In [53]:

```
import numpy as np
import pandas as pd
import scipy.stats as sp
import seaborn as sns

import matplotlib.pyplot as plt
from pandas.plotting import register_matplotlib_converters

from sklearn.linear_model import LinearRegression as lm
import statsmodels.api as sm
```

In [54]:

```
# create a differenced series
def difference(dataset, interval=1):
    diff = list()
    for i in range(interval, len(dataset)):
        value = dataset[i] - dataset[i - interval]
        diff.append(value)
    return (diff)
```

In [55]:

```
def runMyAR1(yin):
    tlen = len(yin)
    y = np.array(yin[2:tlen])
    x = np.array(yin[1:(tlen-1)])
    X = x
    X = sm.add_constant(X)
    regr2 = sm.OLS(y,X)
    model = regr2.fit()
    print(model.summary())
    ypred = model.predict()
    plt.plot((y-ypred))
```

In [56]:

```
# Create large images!
register_matplotlib_converters()
sns.set_style("darkgrid")
plt.rc("figure", figsize=(14, 8)) # was 16,12
plt.rc("font", size=13)
```

In [57]:

```
dfo = pd.read_csv("Ren Gen TX.csv")
#dfo.columns = ['year','Renewable energy production']
dfo.head()
```

Out[57]:

| | Unnamed: 0 | Renewable energy production, Texas (Billion Btu) |
|---|---|---|
| **0** | 1960 | 50155 |
| **1** | 1961 | 52023 |
| **2** | 1962 | 47721 |
| **3** | 1963 | 42718 |
| **4** | 1964 | 43884 |

In [58]:

```
dfo.rename(columns={"Unnamed: 0":"Year","Renewable energy production, Texas (Billion
```

In [59]:

```
dfo.head()
```

Out[59]:

| | Year | REP |
|---|---|---|
| **0** | 1960 | 50155 |
| **1** | 1961 | 52023 |
| **2** | 1962 | 47721 |
| **3** | 1963 | 42718 |
| **4** | 1964 | 43884 |

In [60]:

```
df = dfo['REP']
print(len(df))
```

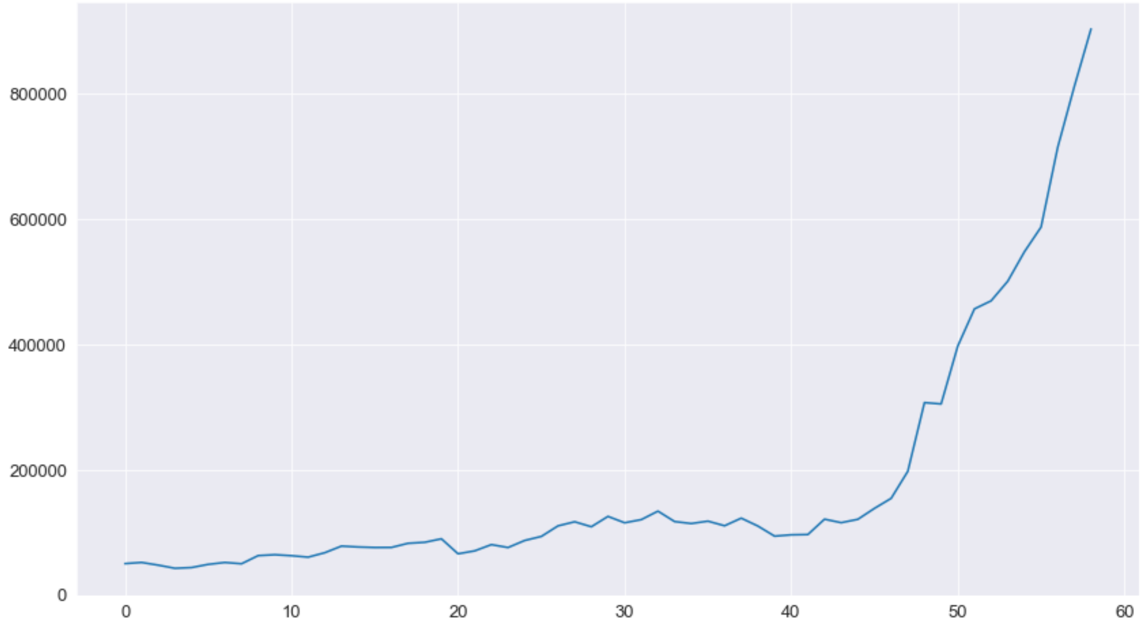
59

In [61]:

```
df.plot()
```

Out[61]:

```
<AxesSubplot:>
```




In [62]:

```
#import chart_studio.plotly as py
import plotly.graph_objs as go
# Offline mode
import plotly.io as pio
#from plotly.offline import init_notebook_mode, iplot
#init_notebook_mode(connected=True)
```

In [63]:

```
#pltobj = go.Scatter(y=dfo['Price'], x=dfo['Month'])
pltobj = go.Scatter(y=dfo['REP'])
```

In [64]:

```
fig = go.Figure(data=pltobj)
pio.show(fig)
```

In [65]:

```
sm.tsa.stattools.adfuller(df)
```

Out[65]:

```
(8.214153484160688,
 1.0,
 0,
 58,
 {'1%': -3.548493559596539,
  '5%': -2.912836594776334,
  '10%': -2.594129155766944},
 1082.551150310405)
```

In [66]:

```
sm.tsa.stattools.kpss(df)
```

```
C:\Users\HP\AppData\Local\Programs\Python\Python310\lib\site-packages\s
tatsmodels\tsa\stattools.py:2018: InterpolationWarning:

The test statistic is outside of the range of p-values available in the
look-up table. The actual p-value is smaller than the p-value returned.
```

Out[66]:

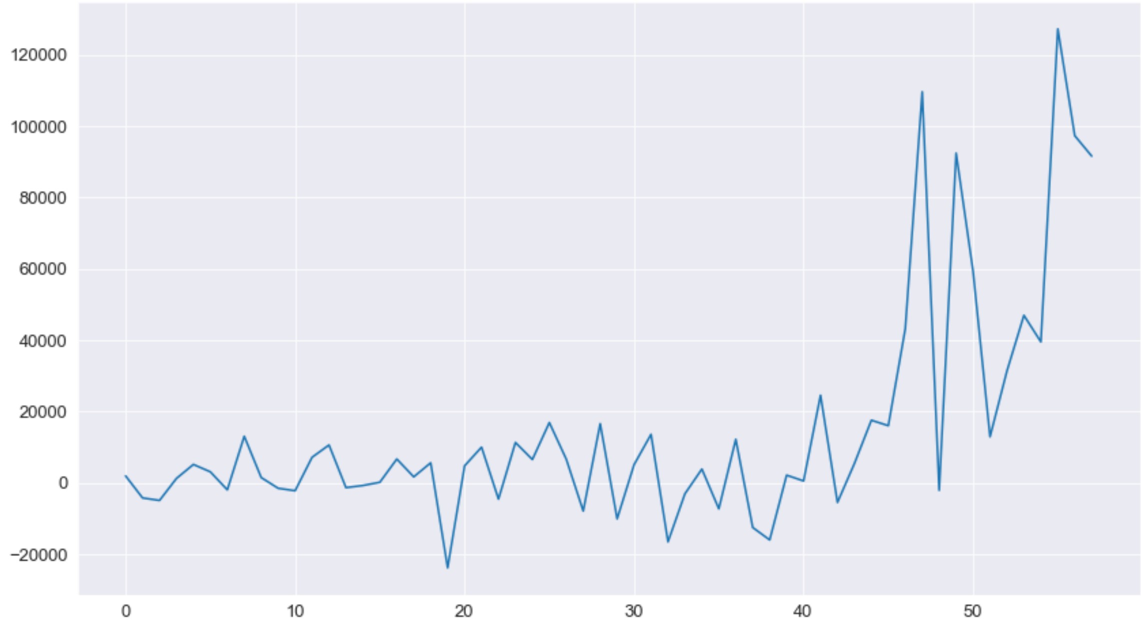
```
(0.8207884424227161,
 0.01,
 4,
 {'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%': 0.739})
```

In [67]:

```
# detrend, if required, and plot
dtrend = difference(np.array(df),1)
#dtrend = df
plt.plot(dtrend)
```

Out[67]:

```
[<matplotlib.lines.Line2D at 0x1d1d78ed270>]
```




In [68]:

```
sm.tsa.stattools.adfuller(dtrend)
```

Out[68]:

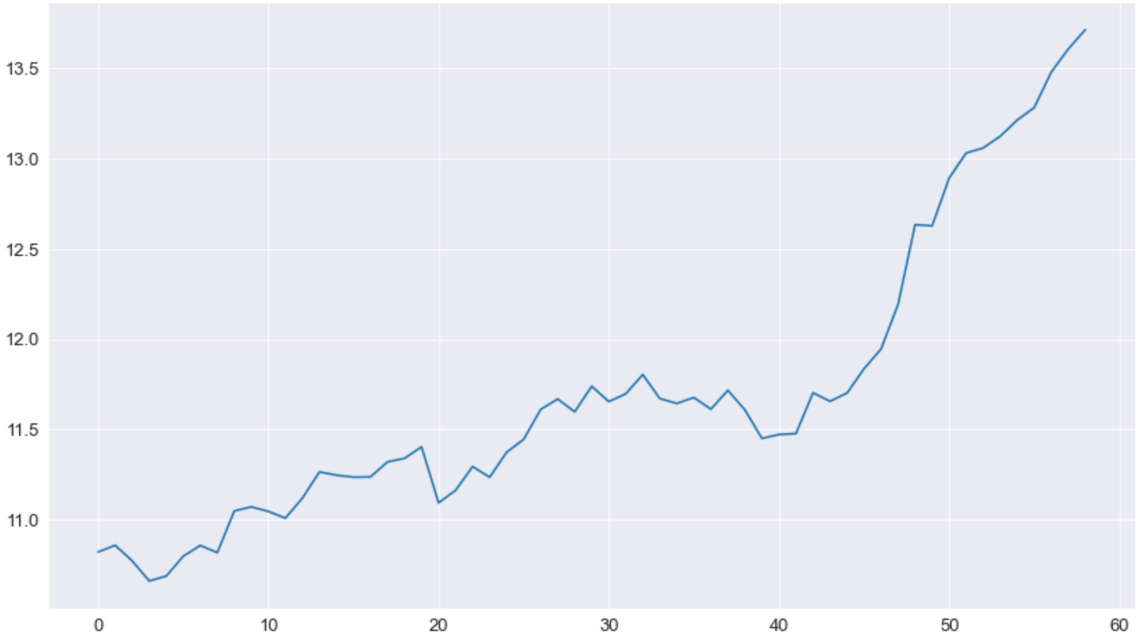
```
(-1.5044854186074923,
 0.5312913110054411,
 11,
 46,
 {'1%': -3.5812576580093696,
  '5%': -2.9267849124681518,
  '10%': -2.6015409829867675},
 1060.9291971278926)
```

In [69]:

```
# Since we see steady increase in variation, lets do a log transformation
dflog = np.log(df)
plt.plot(dflog)
```

Out[69]:

```
[<matplotlib.lines.Line2D at 0x1d1d6b35270>]
```

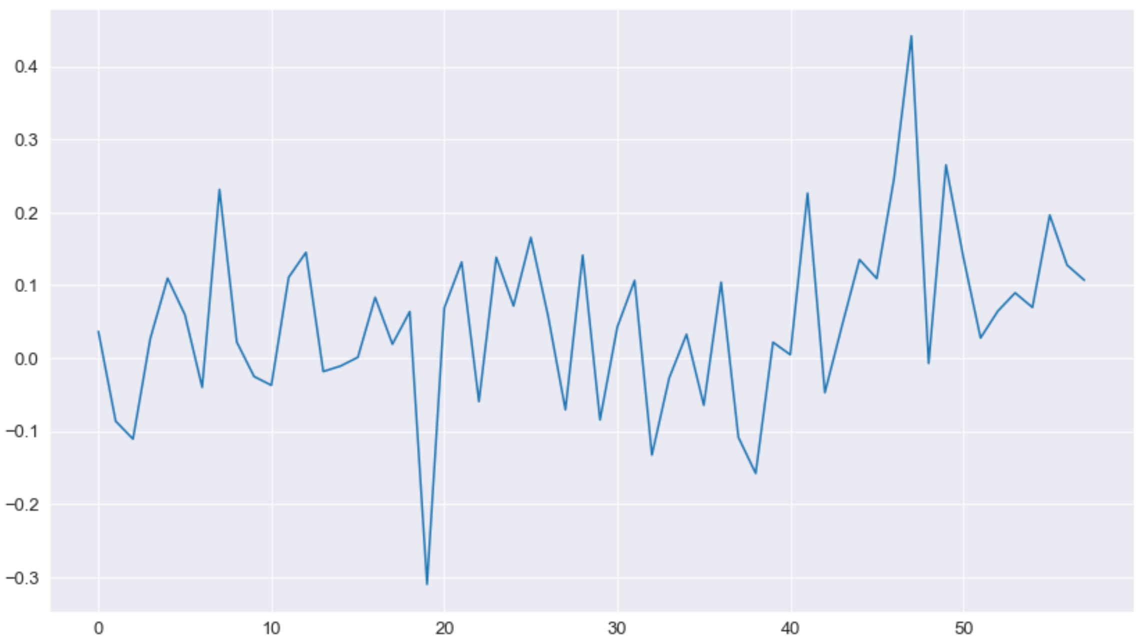



In [70]:

```
dflog_dtrend = difference(dflog,1)
plt.plot(dflog_dtrend)
```

Out[70]:

```
[<matplotlib.lines.Line2D at 0x1d1d6a008e0>]
```



In [71]:

```
sm.tsa.stattools.adfuller(dflog_dtrend)
```

Out[71]:

```
(-3.0496739454382644,
 0.030508735715244165,
 2,
 55,
 {'1%': -3.5552728880540942,
  '5%': -2.9157312396694217,
  '10%': -2.5956695041322315},
 -59.076185968900276)
```

In [72]:

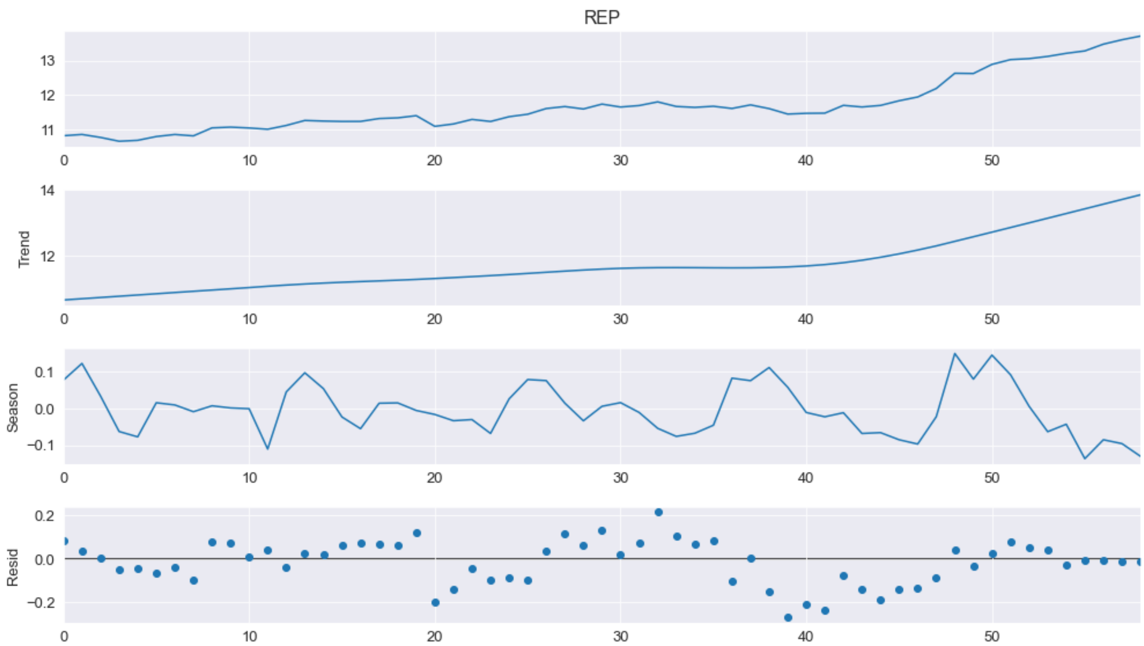
```
from statsmodels.tsa.seasonal import STL
```

