382	0.167	-0.023	0.132
y.L54	-0.0396	0.040	-0.998	0.318	-0.117	0.038
y.L55	0.0816	0.040	2.057	0.040	0.004	0.159
y.L56	-0.0410	0.040	-1.032	0.302	-0.119	0.037
y.L57	-0.0268	0.040	-0.677	0.498	-0.105	0.051
y.L58	0.0429	0.040	1.083	0.279	-0.035	0.120
y.L59	0.0383	0.040	0.967	0.334	-0.039	0.116
y.L60	-0.0636	0.029	-2.191	0.028	-0.120	-0.007

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	-1.0301	-0.0575j	1.0317	-0.4911
AR.2	-1.0301	+0.0575j	1.0317	0.4911
AR.3	-1.0205	-0.1646j	1.0337	-0.4745
AR.4	-1.0205	+0.1646j	1.0337	0.4745
AR.5	-0.9920	-0.2966j	1.0354	-0.4538
AR.6	-0.9920	+0.2966j	1.0354	0.4538
AR.7	-0.9452	-0.4055j	1.0286	-0.4355
AR.8	-0.9452	+0.4055j	1.0286	0.4355
AR.9	-0.8768	-0.5489j	1.0345	-0.4110
AR.10	-0.8768	+0.5489j	1.0345	0.4110
AR.11	-1.1164	-0.5635j	1.2506	-0.4256
AR.12	-1.1164	+0.5635j	1.2506	0.4256

AR.13	-0.8223	-0.6499j	1.0481	-0.3936
AR.14	-0.8223	+0.6499j	1.0481	0.3936
AR.15	-0.7331	-0.7267j	1.0323	-0.3757
AR.16	-0.7331	+0.7267j	1.0323	0.3757
AR.17	-0.6416	-0.8001j	1.0255	-0.3576
AR.18	-0.6416	+0.8001j	1.0255	0.3576
AR.19	-0.5680	-0.8922j	1.0576	-0.3402
AR.20	-0.5680	+0.8922j	1.0576	0.3402
AR.21	-0.4640	-0.9297j	1.0390	-0.3237
AR.22	-0.4640	+0.9297j	1.0390	0.3237
AR.23	-0.3633	-0.9938j	1.0581	-0.3058
AR.24	-0.3633	+0.9938j	1.0581	0.3058
AR.25	-0.2600	-0.9888j	1.0224	-0.2909
AR.26	-0.2600	+0.9888j	1.0224	0.2909
AR.27	-0.1503	-1.0360j	1.0468	-0.2729
AR.28	-0.1503	+1.0360j	1.0468	0.2729
AR.29	-0.0428	-1.0231j	1.0240	-0.2567
AR.30	-0.0428	+1.0231j	1.0240	0.2567
AR.31	0.0746	-1.0248j	1.0275	-0.2384
AR.32	0.0746	+1.0248j	1.0275	0.2384
AR.33	0.1928	-1.0118j	1.0300	-0.2200
AR.34	0.1928	+1.0118j	1.0300	0.2200
AR.35	0.3112	-0.9803j	1.0285	-0.2011
AR.36	0.3112	+0.9803j	1.0285	0.2011
AR.37	0.4621	-0.9337j	1.0417	-0.1769
AR.38	0.4621	+0.9337j	1.0417	0.1769
AR.39	0.5224	-1.0005j	1.1287	-0.1734
AR.40	0.5224	+1.0005j	1.1287	0.1734
AR.41	0.5803	-0.8767j	1.0513	-0.1569
AR.42	0.5803	+0.8767j	1.0513	0.1569
AR.43	0.6588	-0.7850j	1.0248	-0.1389
AR.44	0.6588	+0.7850j	1.0248	0.1389
AR.45	0.7593	-0.7002j	1.0329	-0.1186
AR.46	0.7593	+0.7002j	1.0329	0.1186
AR.47	0.8480	-0.6221j	1.0517	-0.1007
AR.48	0.8480	+0.6221j	1.0517	0.1007
AR.49	0.9212	-0.5275j	1.0615	-0.0828
AR.50	0.9212	+0.5275j	1.0615	0.0828
AR.51	0.9360	-0.4525j	1.0397	-0.0717
AR.52	0.9360	+0.4525j	1.0397	0.0717
AR.53	0.9941	-0.3317j	1.0480	-0.0513
AR.54	0.9941	+0.3317j	1.0480	0.0513
AR.55	1.0144	-0.2287j	1.0398	-0.0353
AR.56	1.0144	+0.2287j	1.0398	0.0353
AR.57	1.0351	-0.1139j	1.0414	-0.0174
AR.58	1.0351	+0.1139j	1.0414	0.0174
AR.59	1.0170	-0.0349j	1.0176	-0.0055
AR.60	1.0170	+0.0349j	1.0176	0.0055

----

[20]:
```
# Previsão de 0 passos à frente
previsao = model_ar_fit.predict(start=len(array2), end=len(array2)+ 640)

print("Previsão das médias futuras (AR):", previsao)
```

```
Previsão das médias futuras (AR): [-0.0602307  -0.06355093 -0.06375526
-0.05837954 -0.05948014 -0.0600288
 -0.05658683 -0.05583314 -0.05822094 -0.05709541 -0.05569757 -0.05485859
 -0.0523286  -0.05161318 -0.04541339 -0.04232935 -0.04068978 -0.03860122
 -0.04400248 -0.04445518 -0.04128352 -0.04054832 -0.04447759 -0.04171924
 -0.04088192 -0.03819706 -0.03554492 -0.03462488 -0.03222155 -0.03154688
 -0.03167294 -0.02833924 -0.03212698 -0.02974319 -0.02761224 -0.02941296
 -0.0298343  -0.02855489 -0.02898059 -0.02670216 -0.02362663 -0.02220037
 -0.02141486 -0.02083179 -0.01939296 -0.01669577 -0.0206265  -0.01909168
 -0.01758674 -0.01714515 -0.01676151 -0.0161129  -0.01745837 -0.01722627
 -0.01646749 -0.01512638 -0.01453448 -0.01408873 -0.01193896 -0.01210502
 -0.01259404 -0.01176442 -0.01122094 -0.01182111 -0.01149461 -0.00951926
 -0.01002079 -0.00960661 -0.00900781 -0.00896156 -0.00813689 -0.00786004
 -0.00740387 -0.00775678 -0.00762255 -0.00716686 -0.00700633 -0.00813197
 -0.00772897 -0.00687503 -0.00773003 -0.0078768  -0.00726365 -0.00757078
 -0.00683145 -0.00674247 -0.00677195 -0.00724514 -0.00767097 -0.00736651
 -0.00733102 -0.0081035  -0.00770019 -0.00776347 -0.00835231 -0.00804703
 -0.00820074 -0.00895136 -0.00862176 -0.0083658  -0.00829437 -0.00885851
 -0.00912694 -0.00924948 -0.00947343 -0.01020807 -0.00988117 -0.01012599
 -0.01054643 -0.01038737 -0.0107097  -0.01113634 -0.01130048 -0.01128125
 -0.01153812 -0.01183475 -0.0118487  -0.01210502 -0.01245563 -0.01278975
 -0.01265415 -0.01294868 -0.01338605 -0.01329947 -0.01344248 -0.01375717
 -0.01382186 -0.01394288 -0.0142851  -0.01429717 -0.01443195 -0.01475054
 -0.01508778 -0.01520342 -0.01515403 -0.01537534 -0.01569951 -0.01565353
 -0.01587345 -0.01616462 -0.01612834 -0.01622138 -0.01649948 -0.01646377
 -0.01657528 -0.01672708 -0.0169531  -0.01710879 -0.01710603 -0.01724887
 -0.0173148  -0.01727872 -0.01750602 -0.01761958 -0.01756262 -0.01768145
 -0.01788671 -0.01778417 -0.01783368 -0.01791272 -0.01802558 -0.01806845
 -0.01809204 -0.01820454 -0.0181938  -0.01815158 -0.01826034 -0.01830047
 -0.01824077 -0.01830664 -0.01836808 -0.01828942 -0.018326   -0.01837851
 -0.01836323 -0.01832509 -0.01836084 -0.01839142 -0.0183397  -0.01827756
 -0.01830821 -0.01831984 -0.0182501  -0.01828643 -0.0182517  -0.01815717
 -0.0181749  -0.01818583 -0.01811592 -0.01808952 -0.01810115 -0.01807537
 -0.01800699 -0.01795578 -0.01794346 -0.01790554 -0.01783406 -0.01786821
 -0.01782024 -0.01772222 -0.01771352 -0.01768605 -0.01761922 -0.01758869
 -0.01756382 -0.0175248  -0.01747632 -0.01743632 -0.01739528 -0.01733265
 -0.01728381 -0.01729661 -0.01723213 -0.01716658 -0.01715757 -0.0171176
 -0.01705094 -0.01703049 -0.01700665 -0.01695682 -0.01691578 -0.01688709
 -0.01685665 -0.01680375 -0.01676983 -0.01676119 -0.01671118 -0.01667509
 -0.01666236 -0.01662172 -0.01657118 -0.01656709 -0.01654978 -0.01650563
 -0.01648121 -0.01646017 -0.01643558 -0.01640145 -0.01638232 -0.01637129
```

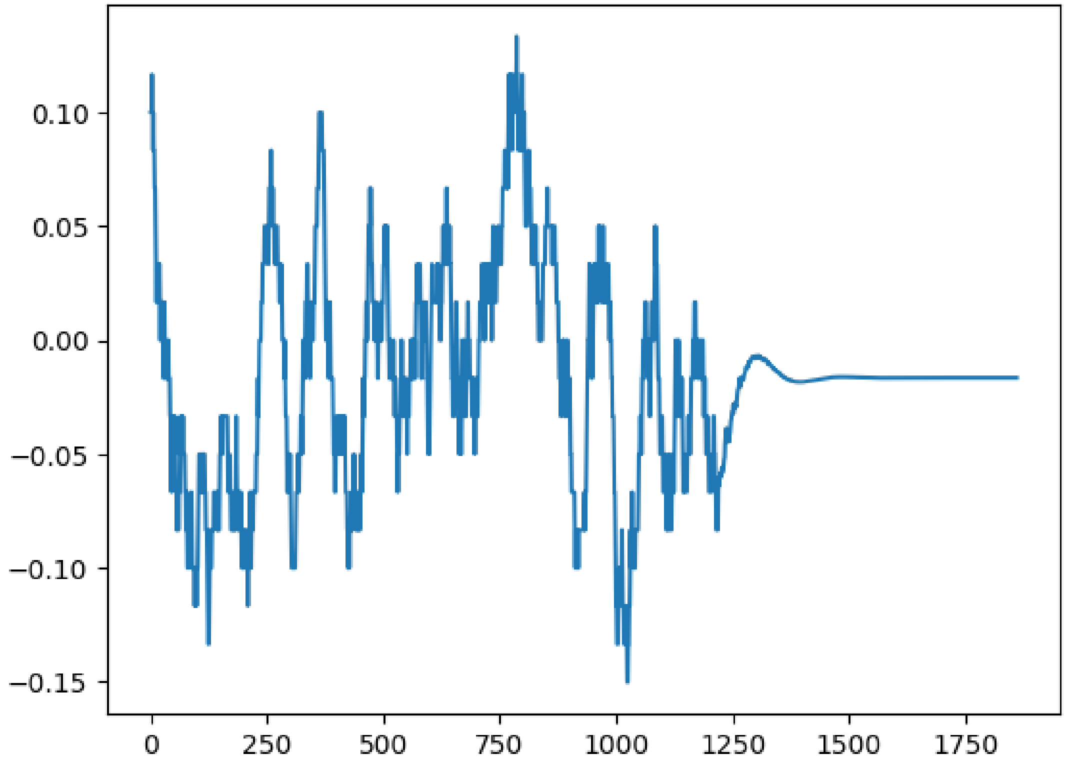
-0.01634164	-0.01632436	-0.01631917	-0.01628493	-0.01625633	-0.01626008
-0.0162453	-0.01621988	-0.01621754	-0.01620552	-0.01618684	-0.01617084
-0.01616741	-0.0161609	-0.01614276	-0.01613961	-0.01614593	-0.01612717
-0.01611475	-0.01612136	-0.01611288	-0.0161062	-0.01611257	-0.01610758
-0.01610139	-0.01610025	-0.0161049	-0.0161021	-0.01609853	-0.01610555
-0.01611244	-0.01610489	-0.01610812	-0.01611955	-0.01611535	-0.01611828
-0.01613109	-0.01613374	-0.01613413	-0.01614043	-0.01614873	-0.01615185
-0.01615805	-0.01616866	-0.01617595	-0.01617692	-0.01618705	-0.01619847
-0.01619862	-0.01620684	-0.01622149	-0.0162273	-0.01623228	-0.01624251
-0.0162499	-0.01625593	-0.01626551	-0.01627639	-0.01628407	-0.01628956
-0.01630082	-0.01631017	-0.01631298	-0.01632339	-0.01633512	-0.01634008
-0.01634788	-0.01635927	-0.01636458	-0.01637004	-0.01637954	-0.01638901
-0.01639531	-0.01640083	-0.01641057	-0.01641772	-0.01642117	-0.01642999
-0.01643786	-0.0164419	-0.01644901	-0.01645721	-0.01646059	-0.01646555
-0.01647271	-0.01647835	-0.0164826	-0.01648777	-0.01649426	-0.01649755
-0.01650029	-0.01650681	-0.01651126	-0.01651315	-0.01651814	-0.01652308
-0.01652439	-0.01652751	-0.01653156	-0.01653387	-0.01653605	-0.01653958
-0.01654268	-0.01654337	-0.01654469	-0.01654804	-0.01654952	-0.01654965
-0.01655238	-0.01655424	-0.01655377	-0.01655513	-0.01655648	-0.01655625
-0.01655668	-0.01655798	-0.01655844	-0.01655773	-0.01655778	-0.01655835
-0.01655758	-0.01655674	-0.01655766	-0.01655699	-0.01655527	-0.01655547
-0.01655503	-0.01655319	-0.01655236	-0.01655213	-0.01655101	-0.01654935
-0.01654838	-0.01654744	-0.01654559	-0.01654408	-0.01654361	-0.01654182
-0.0165398	-0.01653898	-0.01653736	-0.01653512	-0.01653389	-0.01653268
-0.01653068	-0.01652892	-0.01652763	-0.01652592	-0.01652371	-0.01652211
-0.01652102	-0.01651895	-0.01651708	-0.01651592	-0.01651399	-0.01651189
-0.01651065	-0.01650917	-0.01650715	-0.01650567	-0.01650441	-0.01650267
-0.01650078	-0.01649943	-0.01649822	-0.01649643	-0.01649501	-0.01649397
-0.01649231	-0.01649071	-0.01648974	-0.01648844	-0.01648692	-0.01648592
-0.01648486	-0.01648353	-0.01648231	-0.01648141	-0.01648037	-0.01647915
-0.01647836	-0.01647765	-0.01647645	-0.0164755	-0.01647499	-0.01647408
-0.01647316	-0.01647269	-0.01647206	-0.01647126	-0.01647065	-0.01647022
-0.01646963	-0.01646901	-0.01646871	-0.01646838	-0.01646779	-0.01646744
-0.01646728	-0.01646681	-0.0164665	-0.01646647	-0.01646623	-0.01646593
-0.01646584	-0.01646579	-0.01646559	-0.01646548	-0.01646556	-0.01646556
-0.01646544	-0.01646554	-0.01646566	-0.01646556	-0.01646567	-0.01646593
-0.01646598	-0.01646606	-0.01646631	-0.0164665	-0.01646659	-0.01646681
-0.01646712	-0.01646732	-0.0164675	-0.01646784	-0.01646813	-0.01646829
-0.01646861	-0.01646899	-0.01646922	-0.01646952	-0.01646991	-0.01647019
-0.01647046	-0.01647084	-0.01647121	-0.0164715	-0.01647182	-0.01647224
-0.01647256	-0.01647282	-0.01647322	-0.0164736	-0.01647388	-0.01647423
-0.01647463	-0.01647493	-0.01647523	-0.0164756	-0.01647594	-0.01647623
-0.01647656	-0.01647692	-0.0164772	-0.01647747	-0.01647782	-0.01647811
-0.01647836	-0.01647868	-0.01647899	-0.01647921	-0.01647947	-0.01647976
-0.01648	-0.01648022	-0.01648049	-0.01648074	-0.01648093	-0.01648114
-0.01648138	-0.01648156	-0.01648173	-0.01648195	-0.01648214	-0.01648227
-0.01648245	-0.01648262	-0.01648275	-0.01648288	-0.01648304	-0.01648317
-0.01648326	-0.01648338	-0.0164835	-0.01648358	-0.01648366	-0.01648377

```
 -0.01648385 -0.0164839  -0.01648398 -0.01648404 -0.01648407 -0.01648412
 -0.01648418 -0.0164842  -0.01648422 -0.01648425 -0.01648428 -0.01648427
 -0.01648427 -0.0164843  -0.01648429 -0.01648427 -0.01648427 -0.01648426
 -0.01648422 -0.0164842  -0.01648419 -0.01648415 -0.01648411 -0.01648408
 -0.01648404 -0.01648399 -0.01648394 -0.01648391 -0.01648385 -0.01648379
 -0.01648375 -0.01648369 -0.01648362 -0.01648356 -0.01648351 -0.01648343
 -0.01648337 -0.01648332 -0.01648324 -0.01648317 -0.01648311 -0.01648304
 -0.01648296 -0.0164829  -0.01648284 -0.01648276 -0.01648268 -0.01648262
 -0.01648255 -0.01648248 -0.01648241 -0.01648235 -0.01648228 -0.01648221
 -0.01648215 -0.01648208 -0.01648201 -0.01648195 -0.01648189 -0.01648182
 -0.01648176 -0.01648171 -0.01648165 -0.01648158 -0.01648153 -0.01648148
 -0.01648142 -0.01648137 -0.01648132 -0.01648127 -0.01648122 -0.01648118
 -0.01648114 -0.01648109 -0.01648105 -0.01648101 -0.01648097 -0.01648093
 -0.0164809  -0.01648086 -0.01648083 -0.0164808  -0.01648077 -0.01648074
 -0.01648071 -0.01648069 -0.01648067 -0.01648064 -0.01648063 -0.01648061
 -0.01648059 -0.01648057 -0.01648056 -0.01648054 -0.01648053 -0.01648052
 -0.01648051 -0.0164805  -0.01648049 -0.01648049 -0.01648048 -0.01648048
 -0.01648048 -0.01648047 -0.01648047 -0.01648047 -0.01648047 -0.01648047
 -0.01648048 -0.01648048 -0.01648049 -0.01648049 -0.0164805 ]
```