In [73]:

```
stl = STL(dflog, period=12)
#stl = STL(df)
```

In [74]:

```
res = stl.fit()
fig = res.plot()
```




# ARIMA MODEL

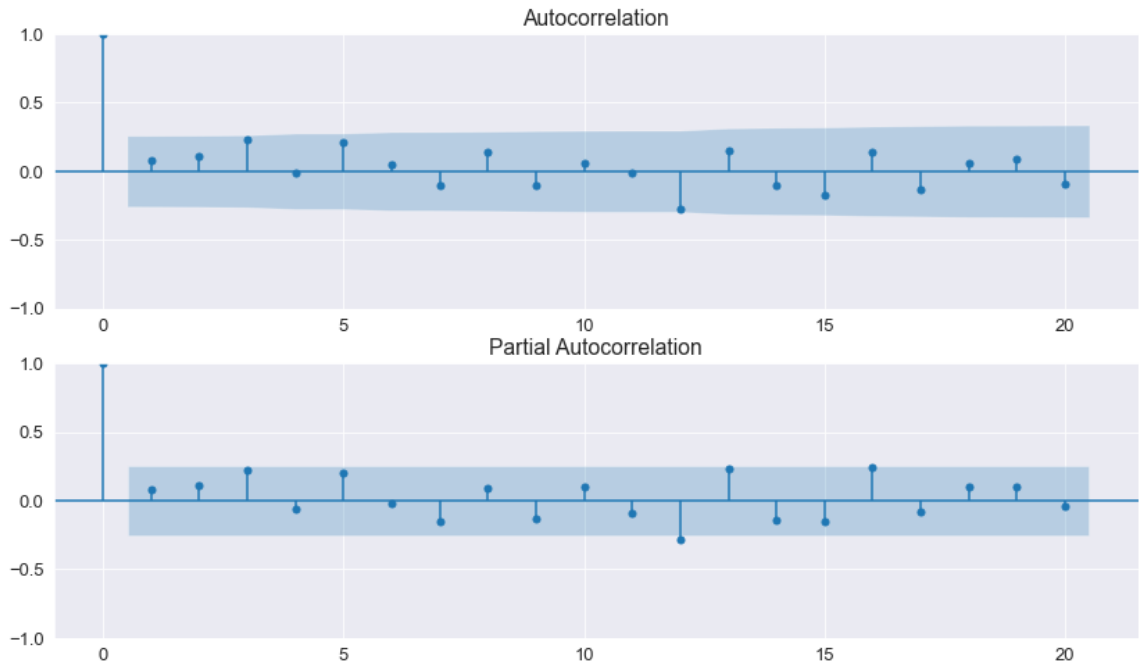
In [75]:

```
import statsmodels.api as sm
from statsmodels.tsa.stattools import acf
from statsmodels.tsa.stattools import pacf
```

In [76]:

```
fig = plt.figure(figsize=(14, 8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(dflog_dtrend, lags=20, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(dflog_dtrend, lags=20, ax=ax2)
```

```
C:\Users\HP\AppData\Local\Programs\Python\Python310\lib\site-packages\s
tatsmodels\graphics\tsaplots.py:348: FutureWarning:

The default method 'yw' can produce PACF values outside of the [-1,1] i
nterval. After 0.13, the default will change tounadjusted Yule-Walker
('ywm'). You can use this method now by setting method='ywm'.
```



In [77]:

```
sm.tsa.stattools.arma_order_select_ic(dflog_dtrend)
```

```
C:\Users\HP\AppData\Local\Programs\Python\Python310\lib\site-packages\s
tatsmodels\tsa\statespace\sarimax.py:966: UserWarning:

Non-stationary starting autoregressive parameters found. Using zeros as
starting parameters.

C:\Users\HP\AppData\Local\Programs\Python\Python310\lib\site-packages\s
tatsmodels\tsa\statespace\sarimax.py:978: UserWarning:

Non-invertible starting MA parameters found. Using zeros as starting pa
rameters.

C:\Users\HP\AppData\Local\Programs\Python\Python310\lib\site-packages\s
tatsmodels\base\model.py:604: ConvergenceWarning:

Maximum Likelihood optimization failed to converge. Check mle_retvals

C:\Users\HP\AppData\Local\Programs\Python\Python310\lib\site-packages\s
tatsmodels\base\model.py:604: ConvergenceWarning:

Maximum Likelihood optimization failed to converge. Check mle_retvals
```

Out[77]:

```
{'bic':            0          1          2
 0 -75.422557 -71.698457 -68.156855
 1 -71.761970 -69.548485 -66.260701
 2 -68.384237 -66.042925 -61.954252
 3 -67.307712 -63.779606 -59.042672
 4 -63.345444 -59.728980 -55.964778,
 'bic_min_order': (0, 0)}
```

In [78]:

```
from statsmodels.tsa.arima.model import ARIMA
```

In [93]:

```
my_model = sm.tsa.arima.ARIMA(dflog,order=(1,1,1),seasonal_order=(1,1,1,12))
my_model_res = my_model.fit()
print(my_model_res.summary())
```

```
C:\Users\HP\AppData\Local\Programs\Python\Python310\lib\site-packages\s
tatsmodels\tsa\statespace\sarimax.py:966: UserWarning:

Non-stationary starting autoregressive parameters found. Using zeros as
starting parameters.

C:\Users\HP\AppData\Local\Programs\Python\Python310\lib\site-packages\s
tatsmodels\tsa\statespace\sarimax.py:978: UserWarning:

Non-invertible starting MA parameters found. Using zeros as starting pa
rameters.

C:\Users\HP\AppData\Local\Programs\Python\Python310\lib\site-packages\s
tatsmodels\tsa\statespace\sarimax.py:1009: UserWarning:

Non-invertible starting seasonal moving average Using zeros as starting
parameters.
```

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                                REP   No. Observations:                   59
Model:             ARIMA(1, 1, 1)x(1, 1, 1, 12)   Log Likelihood                   25.518
Date:                          Tue, 14 Feb 2023   AIC                             -41.036
Time:                                  19:54:13   BIC                             -31.893
Sample:                                       0   HQIC                            -37.611
                                           - 59
Covariance Type:                            opg
==========================================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------------------
ar.L1          0.9933      0.162      6.125      0.000       0.675       1.311
ma.L1         -0.8513      0.203     -4.203      0.000      -1.248      -0.454
ar.S.L12      -0.4407      0.221     -1.993      0.046      -0.874      -0.007
ma.S.L12      -0.8560      1.700     -0.504      0.614      -4.188       2.474
```

In [94]:

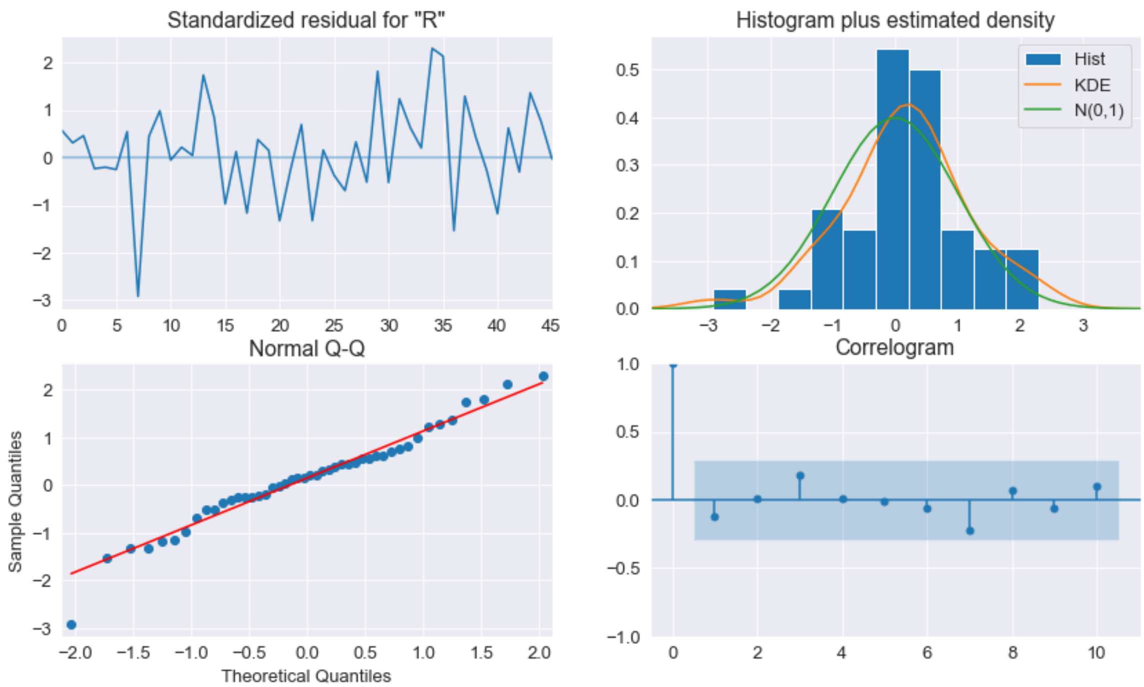
```python
type(my_model_res)
```

Out[94]:

```
statsmodels.tsa.arima.model.ARIMAResultsWrapper
```

In [95]:

```python
pred = my_model_res.plot_diagnostics()
```




```
Maximum Likelihood optimization failed to converge. Check mle_retvals
```

In [96]:

```python
tforecast =  my_model_res.forecast(48)
tforecast2 = my_model_res.get_forecast(48)
confint = np.array(tforecast2.conf_int())
```

In [97]:

```
type(confint)
```

Out[97]:

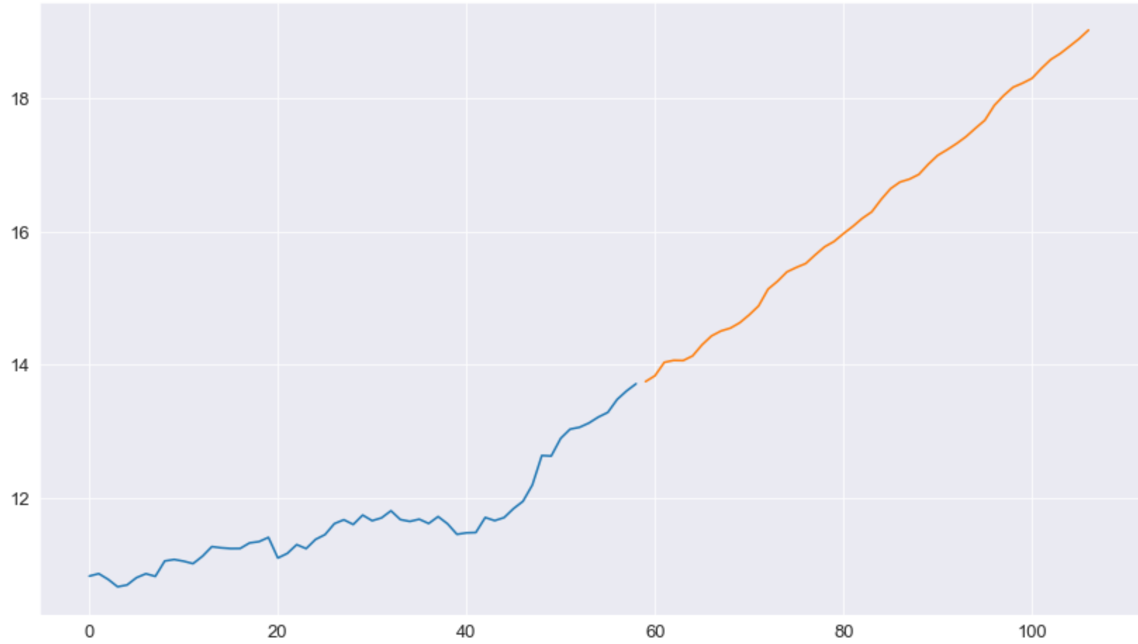
```
numpy.ndarray
```

In [98]:

```
plt.plot(dflog)
plt.plot(tforecast)
```

Out[98]:

```
[<matplotlib.lines.Line2D at 0x1d1d67b72b0>]
```

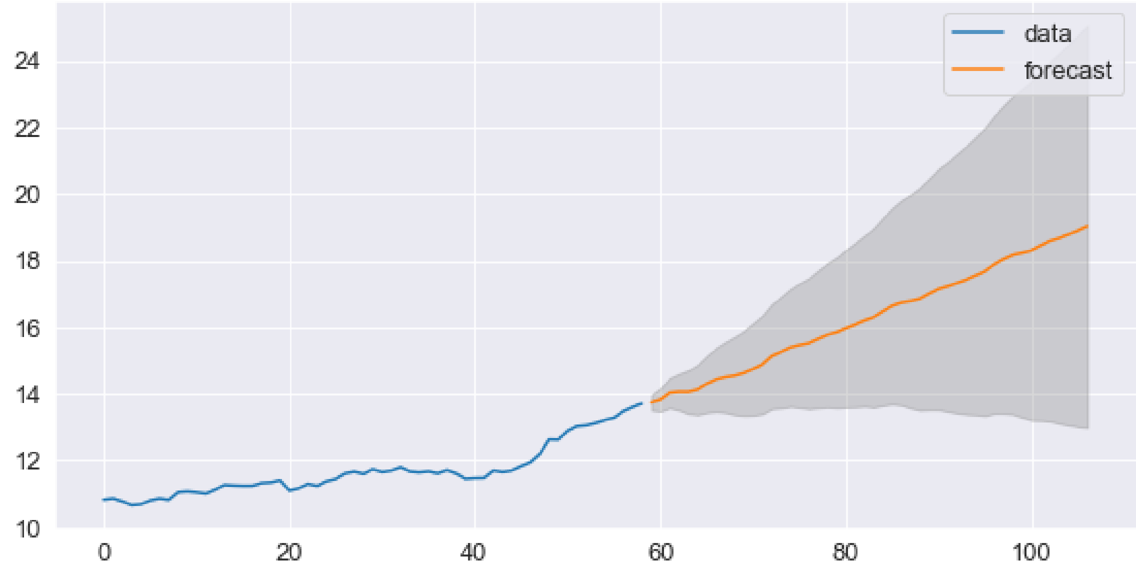


In [99]:

```
fig,ax = plt.subplots(figsize=(10,5))
ax.plot(dflog.index, dflog, label='data')
ax.plot(tforecast2.predicted_mean.index, tforecast2.predicted_mean, label='forecast')
ax.fill_between(tforecast2.predicted_mean.index, confint[:,0], confint[:,1],color='gr
ax.legend()
```

Out[99]:

```
<matplotlib.legend.Legend at 0x1d1db4efa00>
```




# AUTO ARIMA - MODEL

In [91]:

```
import pmdarima as pm
```

In [92]:

```
myfit = pm.auto_arima(dflog,start_p=0, start_q=0,
                             max_p=4, max_q=3, m=12,
                             start_P=0, seasonal=True,
                             d=1, D=1, trace=True,
                             error_action='ignore',  # don't want to know if an order
                             suppress_warnings=True,  # don't want convergence warnin
                             stepwise=True)  # set to stepwise
```

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(0,1,1)[12]             : AIC=inf, Time=0.40 sec
 ARIMA(0,1,0)(0,1,0)[12]             : AIC=-20.219, Time=0.06 sec
 ARIMA(1,1,0)(1,1,0)[12]             : AIC=-36.814, Time=0.32 sec
 ARIMA(0,1,1)(0,1,1)[12]             : AIC=inf, Time=0.82 sec
 ARIMA(1,1,0)(0,1,0)[12]             : AIC=-18.294, Time=0.08 sec
 ARIMA(1,1,0)(2,1,0)[12]             : AIC=-38.243, Time=1.42 sec
 ARIMA(1,1,0)(2,1,1)[12]             : AIC=-36.622, Time=3.52 sec
 ARIMA(1,1,0)(1,1,1)[12]             : AIC=-38.611, Time=0.90 sec
 ARIMA(1,1,0)(0,1,1)[12]             : AIC=inf, Time=0.52 sec
 ARIMA(1,1,0)(1,1,2)[12]             : AIC=-36.622, Time=2.06 sec
 ARIMA(1,1,0)(0,1,2)[12]             : AIC=-38.371, Time=1.47 sec
 ARIMA(1,1,0)(2,1,2)[12]             : AIC=-34.625, Time=2.20 sec
 ARIMA(0,1,0)(1,1,1)[12]             : AIC=-40.066, Time=0.37 sec
 ARIMA(0,1,0)(1,1,0)[12]             : AIC=-38.527, Time=0.20 sec
 ARIMA(0,1,0)(2,1,1)[12]             : AIC=-38.069, Time=1.60 sec
 ARIMA(0,1,0)(1,1,2)[12]             : AIC=-38.070, Time=1.19 sec
 ARIMA(0,1,0)(0,1,2)[12]             : AIC=-39.858, Time=0.99 sec
 ARIMA(0,1,0)(2,1,0)[12]             : AIC=-39.764, Time=0.73 sec
 ARIMA(0,1,0)(2,1,2)[12]             : AIC=-36.070, Time=1.96 sec
 ARIMA(0,1,1)(1,1,1)[12]             : AIC=-38.480, Time=1.01 sec
 ARIMA(1,1,1)(1,1,1)[12]             : AIC=-41.036, Time=2.06 sec
 ARIMA(1,1,1)(0,1,1)[12]             : AIC=inf, Time=0.98 sec
 ARIMA(1,1,1)(1,1,0)[12]             : AIC=-38.038, Time=1.00 sec
 ARIMA(1,1,1)(2,1,1)[12]             : AIC=inf, Time=3.68 sec
 ARIMA(1,1,1)(1,1,2)[12]             : AIC=inf, Time=3.12 sec
 ARIMA(1,1,1)(0,1,0)[12]             : AIC=-16.319, Time=0.18 sec
 ARIMA(1,1,1)(0,1,2)[12]             : AIC=inf, Time=2.15 sec
 ARIMA(1,1,1)(2,1,0)[12]             : AIC=-40.291, Time=2.75 sec
 ARIMA(1,1,1)(2,1,2)[12]             : AIC=inf, Time=3.92 sec
 ARIMA(2,1,1)(1,1,1)[12]             : AIC=inf, Time=1.58 sec
 ARIMA(1,1,2)(1,1,1)[12]             : AIC=inf, Time=2.13 sec
 ARIMA(0,1,2)(1,1,1)[12]             : AIC=-37.446, Time=1.28 sec
 ARIMA(2,1,0)(1,1,1)[12]             : AIC=-38.096, Time=1.31 sec
 ARIMA(2,1,2)(1,1,1)[12]             : AIC=inf, Time=2.37 sec
 ARIMA(1,1,1)(1,1,1)[12] intercept   : AIC=inf, Time=2.43 sec

Best model:  ARIMA(1,1,1)(1,1,1)[12]
Total fit time: 52.810 seconds
```

# WINTER-HOLTS MODEL

In [102]:

```
rolling = dfo['REP'].rolling(20)
type(rolling)
```

Out[102]:

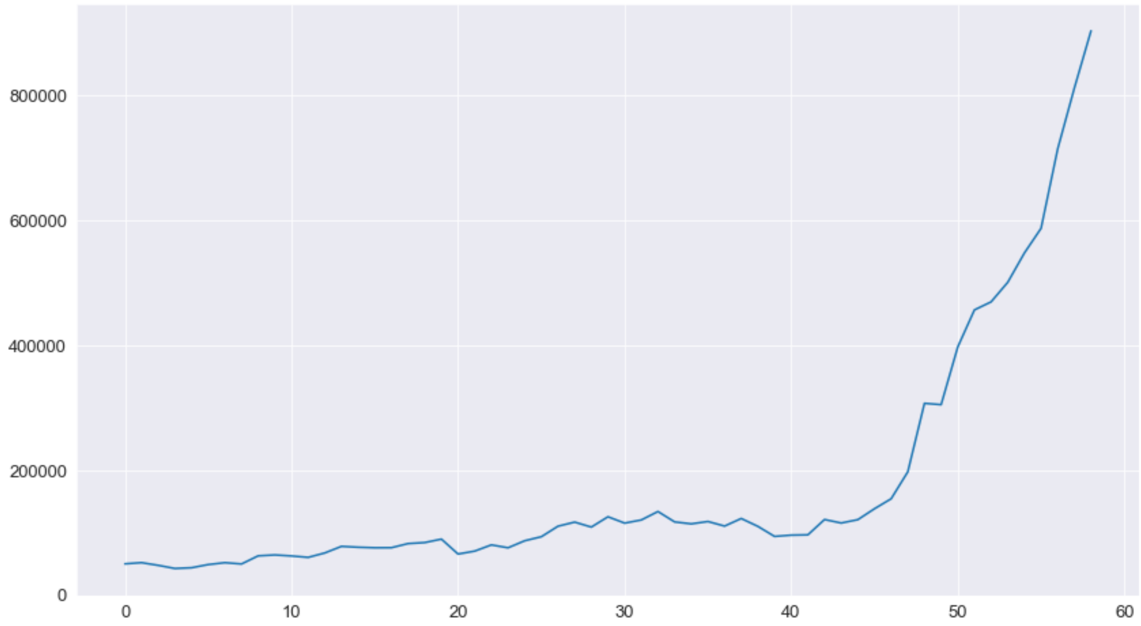
```
pandas.core.window.rolling.Rolling
```

In [103]:

```
df.plot()
```

Out[103]:

```
<AxesSubplot:>
```




In [113]:

```
rolling = dfo['REP'].rolling(2)
type(rolling)
```

Out[113]:

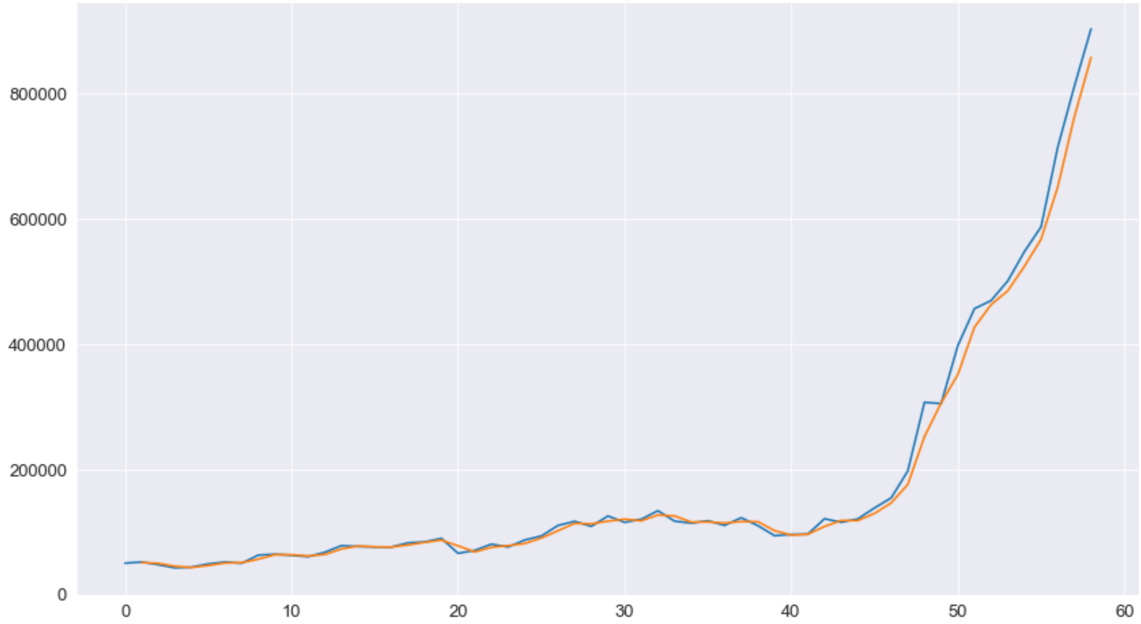
```
pandas.core.window.rolling.Rolling
```

In [114]:

```
mav = rolling.mean()
plt.plot(dfo['REP'])
plt.plot(mav)
```

Out[114]:

```
[&lt;matplotlib.lines.Line2D at 0x1d1e5c1ff10&gt;]
```




In [115]:

```
type(mav)
```

Out[115]:

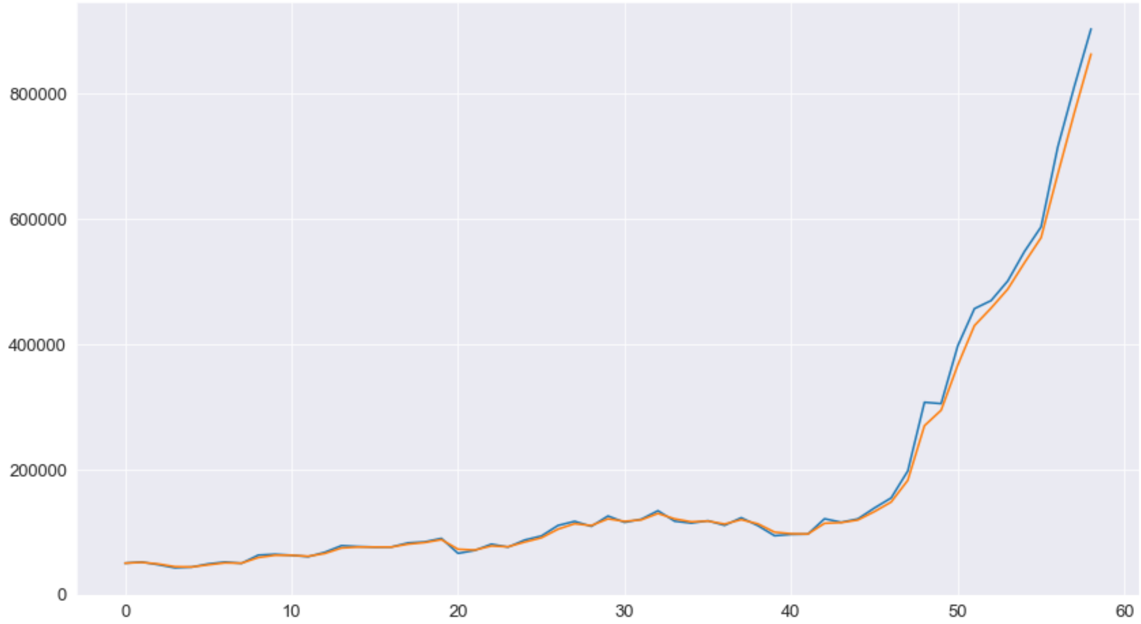
```
pandas.core.series.Series
```

In [119]:

```
# Try out the following with various values of 'alpha' and evaluate the results
ewma = dfo['REP'].ewm(alpha=0.7, adjust=False).mean()
plt.plot(dfo['REP'])
plt.plot(ewma)
```

Out[119]:

```
[<matplotlib.lines.Line2D at 0x1d1f17e8af0>]
```




In [169]:

```
from statsmodels.tsa.holtwinters import SimpleExpSmoothing
```

In [170]:

```
ses = SimpleExpSmoothing(df)
```

In [171]:

```
type(ses)
```

Out[171]:

```
statsmodels.tsa.holtwinters.model.SimpleExpSmoothing
```

In [172]:

```
result = ses.fit(smoothing_level=0.1, optimized=False)
```

In [173]:

```
result.summary()
```

Out[173]:

SimpleExpSmoothing Model Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | REP | **No. Observations:** | 59 |
| **Model:** | SimpleExpSmoothing | **SSE** | 1133099166623.606 |
| **Optimized:** | False | **AIC** | 1401.028 |
| **Trend:** | None | **BIC** | 1405.183 |
| **Seasonal:** | None | **AICC** | 1401.769 |
| **Seasonal Periods:** | None | **Date:** | Tue, 14 Feb 2023 |
| **Box-Cox:** | False | **Time:** | 20:15:40 |
| **Box-Cox Coeff.:** | None | | |

| | **coeff** | **code** | **optimized** |
|---|---|---|---|
| **smoothing_level** | 0.1000000 | alpha | False |
| **initial_level** | 50155.000 | l.0 | False |