[26]:
```
array_previsao = np.array(previsao)

junto = np.concat([array2, array_previsao])
```

[27]:
```
plt.plot(junto)
```

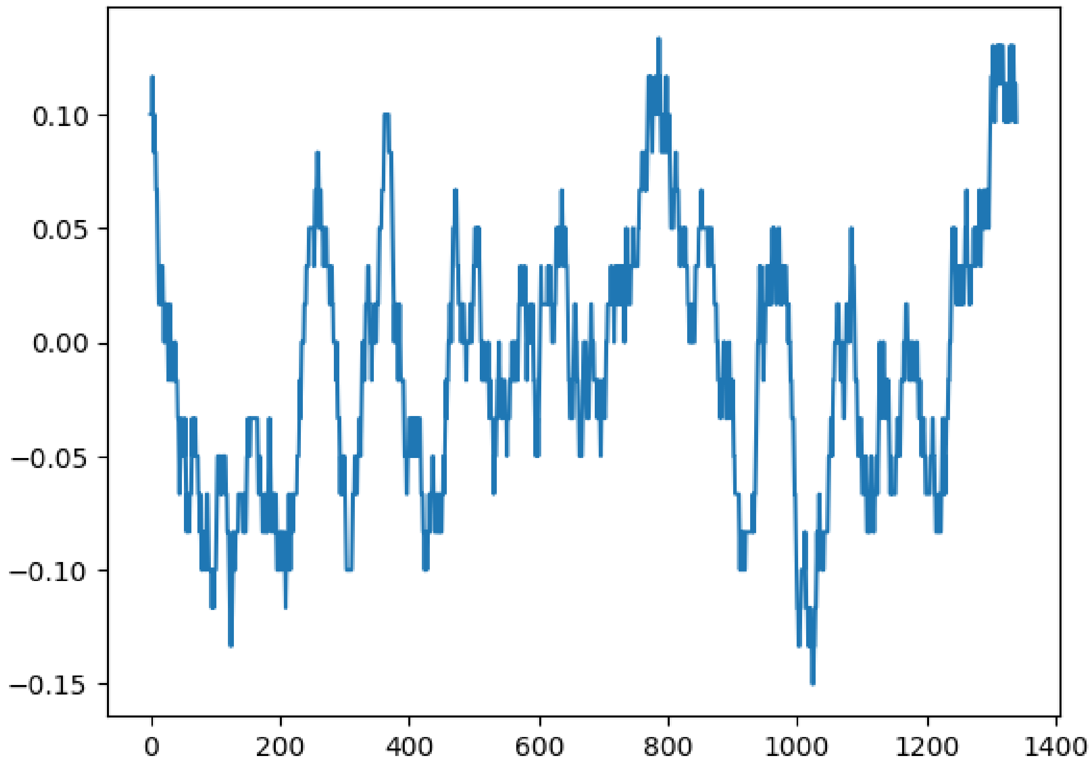
[27]:
```
[<matplotlib.lines.Line2D at 0x7859edf72870>]
```



[32]:
```
# Função para gerar oscilação controlada
def gerar_oscillacao(valor_inicial, incremento, tamanho, limite_inferior=0.28 -
    ↪0.5, limite_superior=0.63 - 0.5):
    osc_final = [valor_inicial]
    for i in range(1, tamanho):
        probabilidade = np.random.rand()
        if probabilidade < 1/3:
            proximo_valor = osc_final[-1] + incremento
        elif probabilidade < 2/3:
            proximo_valor = osc_final[-1]
        else:
            proximo_valor = osc_final[-1] - incremento
        proximo_valor = np.clip(proximo_valor, limite_inferior, limite_superior)
        osc_final.append(proximo_valor)

    return osc_final


array_osc = gerar_oscillacao(valor_inicial=array2[-1], incremento=1/60,
    ↪tamanho=120)

junto2 = np.concatenate([array2,array_osc])
```