In [174]:

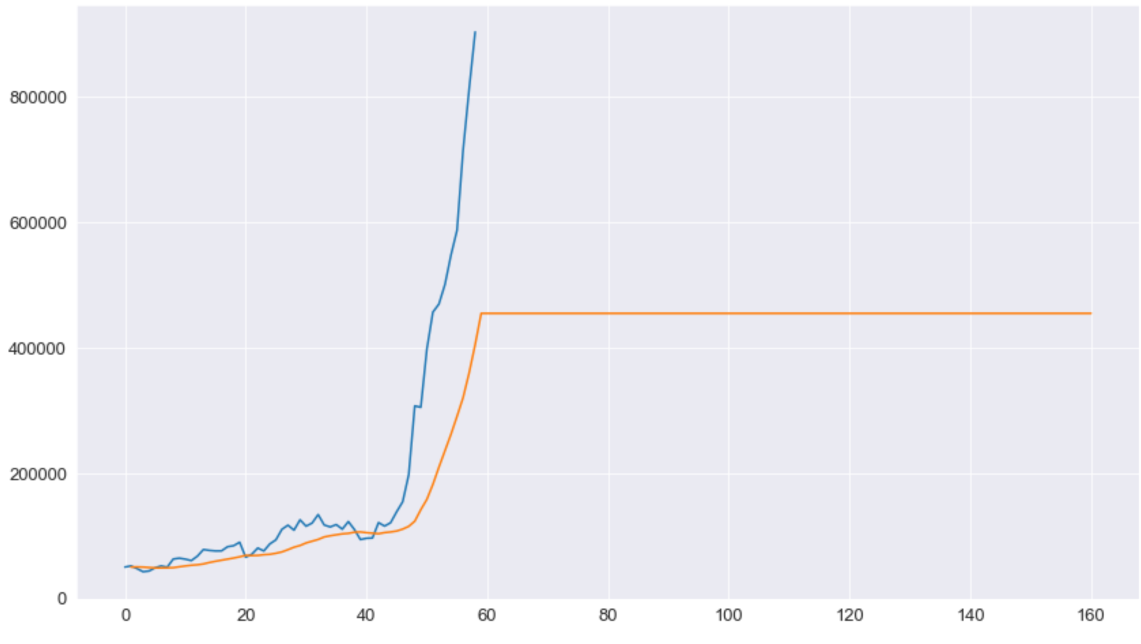
```
mypred = result.predict(start=1, end=160)
```

In [175]:

```
plt.plot(df)
plt.plot(mypred)
```

Out[175]:

```
[<matplotlib.lines.Line2D at 0x1d1f46e3ee0>]
```



In [176]:

```
result.params
```

Out[176]:

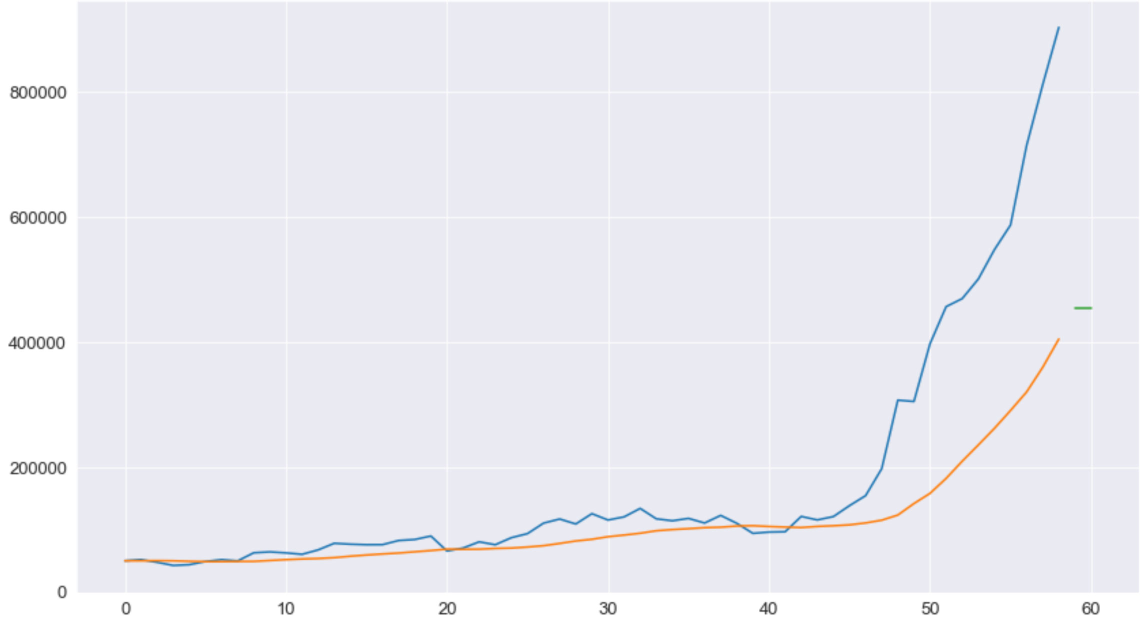
```
{'smoothing_level': 0.1,
 'smoothing_trend': None,
 'smoothing_seasonal': None,
 'damping_trend': nan,
 'initial_level': 50155.0,
 'initial_trend': nan,
 'initial_seasons': array([], dtype=float64),
 'use_boxcox': False,
 'lamda': None,
 'remove_bias': False}
```

In [177]:

```
plt.plot(df)
plt.plot(result.fittedvalues)
plt.plot(result.forecast(2))
```

Out[177]:

```
[<matplotlib.lines.Line2D at 0x1d1f3dec250>]
```




In [178]:

```
result2 = ses.fit() # optimize the values of alpha
```

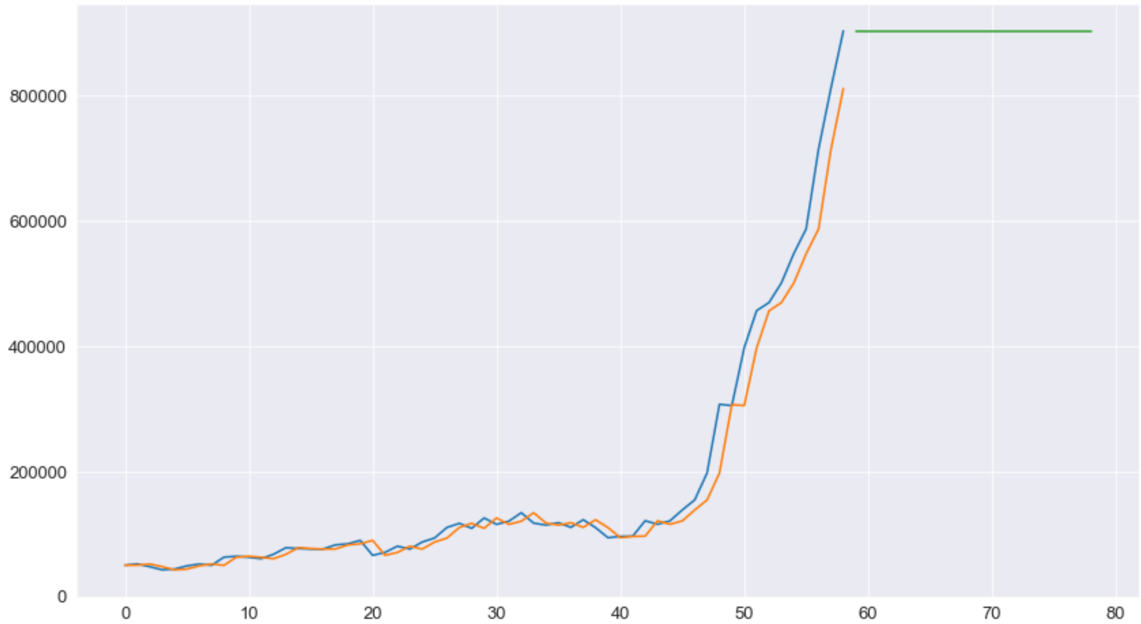
```
C:\Users\HP\AppData\Local\Programs\Python\Python310\lib\site-packages\s
tatsmodels\tsa\holtwinters\model.py:915: ConvergenceWarning:

Optimization failed to converge. Check mle_retvals.
```

In [179]:

```
plt.plot(df)
plt.plot(result2.fittedvalues)
plt.plot(result2.forecast(20))
```

Out[179]:

```
[<matplotlib.lines.Line2D at 0x1d1f3e27280>]
```




In [180]:

```
result2.params
```

Out[180]:

```
{'smoothing_level': 0.995,
 'smoothing_trend': nan,
 'smoothing_seasonal': nan,
 'damping_trend': nan,
 'initial_level': 50155.0,
 'initial_trend': nan,
 'initial_seasons': array([], dtype=float64),
 'use_boxcox': False,
 'lamda': None,
 'remove_bias': False}
```