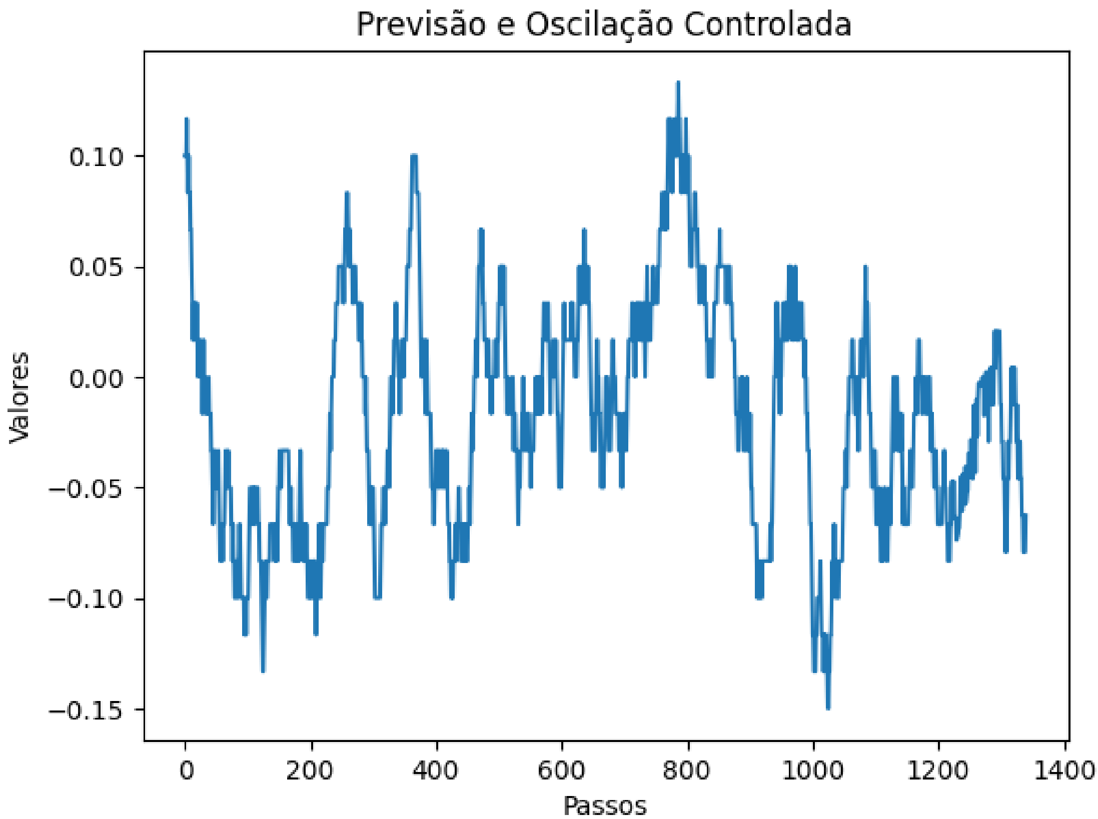
```
plt.plot(junto2)
```

[32]: [<matplotlib.lines.Line2D at 0x7859edde2780>]



[33]:
```
import numpy as np
import matplotlib.pyplot as plt

# Função para gerar oscilação controlada, agora com referência ao modelo AR
def gerar_oscillacao(valor_inicial, incremento, tamanho, previsao_ar,␣
↪limite_inferior=0.28 - 0.5, limite_superior=0.63 - 0.5):
    osc_final = [valor_inicial]

    for i in range(1, tamanho):
        probabilidade = np.random.rand()

        # Ajuste para seguir a previsão AR
        if i < len(previsao_ar):
            referencia_ar = previsao_ar[i]
        else:
            referencia_ar = osc_final[-1]  # Continue oscilando baseado no␣
↪último valor gerado
```

```
        if probabilidade < 1/3:
            proximo_valor = osc_final[-1] + incremento
        elif probabilidade < 2/3:
            proximo_valor = osc_final[-1]
        else:
            proximo_valor = osc_final[-1] - incremento

        # Aplicar os limites e o controle da previsão AR
        proximo_valor = np.clip(proximo_valor, max(limite_inferior,␣
 ↪referencia_ar - incremento),
                                min(limite_superior, referencia_ar +␣
 ↪incremento))

        osc_final.append(proximo_valor)

    return osc_final

# Supondo que você já tenha um modelo AR treinado e gerado previsões de 60␣
 ↪passos
previsao_ar = model_ar_fit.predict(start=len(array2), end=len(array2) + 60)

# Gerar oscilações baseadas na previsão AR
array_osc = gerar_oscillacao(valor_inicial=array2[-1], incremento=1/60,␣
 ↪tamanho=120, previsao_ar=previsao_ar)

# Concatenar a previsão e a oscilação
junto2 = np.concatenate([array2, array_osc])

# Plotar o gráfico resultante
plt.plot(junto2)
plt.title('Previsão e Oscilação Controlada')
plt.xlabel('Passos')
plt.ylabel('Valores')
plt.show()
```



[15]:
```python
from statsmodels.tsa.arima.model import ARIMA

# Ajustar o modelo ARIMA ao array2
# (p, d, q) são os parâmetros do ARIMA:
# p: lags de autoregressão
# d: número de diferenciações necessárias para estacionariedade
# q: lags de médias móveis
model_arima = ARIMA(array2, order=(60, 0, 0))  # O "d" é 0 porque não estamos␣
↪diferenciando aqui
model_arima_fit = model_arima.fit()

# Exibir sumário do modelo ARIMA
print(model_arima_fit.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                 1220
Model:                ARIMA(60, 0, 0)   Log Likelihood                3735.235
Date:                Sun, 13 Oct 2024   AIC                          -7346.469
Time:                        18:12:09   BIC                          -7029.860
Sample:                             0   HQIC                         -7227.302
```