In [181]:

```
from statsmodels.tsa.holtwinters import Holt
```

In [182]:

```
model = Holt(df, exponential=True)
result = model.fit()
result.params
```

```
C:\Users\HP\AppData\Local\Programs\Python\Python310\lib\site-packages\s
tatsmodels\tsa\holtwinters\model.py:915: ConvergenceWarning:

Optimization failed to converge. Check mle_retvals.
```

Out[182]:

```
{'smoothing_level': 0.9478571428571428,
 'smoothing_trend': 0.11559233449477352,
 'smoothing_seasonal': nan,
 'damping_trend': nan,
 'initial_level': 50155.0,
 'initial_trend': 1.0372445419200478,
 'initial_seasons': array([], dtype=float64),
 'use_boxcox': False,
 'lamda': None,
 'remove_bias': False}
```

In [183]:

```
result.summary()
```

Out[183]:

Holt Model Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | REP | **No. Observations:** | 59 |
| **Model:** | Holt | **SSE** | 28120080916.330 |
| **Optimized:** | True | **AIC** | 1186.951 |
| **Trend:** | Multiplicative | **BIC** | 1195.261 |
| **Seasonal:** | None | **AICC** | 1188.566 |
| **Seasonal Periods:** | None | **Date:** | Tue, 14 Feb 2023 |
| **Box-Cox:** | False | **Time:** | 20:16:04 |
| **Box-Cox Coeff.:** | None | | |

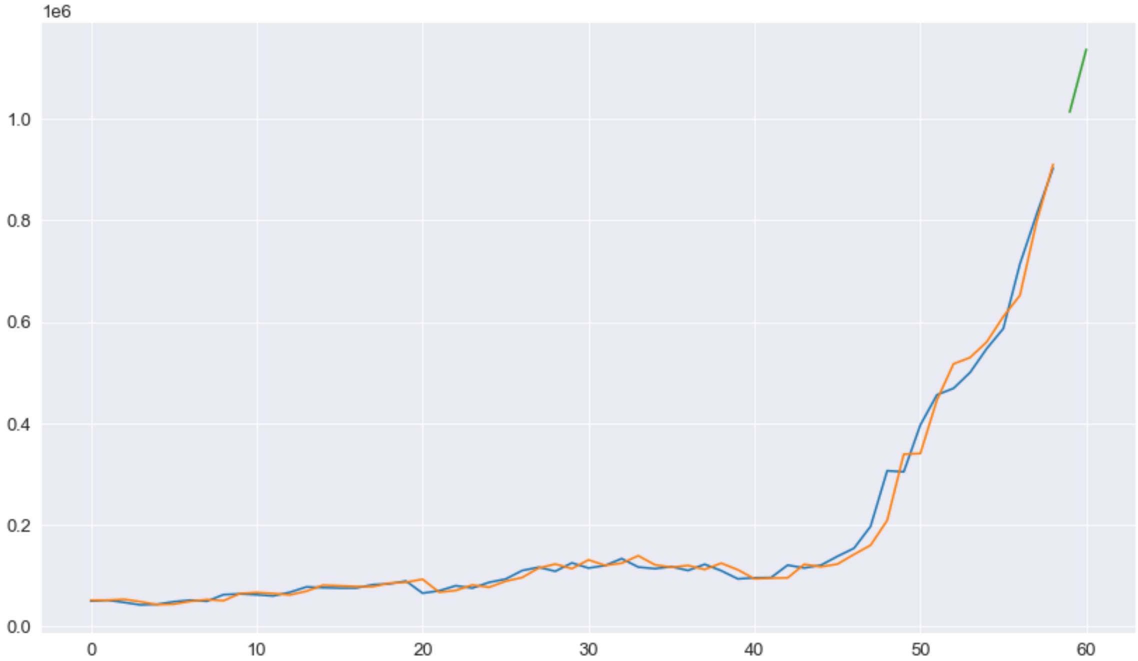
| | coeff | code | optimized |
|---|---|---|---|
| **smoothing_level** | 0.9478571 | alpha | True |
| **smoothing_trend** | 0.1155923 | beta | True |
| **initial_level** | 50155.000 | l.0 | True |
| **initial_trend** | 1.0372445 | b.0 | True |

In [184]:

```
plt.plot(df)
plt.plot(result.fittedvalues)
plt.plot(result.forecast(2))
```

Out[184]:

```
[<matplotlib.lines.Line2D at 0x1d1f3eb8580>]
```




In [185]:

```
from statsmodels.tsa.holtwinters import ExponentialSmoothing
```

In [186]:

```
model = ExponentialSmoothing(df, trend='mul', seasonal='mul', seasonal_periods=12)
```

In [187]:

```
result3 = model.fit()
result3.params
```

```
C:\Users\HP\AppData\Local\Programs\Python\Python310\lib\site-packages\s
tatsmodels\tsa\holtwinters\model.py:915: ConvergenceWarning:

Optimization failed to converge. Check mle_retvals.
```

Out[187]:

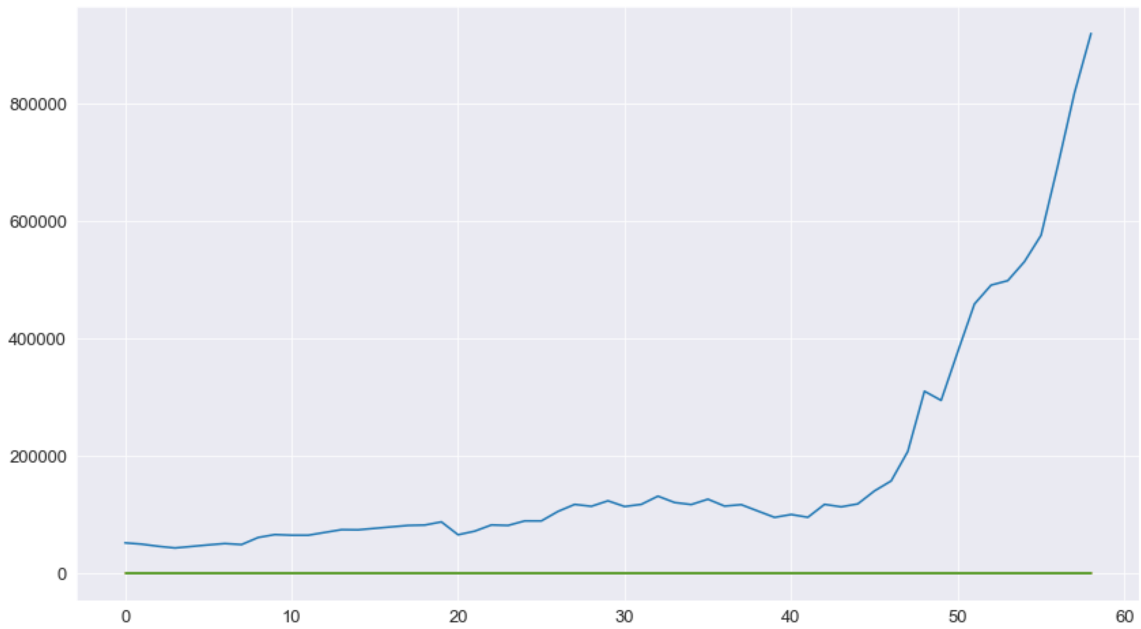
```
{'smoothing_level': 0.9242857142857143,
 'smoothing_trend': 0.1026984126984127,
 'smoothing_seasonal': 0.07571428571428573,
 'damping_trend': nan,
 'initial_level': 51163.31666666666,
 'initial_trend': 1.0475739616828332,
 'initial_seasons': array([0.97107962, 1.05686224, 1.04917597, 0.998723
73, 0.95822798,
        1.01088147, 1.02549094, 1.02765088, 1.01764936, 0.97396842,
        0.97367414, 0.93661526]),
 'use_boxcox': False,
 'lamda': None,
 'remove_bias': False}
```

In [188]:

```
plt.plot(result3.level)
plt.plot(result3.trend)
plt.plot(result3.season)
```

Out[188]:

```
[<matplotlib.lines.Line2D at 0x1d1f3ef3c10>]
```



In [189]:

```
result3.summary()
```

Out[189]:

ExponentialSmoothing Model Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | REP | **No. Observations:** | 59 |
| **Model:** | ExponentialSmoothing | **SSE** | 34776724113.134 |
| **Optimized:** | True | **AIC** | 1223.486 |
| **Trend:** | Multiplicative | **BIC** | 1256.727 |
| **Seasonal:** | Multiplicative | **AICC** | 1240.586 |
| **Seasonal Periods:** | 12 | **Date:** | Tue, 14 Feb 2023 |
| **Box-Cox:** | False | **Time:** | 20:16:16 |
| **Box-Cox Coeff.:** | None | | |