- 1220

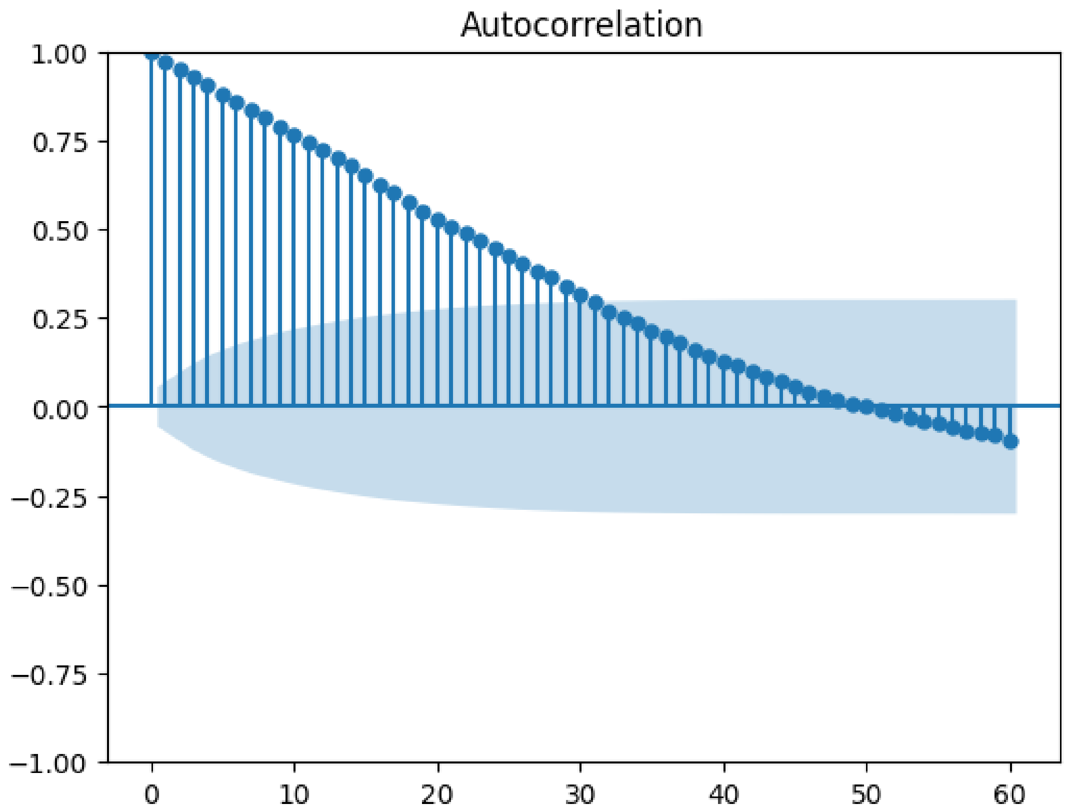
Covariance Type: opg

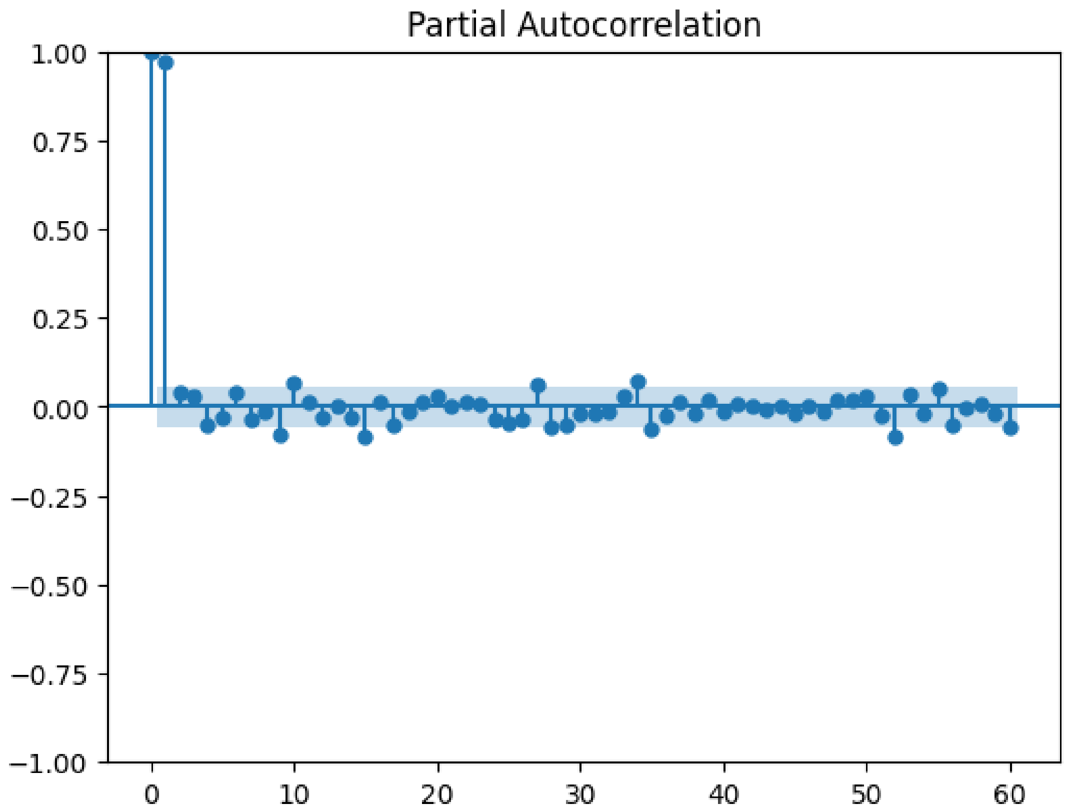
	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.0148	0.008	-1.841	0.066	-0.031	0.001
ar.L1	0.9263	0.029	32.151	0.000	0.870	0.983
ar.L2	0.0297	0.039	0.766	0.444	-0.046	0.106
ar.L3	0.0593	0.040	1.494	0.135	-0.018	0.137
ar.L4	-0.0085	0.039	-0.217	0.829	-0.086	0.069
ar.L5	-0.0583	0.039	-1.480	0.139	-0.135	0.019
ar.L6	0.0580	0.041	1.421	0.155	-0.022	0.138
ar.L7	-0.0120	0.040	-0.300	0.764	-0.090	0.066
ar.L8	0.0533	0.039	1.350	0.177	-0.024	0.131
ar.L9	-0.1322	0.039	-3.394	0.001	-0.209	-0.056
ar.L10	0.0359	0.041	0.874	0.382	-0.045	0.116
ar.L11	0.0540	0.041	1.323	0.186	-0.026	0.134
ar.L12	-0.0208	0.041	-0.511	0.610	-0.100	0.059
ar.L13	0.0334	0.040	0.832	0.405	-0.045	0.112
ar.L14	0.0184	0.040	0.455	0.649	-0.061	0.097
ar.L15	-0.0829	0.041	-2.045	0.041	-0.162	-0.003
ar.L16	0.0569	0.038	1.490	0.136	-0.018	0.132
ar.L17	-0.0309	0.041	-0.757	0.449	-0.111	0.049
ar.L18	-0.0249	0.041	-0.614	0.539	-0.104	0.055
ar.L19	-0.0134	0.041	-0.325	0.745	-0.094	0.067
ar.L20	0.0286	0.041	0.691	0.490	-0.053	0.110
ar.L21	-0.0196	0.040	-0.484	0.628	-0.099	0.060
ar.L22	0.0119	0.042	0.282	0.778	-0.071	0.095
ar.L23	0.0363	0.040	0.897	0.370	-0.043	0.116
ar.L24	0.0106	0.041	0.255	0.799	-0.071	0.092
ar.L25	-0.0016	0.042	-0.039	0.969	-0.084	0.081
ar.L26	-0.0919	0.041	-2.250	0.024	-0.172	-0.012
ar.L27	0.1121	0.040	2.776	0.006	0.033	0.191
ar.L28	-0.0089	0.040	-0.222	0.824	-0.088	0.070
ar.L29	-0.0321	0.041	-0.786	0.432	-0.112	0.048
ar.L30	-0.0124	0.040	-0.312	0.755	-0.090	0.066
ar.L31	-0.0024	0.041	-0.060	0.952	-0.082	0.077
ar.L32	-0.0411	0.042	-0.981	0.327	-0.123	0.041
ar.L33	-0.0226	0.041	-0.558	0.577	-0.102	0.057
ar.L34	0.1148	0.042	2.755	0.006	0.033	0.196
ar.L35	-0.0380	0.039	-0.961	0.337	-0.115	0.039
ar.L36	-0.0444	0.040	-1.121	0.262	-0.122	0.033
ar.L37	0.0388	0.040	0.961	0.337	-0.040	0.118
ar.L38	-0.0477	0.041	-1.161	0.246	-0.128	0.033
ar.L39	0.0488	0.041	1.194	0.232	-0.031	0.129
ar.L40	-0.0145	0.041	-0.355	0.722	-0.094	0.065
ar.L41	0.0030	0.040	0.075	0.940	-0.076	0.082
ar.L42	0.0164	0.039	0.417	0.677	-0.061	0.094

```
ar.L43        -0.0264      0.039     -0.673      0.501      -0.103       0.051
ar.L44         0.0333      0.040      0.827      0.408      -0.046       0.112
ar.L45        -0.0220      0.040     -0.549      0.583      -0.101       0.057
ar.L46         0.0072      0.041      0.177      0.860      -0.073       0.087
ar.L47        -0.0604      0.042     -1.433      0.152      -0.143       0.022
ar.L48         0.0110      0.041      0.267      0.789      -0.069       0.091
ar.L49         0.0243      0.042      0.581      0.561      -0.058       0.106
ar.L50         0.0506      0.041      1.238      0.216      -0.029       0.131
ar.L51         0.0421      0.039      1.069      0.285      -0.035       0.119
ar.L52        -0.1306      0.041     -3.191      0.001      -0.211      -0.050
ar.L53         0.0507      0.042      1.218      0.223      -0.031       0.132
ar.L54        -0.0332      0.040     -0.835      0.404      -0.111       0.045
ar.L55         0.0784      0.041      1.934      0.053      -0.001       0.158
ar.L56        -0.0417      0.040     -1.055      0.292      -0.119       0.036
ar.L57        -0.0261      0.041     -0.639      0.523      -0.106       0.054
ar.L58         0.0426      0.041      1.043      0.297      -0.037       0.123
ar.L59         0.0391      0.041      0.943      0.346      -0.042       0.120
ar.L60        -0.0640      0.031     -2.097      0.036      -0.124      -0.004
sigma2         0.0001   7.15e-06     17.856      0.000       0.000       0.000
================================================================================
===
Ljung-Box (L1) (Q):                   1.14   Jarque-Bera (JB):
39.12
Prob(Q):                              0.29   Prob(JB):
0.00
Heteroskedasticity (H):               0.98   Skew:
-0.02
Prob(H) (two-sided):                  0.83   Kurtosis:
2.12
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

[16]:

```python
import statsmodels.api as sm
import matplotlib.pyplot as plt

# Plotar o gráfico ACF (Autocorrelação)
sm.graphics.tsa.plot_acf(array2, lags=60)  # Ajuste o número de lags conforme
 ↪necessário
plt.show()

# Plotar o gráfico PACF (Autocorrelação Parcial)
sm.graphics.tsa.plot_pacf(array2, lags=60)
plt.show()
```


Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
10
20
30
40
50
60



[17]:

```
# Calcular a primeira diferença
array2_diff = np.diff(array2)

# Agora, você pode aplicar o mesmo modelo ARIMA na série diferenciada
# Ajustar o modelo ARIMA ao array2 diferenciado
model_arima_diff = ARIMA(array2_diff, order=(60, 0, 0))  # "d" ainda 0 após a␣
 ↪diferenciação
model_arima_diff_fit = model_arima_diff.fit()

# Exibir sumário do modelo ARIMA diferenciado
print(model_arima_diff_fit.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                 1219
Model:                ARIMA(60, 0, 0)   Log Likelihood                3896.610
Date:                Sun, 13 Oct 2024   AIC                          -7669.220
Time:                        18:23:45   BIC                          -7352.661
Sample:                             0   HQIC                         -7550.067
                               - 1219
Covariance Type:                  opg
```

	coef	std err	z	P>|z|	[0.025	0.975]
const	-7.677e-05	0.000	-0.492	0.623	-0.000	0.000
ar.L1	-0.0335	0.025	-1.355	0.175	-0.082	0.015
ar.L2	-0.0227	0.024	-0.939	0.348	-0.070	0.025
ar.L3	0.0169	0.025	0.667	0.505	-0.033	0.067
ar.L4	0.0192	0.025	0.752	0.452	-0.031	0.069
ar.L5	-0.0152	0.025	-0.604	0.546	-0.065	0.034
ar.L6	-0.0007	0.026	-0.027	0.979	-0.051	0.050
ar.L7	0.0099	0.025	0.404	0.686	-0.038	0.058
ar.L8	0.0341	0.025	1.353	0.176	-0.015	0.083
ar.L9	-0.0327	0.025	-1.333	0.182	-0.081	0.015
ar.L10	-0.0176	0.025	-0.695	0.487	-0.067	0.032
ar.L11	0.0069	0.026	0.262	0.793	-0.044	0.058
ar.L12	-0.0185	0.025	-0.729	0.466	-0.068	0.031
ar.L13	0.0026	0.025	0.105	0.916	-0.046	0.052
ar.L14	0.0617	0.025	2.435	0.015	0.012	0.111
ar.L15	-0.0343	0.026	-1.342	0.179	-0.084	0.016
ar.L16	0.0335	0.025	1.342	0.180	-0.015	0.082
ar.L17	-0.0152	0.026	-0.585	0.559	-0.066	0.036
ar.L18	-0.0246	0.025	-0.972	0.331	-0.074	0.025
ar.L19	-0.0458	0.025	-1.798	0.072	-0.096	0.004
ar.L20	-0.0179	0.026	-0.680	0.497	-0.070	0.034
ar.L21	-0.0283	0.025	-1.132	0.258	-0.077	0.021
ar.L22	-0.0422	0.025	-1.679	0.093	-0.092	0.007
ar.L23	0.0175	0.026	0.680	0.496	-0.033	0.068
ar.L24	0.0144	0.025	0.573	0.567	-0.035	0.064
ar.L25	0.0285	0.026	1.096	0.273	-0.023	0.080
ar.L26	-0.0448	0.025	-1.776	0.076	-0.094	0.005
ar.L27	0.0099	0.026	0.380	0.704	-0.041	0.061
ar.L28	0.0152	0.026	0.594	0.553	-0.035	0.065
ar.L29	0.0063	0.025	0.250	0.802	-0.043	0.056
ar.L30	-0.0071	0.026	-0.275	0.783	-0.058	0.044
ar.L31	-0.0051	0.026	-0.199	0.842	-0.055	0.045
ar.L32	-0.0339	0.026	-1.302	0.193	-0.085	0.017
ar.L33	-0.0410	0.025	-1.622	0.105	-0.090	0.009
ar.L34	0.0126	0.025	0.502	0.616	-0.037	0.062
ar.L35	0.0211	0.024	0.882	0.378	-0.026	0.068
ar.L36	-0.0288	0.026	-1.123	0.261	-0.079	0.021
ar.L37	0.0052	0.026	0.200	0.842	-0.045	0.056
ar.L38	-0.0564	0.026	-2.153	0.031	-0.108	-0.005
ar.L39	-0.0117	0.025	-0.460	0.646	-0.062	0.038
ar.L40	-0.0115	0.025	-0.457	0.648	-0.061	0.038
ar.L41	-0.0321	0.025	-1.276	0.202	-0.081	0.017
ar.L42	-0.0020	0.025	-0.082	0.935	-0.050	0.046
ar.L43	-0.0221	0.025	-0.877	0.380	-0.071	0.027
ar.L44	0.0258	0.025	1.023	0.307	-0.024	0.075

```
ar.L45        -0.0213      0.026     -0.818      0.413      -0.072       0.030
ar.L46         0.0251      0.026      0.956      0.339      -0.026       0.077
ar.L47        -0.0369      0.026     -1.436      0.151      -0.087       0.013
ar.L48        -0.0470      0.025     -1.882      0.060      -0.096       0.002
ar.L49        -0.0175      0.025     -0.701      0.483      -0.066       0.031
ar.L50         0.0117      0.026      0.452      0.652      -0.039       0.062
ar.L51         0.0363      0.025      1.456      0.145      -0.013       0.085
ar.L52        -0.0284      0.026     -1.112      0.266      -0.078       0.022
ar.L53        -0.0010      0.025     -0.039      0.969      -0.051       0.049
ar.L54        -0.0338      0.026     -1.307      0.191      -0.084       0.017
ar.L55         0.0126      0.026      0.481      0.631      -0.039       0.064
ar.L56         0.0072      0.025      0.286      0.775      -0.042       0.056
ar.L57        -0.0136      0.026     -0.528      0.598      -0.064       0.037
ar.L58        -0.0002      0.025     -0.007      0.995      -0.049       0.049
ar.L59         0.0217      0.026      0.845      0.398      -0.029       0.072
ar.L60        -0.5088      0.029    -17.422      0.000      -0.566      -0.452
sigma2      9.623e-05   5.51e-06     17.474      0.000    8.54e-05       0.000
================================================================================
===
Ljung-Box (L1) (Q):                   0.44   Jarque-Bera (JB):
43.11
Prob(Q):                              0.51   Prob(JB):
0.00
Heteroskedasticity (H):               0.92   Skew:
0.05
Prob(H) (two-sided):                  0.42   Kurtosis:
2.08
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

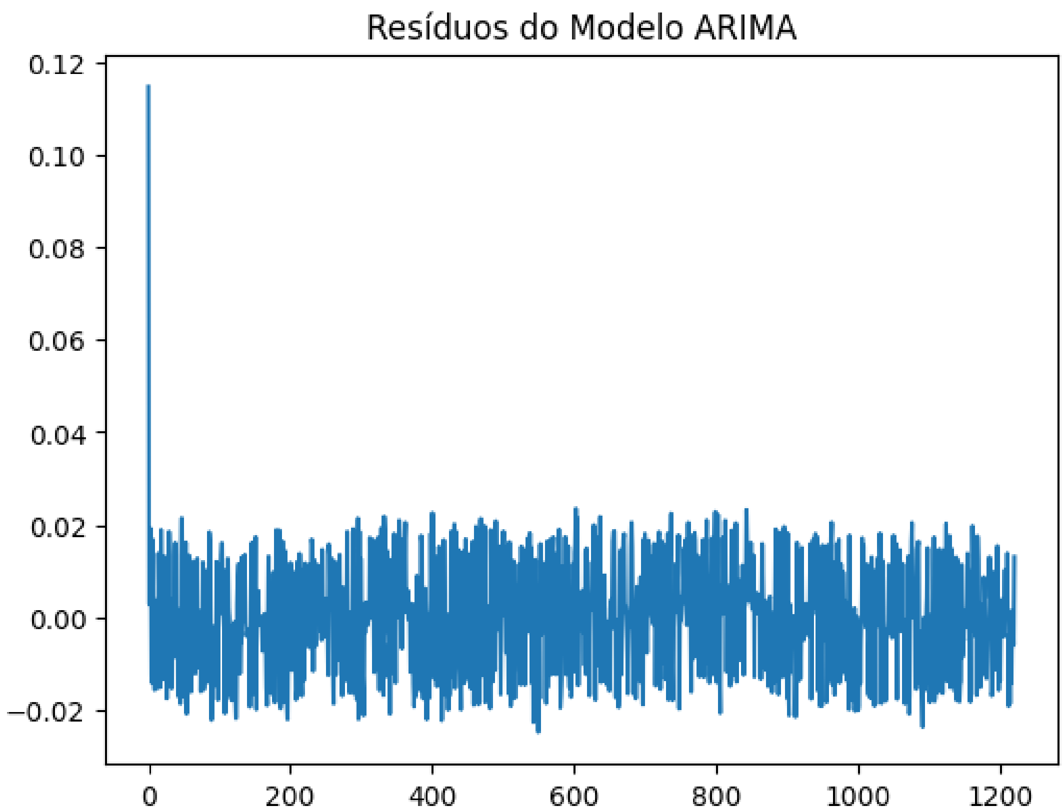
[18]:

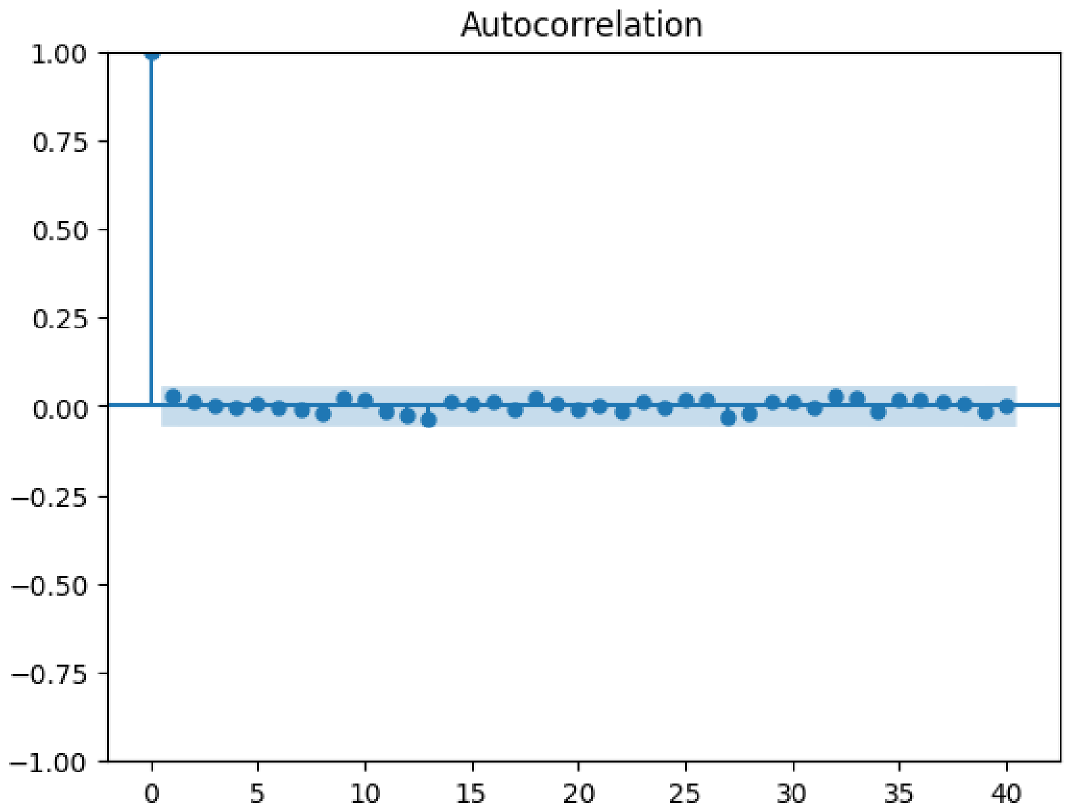
```python
from statsmodels.tsa.stattools import adfuller

# Realizar o teste de Dickey-Fuller na série array2
adf_result = adfuller(array2)
print('ADF Statistic: %f' % adf_result[0])
print('p-value: %f' % adf_result[1])

# Se o p-value for menor que 0.05, rejeitamos a hipótese nula e consideramos a
    série estacionária.
```

```
ADF Statistic: -4.260079
p-value: 0.000520
```

[19]:

```
# Obter os resíduos do modelo ARIMA ajustado
residuals = model_arima_fit.resid

# Plotar os resíduos
plt.plot(residuals)
plt.title('Resíduos do Modelo ARIMA')
plt.show()

# Testar autocorrelação nos resíduos (devem ser ruído branco)
sm.graphics.tsa.plot_acf(residuals, lags=40)
plt.show()
```





[29]:
```python
# Ajustar o modelo AR apenas com lags significativos
significant_lags = [1, 9, 26, 27, 34]
model_ar1 = AutoReg(array2, lags=significant_lags)
model_ar_fit1 = model_ar.fit()
print(model_ar_fit1.summary())
```

```
                            AutoReg Model Results
==============================================================================
Dep. Variable:                      y   No. Observations:                 1220
Model:                    AutoReg(60)   Log Likelihood                3558.778
Method:               Conditional MLE   S.D. of innovations              0.011
Date:                Sun, 13 Oct 2024   AIC                          -6993.556
Time:                        18:56:07   BIC                          -6680.073
Sample:                            60   HQIC                         -6875.272
                                 1220
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0006      0.000     -1.728      0.084      -0.001    8.41e-05
y.L1           0.9328      0.029     31.812      0.000       0.875       0.990
y.L2           0.0283      0.040      0.706      0.480      -0.050       0.107
```

y.L3	0.0610	0.040	1.520	0.128	-0.018	0.140
y.L4	-0.0150	0.040	-0.374	0.708	-0.094	0.064
y.L5	-0.0636	0.040	-1.586	0.113	-0.142	0.015
y.L6	0.0613	0.040	1.529	0.126	-0.017	0.140
y.L7	-0.0097	0.040	-0.242	0.809	-0.088	0.069
y.L8	0.0539	0.040	1.348	0.178	-0.024	0.132
y.L9	-0.1323	0.040	-3.322	0.001	-0.210	-0.054
y.L10	0.0351	0.040	0.876	0.381	-0.043	0.114
y.L11	0.0469	0.040	1.172	0.241	-0.032	0.125
y.L12	-0.0164	0.040	-0.411	0.681	-0.095	0.062
y.L13	0.0378	0.040	0.947	0.344	-0.041	0.116
y.L14	0.0183	0.040	0.459	0.647	-0.060	0.097
y.L15	-0.0845	0.040	-2.119	0.034	-0.163	-0.006
y.L16	0.0507	0.040	1.270	0.204	-0.028	0.129
y.L17	-0.0249	0.040	-0.623	0.533	-0.103	0.053
y.L18	-0.0206	0.040	-0.515	0.606	-0.099	0.058
y.L19	-0.0203	0.040	-0.509	0.610	-0.099	0.058
y.L20	0.0396	0.040	0.992	0.321	-0.039	0.118
y.L21	-0.0296	0.040	-0.741	0.459	-0.108	0.049
y.L22	0.0125	0.040	0.314	0.753	-0.066	0.091
y.L23	0.0308	0.040	0.773	0.440	-0.047	0.109
y.L24	0.0090	0.040	0.226	0.821	-0.069	0.087
y.L25	0.0178	0.040	0.448	0.654	-0.060	0.096
y.L26	-0.1005	0.040	-2.522	0.012	-0.179	-0.022
y.L27	0.1177	0.040	2.957	0.003	0.040	0.196
y.L28	-0.0260	0.040	-0.650	0.515	-0.104	0.052
y.L29	-0.0272	0.040	-0.683	0.495	-0.105	0.051
y.L30	-0.0068	0.040	-0.170	0.865	-0.085	0.071
y.L31	-0.0014	0.040	-0.034	0.973	-0.080	0.077
y.L32	-0.0501	0.040	-1.257	0.209	-0.128	0.028
y.L33	-0.0192	0.040	-0.483	0.629	-0.097	0.059
y.L34	0.1172	0.040	2.951	0.003	0.039	0.195
y.L35	-0.0432	0.040	-1.087	0.277	-0.121	0.035
y.L36	-0.0298	0.040	-0.749	0.454	-0.108	0.048
y.L37	0.0274	0.040	0.688	0.492	-0.051	0.105
y.L38	-0.0470	0.040	-1.180	0.238	-0.125	0.031
y.L39	0.0513	0.040	1.290	0.197	-0.027	0.129
y.L40	-0.0130	0.040	-0.326	0.744	-0.091	0.065
y.L41	0.0035	0.040	0.088	0.930	-0.075	0.082
y.L42	0.0163	0.040	0.409	0.683	-0.062	0.094
y.L43	-0.0344	0.040	-0.865	0.387	-0.112	0.044
y.L44	0.0374	0.040	0.941	0.347	-0.041	0.115
y.L45	-0.0243	0.040	-0.611	0.542	-0.102	0.054
y.L46	0.0164	0.040	0.413	0.680	-0.061	0.094
y.L47	-0.0715	0.040	-1.804	0.071	-0.149	0.006
y.L48	0.0207	0.040	0.521	0.602	-0.057	0.098
y.L49	0.0209	0.040	0.527	0.598	-0.057	0.099
y.L50	0.0482	0.040	1.214	0.225	-0.030	0.126

y.L51	0.0442	0.040	1.114	0.265	-0.034	0.122
y.L52	-0.1304	0.039	-3.302	0.001	-0.208	-0.053
y.L53	0.0548	0.040	1.382	0.167	-0.023	0.132
y.L54	-0.0396	0.040	-0.998	0.318	-0.117	0.038
y.L55	0.0816	0.040	2.057	0.040	0.004	0.159
y.L56	-0.0410	0.040	-1.032	0.302	-0.119	0.037
y.L57	-0.0268	0.040	-0.677	0.498	-0.105	0.051
y.L58	0.0429	0.040	1.083	0.279	-0.035	0.120
y.L59	0.0383	0.040	0.967	0.334	-0.039	0.116
y.L60	-0.0636	0.029	-2.191	0.028	-0.120	-0.007

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	-1.0301	-0.0575j	1.0317	-0.4911
AR.2	-1.0301	+0.0575j	1.0317	0.4911
AR.3	-1.0205	-0.1646j	1.0337	-0.4745
AR.4	-1.0205	+0.1646j	1.0337	0.4745
AR.5	-0.9920	-0.2966j	1.0354	-0.4538
AR.6	-0.9920	+0.2966j	1.0354	0.4538
AR.7	-0.9452	-0.4055j	1.0286	-0.4355
AR.8	-0.9452	+0.4055j	1.0286	0.4355
AR.9	-0.8768	-0.5489j	1.0345	-0.4110
AR.10	-0.8768	+0.5489j	1.0345	0.4110
AR.11	-1.1164	-0.5635j	1.2506	-0.4256
AR.12	-1.1164	+0.5635j	1.2506	0.4256
AR.13	-0.8223	-0.6499j	1.0481	-0.3936
AR.14	-0.8223	+0.6499j	1.0481	0.3936
AR.15	-0.7331	-0.7267j	1.0323	-0.3757
AR.16	-0.7331	+0.7267j	1.0323	0.3757
AR.17	-0.6416	-0.8001j	1.0255	-0.3576
AR.18	-0.6416	+0.8001j	1.0255	0.3576
AR.19	-0.5680	-0.8922j	1.0576	-0.3402
AR.20	-0.5680	+0.8922j	1.0576	0.3402
AR.21	-0.4640	-0.9297j	1.0390	-0.3237
AR.22	-0.4640	+0.9297j	1.0390	0.3237
AR.23	-0.3633	-0.9938j	1.0581	-0.3058
AR.24	-0.3633	+0.9938j	1.0581	0.3058
AR.25	-0.2600	-0.9888j	1.0224	-0.2909
AR.26	-0.2600	+0.9888j	1.0224	0.2909
AR.27	-0.1503	-1.0360j	1.0468	-0.2729
AR.28	-0.1503	+1.0360j	1.0468	0.2729
AR.29	-0.0428	-1.0231j	1.0240	-0.2567
AR.30	-0.0428	+1.0231j	1.0240	0.2567
AR.31	0.0746	-1.0248j	1.0275	-0.2384
AR.32	0.0746	+1.0248j	1.0275	0.2384
AR.33	0.1928	-1.0118j	1.0300	-0.2200
AR.34	0.1928	+1.0118j	1.0300	0.2200

AR.35	0.3112	-0.9803j	1.0285	-0.2011
AR.36	0.3112	+0.9803j	1.0285	0.2011
AR.37	0.4621	-0.9337j	1.0417	-0.1769
AR.38	0.4621	+0.9337j	1.0417	0.1769
AR.39	0.5224	-1.0005j	1.1287	-0.1734
AR.40	0.5224	+1.0005j	1.1287	0.1734
AR.41	0.5803	-0.8767j	1.0513	-0.1569
AR.42	0.5803	+0.8767j	1.0513	0.1569
AR.43	0.6588	-0.7850j	1.0248	-0.1389
AR.44	0.6588	+0.7850j	1.0248	0.1389
AR.45	0.7593	-0.7002j	1.0329	-0.1186
AR.46	0.7593	+0.7002j	1.0329	0.1186
AR.47	0.8480	-0.6221j	1.0517	-0.1007
AR.48	0.8480	+0.6221j	1.0517	0.1007
AR.49	0.9212	-0.5275j	1.0615	-0.0828
AR.50	0.9212	+0.5275j	1.0615	0.0828
AR.51	0.9360	-0.4525j	1.0397	-0.0717
AR.52	0.9360	+0.4525j	1.0397	0.0717
AR.53	0.9941	-0.3317j	1.0480	-0.0513
AR.54	0.9941	+0.3317j	1.0480	0.0513
AR.55	1.0144	-0.2287j	1.0398	-0.0353
AR.56	1.0144	+0.2287j	1.0398	0.0353
AR.57	1.0351	-0.1139j	1.0414	-0.0174
AR.58	1.0351	+0.1139j	1.0414	0.0174
AR.59	1.0170	-0.0349j	1.0176	-0.0055
AR.60	1.0170	+0.0349j	1.0176	0.0055