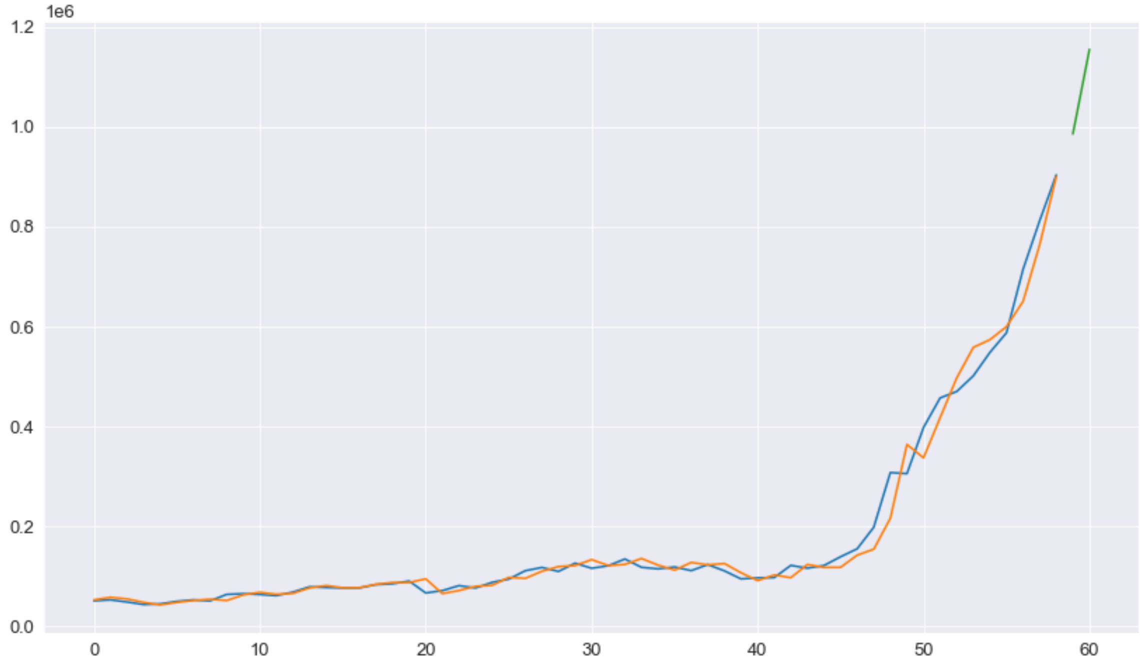
| | coeff | code | optimized |
|---|---|---|---|
| **smoothing_level** | 0.9242857 | alpha | True |
| **smoothing_trend** | 0.1026984 | beta | True |
| **smoothing_seasonal** | 0.0757143 | gamma | True |
| **initial_level** | 51163.317 | l.0 | True |
| **initial_trend** | 1.0475740 | b.0 | True |
| **initial_seasons.0** | 0.9710796 | s.0 | True |
| **initial_seasons.1** | 1.0568622 | s.1 | True |
| **initial_seasons.2** | 1.0491760 | s.2 | True |
| **initial_seasons.3** | 0.9987237 | s.3 | True |
| **initial_seasons.4** | 0.9582280 | s.4 | True |
| **initial_seasons.5** | 1.0108815 | s.5 | True |
| **initial_seasons.6** | 1.0254909 | s.6 | True |
| **initial_seasons.7** | 1.0276509 | s.7 | True |
| **initial_seasons.8** | 1.0176494 | s.8 | True |
| **initial_seasons.9** | 0.9739684 | s.9 | True |
| **initial_seasons.10** | 0.9736741 | s.10 | True |
| **initial_seasons.11** | 0.9366153 | s.11 | True |

In [190]:

```
plt.plot(df)
plt.plot(result3.fittedvalues)
plt.plot(result3.forecast(2))
```

Out[190]:

```
[<matplotlib.lines.Line2D at 0x1d1f3f71420>]
```




In [191]:

```
model2 = ExponentialSmoothing(df, trend='add', seasonal='mul', seasonal_periods=12)
```

In [192]:

```
result4 = model2.fit()
result4.params
```

```
C:\Users\HP\AppData\Local\Programs\Python\Python310\lib\site-packages\s
tatsmodels\tsa\holtwinters\model.py:915: ConvergenceWarning:

Optimization failed to converge. Check mle_retvals.
```

Out[192]:

```
{'smoothing_level': 0.9242857142857143,
 'smoothing_trend': 0.37656084656084654,
 'smoothing_seasonal': 0.07571428571428573,
 'damping_trend': nan,
 'initial_level': 51163.31666666666,
 'initial_trend': 2434.041666666668,
 'initial_seasons': array([0.97107962, 1.05686224, 1.04917597, 0.998723
73, 0.95822798,
        1.01088147, 1.02549094, 1.02765088, 1.01764936, 0.97396842,
        0.97367414, 0.93661526]),
 'use_boxcox': False,
 'lamda': None,
 'remove_bias': False}
```

In [193]:

```
result4.summary()
```

Out[193]:

ExponentialSmoothing Model Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | REP | **No. Observations:** | 59 |
| **Model:** | ExponentialSmoothing | **SSE** | 38556273797.311 |
| **Optimized:** | True | **AIC** | 1229.573 |
| **Trend:** | Additive | **BIC** | 1262.814 |
| **Seasonal:** | Multiplicative | **AICC** | 1246.673 |
| **Seasonal Periods:** | 12 | **Date:** | Tue, 14 Feb 2023 |
| **Box-Cox:** | False | **Time:** | 20:16:30 |
| **Box-Cox Coeff.:** | None | | |

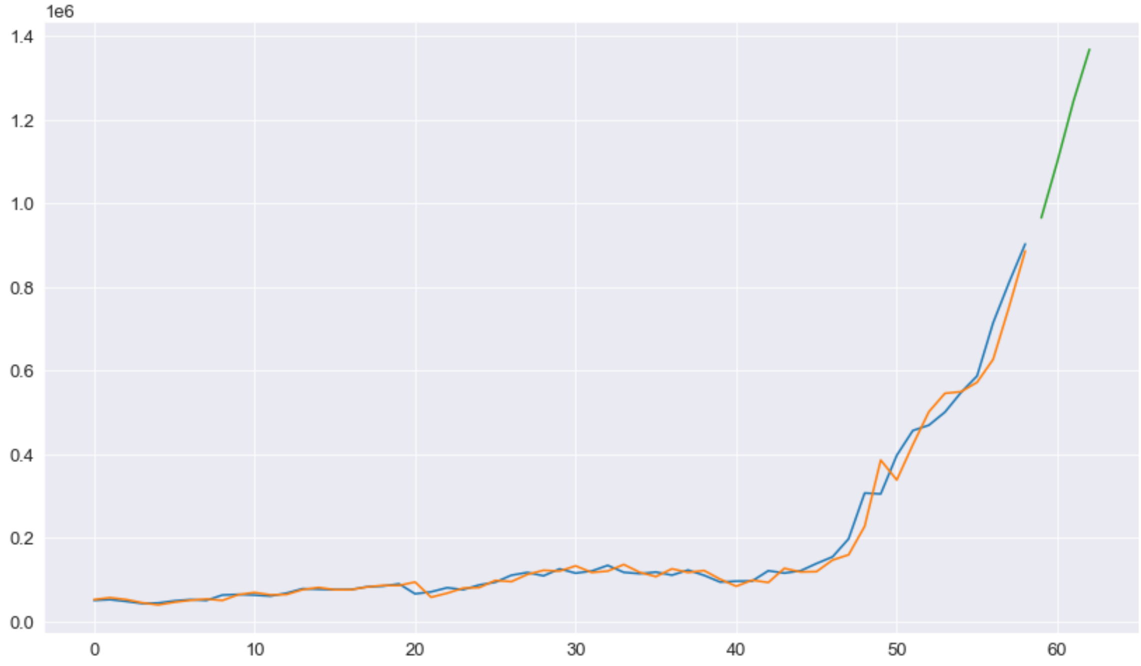
| | coeff | code | optimized |
|---|---|---|---|
| **smoothing_level** | 0.9242857 | alpha | True |
| **smoothing_trend** | 0.3765608 | beta | True |
| **smoothing_seasonal** | 0.0757143 | gamma | True |
| **initial_level** | 51163.317 | l.0 | True |
| **initial_trend** | 2434.0417 | b.0 | True |
| **initial_seasons.0** | 0.9710796 | s.0 | True |
| **initial_seasons.1** | 1.0568622 | s.1 | True |
| **initial_seasons.2** | 1.0491760 | s.2 | True |
| **initial_seasons.3** | 0.9987237 | s.3 | True |
| **initial_seasons.4** | 0.9582280 | s.4 | True |
| **initial_seasons.5** | 1.0108815 | s.5 | True |
| **initial_seasons.6** | 1.0254909 | s.6 | True |
| **initial_seasons.7** | 1.0276509 | s.7 | True |
| **initial_seasons.8** | 1.0176494 | s.8 | True |
| **initial_seasons.9** | 0.9739684 | s.9 | True |
| **initial_seasons.10** | 0.9736741 | s.10 | True |
| **initial_seasons.11** | 0.9366153 | s.11 | True |

In [194]:

```
plt.plot(df)
plt.plot(result4.fittedvalues)
plt.plot(result4.forecast(4))
```

Out[194]:

```
[<matplotlib.lines.Line2D at 0x1d1f4c23a90>]
```




In [ ]: