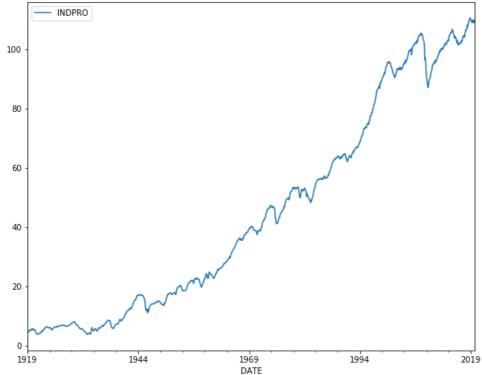
Modelling and Forecasting an Industrial Production with Simple Eponential Smoothing, Double Exponential Smoothing and Triple Exponential Smoothing.

```
In [113]:
import pandas as pd
import pandas as pd
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
In [114]:
df=pd.read csv(r'C:\Users\chumj\Downloads\509982 941525 bundle archive\INDPRODUCTION.csv',index col
='DATE',parse dates=True)
                                                                                                        P
In [115]:
df.tail(5)
Out[115]:
          INDPRO
    DATE
2019-08-01 109.9634
2019-09-01 109 4437
2019-10-01 108.8532
2019-11-01 109.7573
2019-12-01 109.4330
In [116]:
df.dropna(inplace=True)
In [117]:
df.index
Out[117]:
DatetimeIndex(['1919-01-01', '1919-02-01', '1919-03-01', '1919-04-01',
                '1919-05-01', '1919-06-01', '1919-07-01', '1919-08-01', '1919-09-01', '1919-10-01',
                '2019-03-01', '2019-04-01', '2019-05-01', '2019-06-01',
                '2019-07-01', '2019-08-01', '2019-09-01', '2019-10-01',
                '2019-11-01', '2019-12-01'],
               dtype='datetime64[ns]', name='DATE', length=1212, freq=None)
In [119]:
df.index.freq='MS'
In [120]:
df.index
Out[120]:
```



In [9]:

```
#Using Hodrick Prescott filter to get Trend
from statsmodels.tsa.filters.hp_filter import hpfilter
```

In [10]:

```
df_trend,df_cyle=hpfilter(df['INDPRO'],lamb=1600)
```

In [11]:

```
df['Trend']=df_trend
```

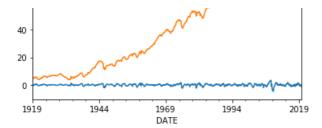
In [12]:

```
df[['Trend','INDPRO']].plot()
```

Out[12]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e0d562788>



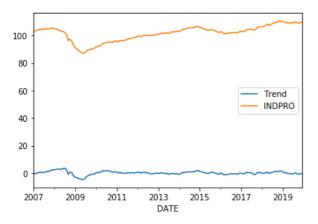


In [13]:

```
df[['Trend','INDPRO']]['2007-01-01':].plot()
```

Out[13]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e10dfcc08>



In [14]:

#Applying ETS
from statsmodels.tsa.seasonal import seasonal_decompose

In [15]:

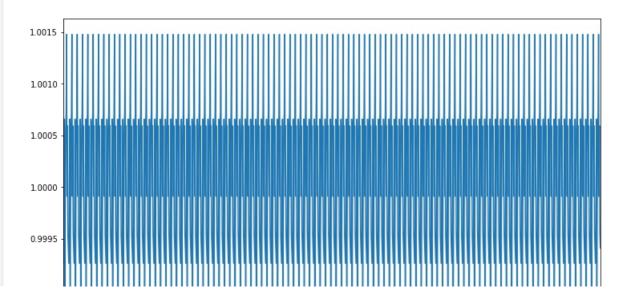
```
result=seasonal_decompose(df['INDPRO'], model='mul')
```

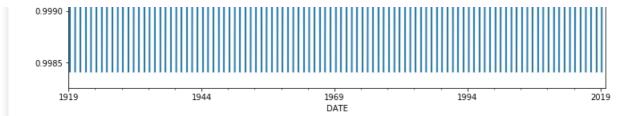
In [16]:

```
result.seasonal.plot(figsize=(12,8))
```

Out[16]:

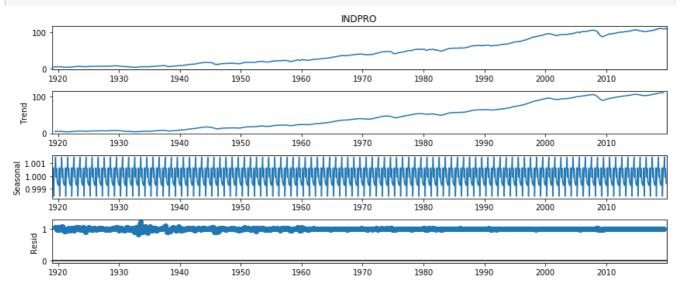
<matplotlib.axes._subplots.AxesSubplot at 0x12e12badb08>





In [17]:

```
from pylab import rcParams
rcParams['figure.figsize']=12,5
result.plot();
```



In [18]:

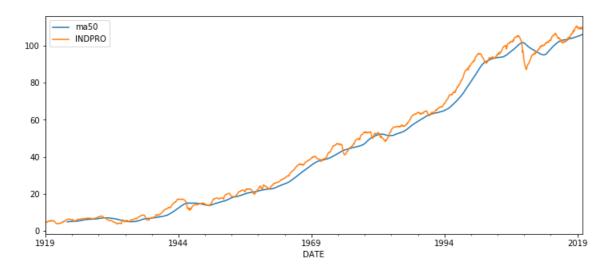
```
#SMA
df['ma50']=df['INDPRO'].rolling(50).mean()
```

In [19]:

```
df[['ma50','INDPRO']].plot()
```

Out[19]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e12dd3388>



In [20]:

```
span=24
alpha=2/(span+1)
from statsmodels.tsa.holtwinters import SimpleExpSmoothing
df['EWA24']=df['INDPRO'].ewm(alpha=alpha,adjust=False).mean()
{\tt df['SES24']=SimpleExpSmoothing(df['INDPRO']).fit(smoothing\_level=alpha, optimized={\bf False}).fitted value}
s.shift(-1)
4
                                                                                                              |
In [21]:
df
Out[21]:
           INDPRO
                                         EWA24
                                                    SES24
                      Trend
                                 ma50
    DATE
 1919-01-01
            5.0124 -0.040006
                                  NaN
                                        5.012400
                                                   5.012400
 1919-02-01
            4.7908 -0.286230
                                  NaN
                                        4.994672
                                                   4.994672
 1919-03-01
            4.6524 -0.449230
                                  NaN
                                        4.967290
                                                   4.967290
 1919-04-01
            4.7355 -0.390501
                                        4.948747
                                                   4.948747
                                  NaN
 1919-05-01
            4.7632 -0.386458
                                  NaN
                                        4.933903
                                                   4.933903
 2019-08-01 109.9634 0.139045 105.545012 108.269967 108.269967
 2019-09-01 109.4437 -0.428749 105.647400 108.363866 108.363866
 2019-10-01 108.8532 -1.065339 105.741222 108.403013 108.403013
 2019-11-01 109.7573 -0.206481 105.860832 108.511356 108.511356
 2019-12-01 109.4330 -0.575664 105.981540 108.585087
                                                      NaN
1212 rows × 5 columns
In [22]:
df.columns
Out[22]:
Index(['INDPRO', 'Trend', 'ma50', 'EWA24', 'SES24'], dtype='object')
In [23]:
df[['INDPRO', 'ma50', 'EWA24', 'SES24']].plot(figsize=(12,8))
Out[23]:
<matplotlib.axes._subplots.AxesSubplot at 0x12e12fff148>

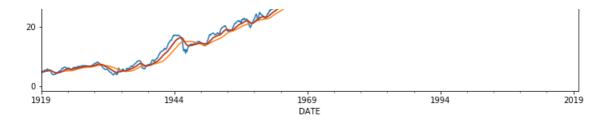
    INDPRO

        ma50

    EWA24

    SES24

 100
  80
                                            60
  40
```

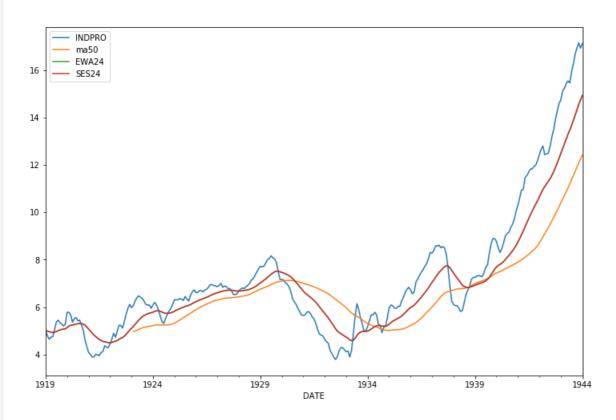


In [24]:

```
df[['INDPRO','ma50','EWA24','SES24']][:'1944-01-01'].plot(figsize=(12,8))
```

Out[24]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e12d3d1c8>

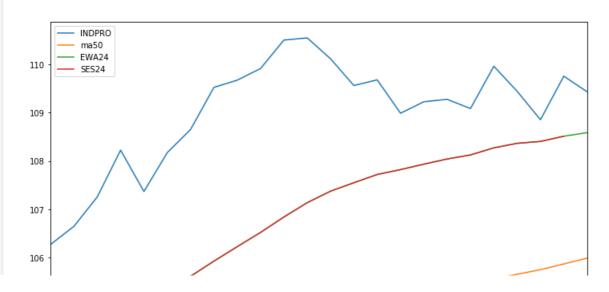


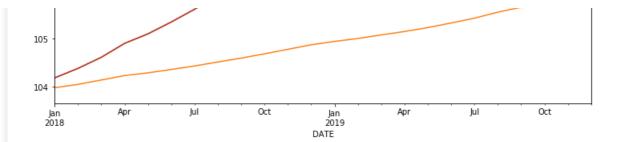
In [25]:

```
df[['INDPRO','ma50','EWA24','SES24']]['2018-01-01':].plot(figsize=(12,8)).plot(figsize=(12,8))
```

Out[25]:

[]





In [26]:

#Double Exponential Smoothing with alpha and beta, that addresses the trend of the data using the multiplicative approach

 $\textbf{from statsmodels.tsa.holtwinters import} \ \texttt{ExponentialSmoothing}$

df['DES_MUL24']=ExponentialSmoothing(df['INDPRO'],trend='mul').fit().fittedvalues.shift(-1)

loc = initial_p >= ub

In [27]:

df

Out[27]:

	INDPRO	Trend	ma50	EWA24	SES24	DES_MUL24
DATE						
1919-01-01	5.0124	-0.040006	NaN	5.012400	5.012400	4.979524
1919-02-01	4.7908	-0.286230	NaN	4.994672	4.994672	4.716834
1919-03-01	4.6524	-0.449230	NaN	4.967290	4.967290	4.565812
1919-04-01	4.7355	-0.390501	NaN	4.948747	4.948747	4.688103
1919-05-01	4.7632	-0.386458	NaN	4.933903	4.933903	4.733341
2019-08-01	109.9634	0.139045	105.545012	108.269967	108.269967	110.118578
2019-09-01	109.4437	-0.428749	105.647400	108.363866	108.363866	109.439723
2019-10-01	108.8532	-1.065339	105.741222	108.403013	108.403013	108.711656
2019-11-01	109.7573	-0.206481	105.860832	108.511356	108.511356	109.863250
2019-12-01	109.4330	-0.575664	105.981540	108.585087	NaN	NaN

1212 rows × 6 columns

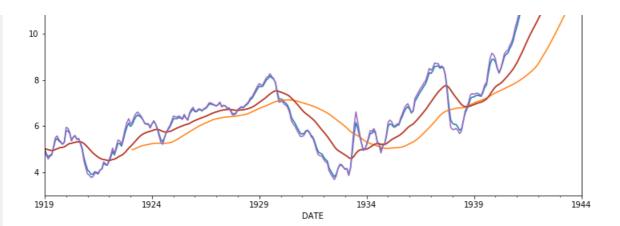
In [28]:

```
df[['INDPRO','ma50','EWA24','SES24','DES_MUL24']][:'1944-01-01'].plot(figsize=(12,8))
```

Out[28]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e134b0b08>



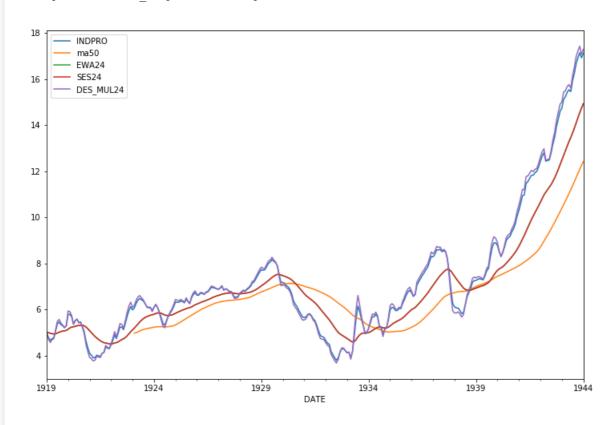


In [29]:

```
df[['INDPRO', 'ma50', 'EWA24', 'SES24', 'DES_MUL24']][:'1944-01-01'].plot(figsize=(12,8))
```

Out[29]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e135dc6c8>

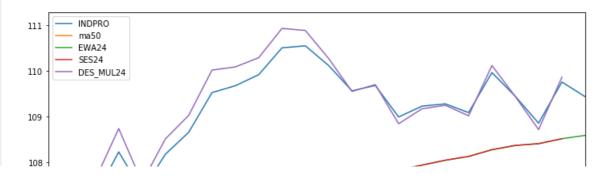


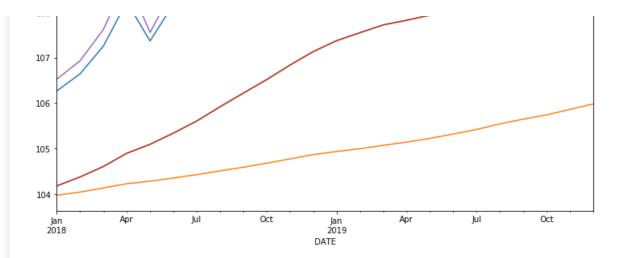
In [30]:

```
df[['INDPRO','ma50','EWA24','SES24','DES_MUL24']]['2018-01-01':].plot(figsize=(12,8))
```

Out[30]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e135dcb88>





In [31]:

 $\# Double\ Exponential\ Smoothing\ with\ alpha\$ and beta, that addresses the trend of the data using the addiction approach

from statsmodels.tsa.holtwinters import ExponentialSmoothing

 ${\tt df['DES_ADD24']=} \\ {\tt ExponentialSmoothing(df['INDPRO'], trend='add').fit().fitted values.shift(-1)} \\ {\tt \\ {\tt exponentialSmoothing(df['INDPRO'], trend='add').fit()$

C:\Users\chumj\Anaconda3\Ben\lib\site-packages\statsmodels\tsa\holtwinters.py:731: RuntimeWarning:
invalid value encountered in greater equal

loc = initial_p >= ub

In [34]:

df

Out[34]:

	INDPRO	Trend	ma50	EWA24	SES24	DES_MUL24	DES_ADD24
DATE							
1919-01-01	5.0124	-0.040006	NaN	5.012400	5.012400	4.979524	5.010177
1919-02-01	4.7908	-0.286230	NaN	4.994672	4.994672	4.716834	4.736807
1919-03-01	4.6524	-0.449230	NaN	4.967290	4.967290	4.565812	4.578488
1919-04-01	4.7355	-0.390501	NaN	4.948747	4.948747	4.688103	4.698641
1919-05-01	4.7632	-0.386458	NaN	4.933903	4.933903	4.733341	4.741576
2019-08-01	109.9634	0.139045	105.545012	108.269967	108.269967	110.118578	110.116475
2019-09-01	109.4437	-0.428749	105.647400	108.363866	108.363866	109.439723	109.438010
2019-10-01	108.8532	-1.065339	105.741222	108.403013	108.403013	108.711656	108.709504
2019-11-01	109.7573	-0.206481	105.860832	108.511356	108.511356	109.863250	109.860868
2019-12-01	109.4330	-0.575664	105.981540	108.585087	NaN	NaN	NaN

1212 rows × 7 columns

In [35]:

df.columns

Out[35]:

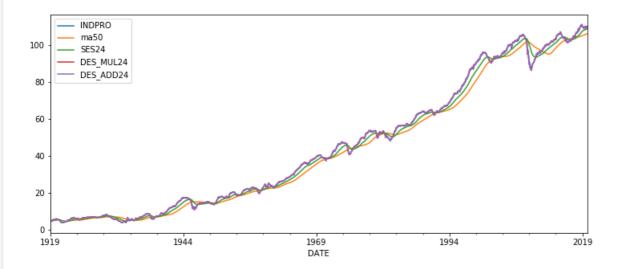
Index(['INDPRO', 'Trend', 'ma50', 'EWA24', 'SES24', 'DES_MUL24', 'DES_ADD24'], dtype='object')

In [36]:

```
df[['INDPRO', 'ma50', 'SES24','DES_MUL24', 'DES_ADD24']].plot()
```

ouctooj.

<matplotlib.axes._subplots.AxesSubplot at 0x12e13a3b308>

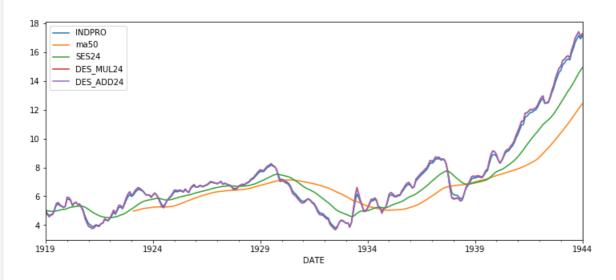


In [37]:

```
df[['INDPRO', 'ma50', 'SES24','DES_MUL24', 'DES_ADD24']][:'1944-01-01'].plot()
```

Out[37]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e152c3cc8>

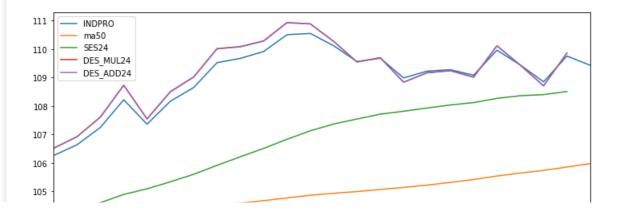


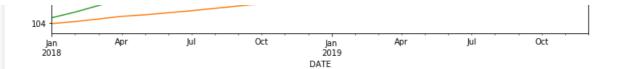
In [38]:

```
df[['INDPRO', 'ma50', 'SES24','DES_MUL24', 'DES_ADD24']]['2018-01-01':].plot()
```

Out[38]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e153877c8>



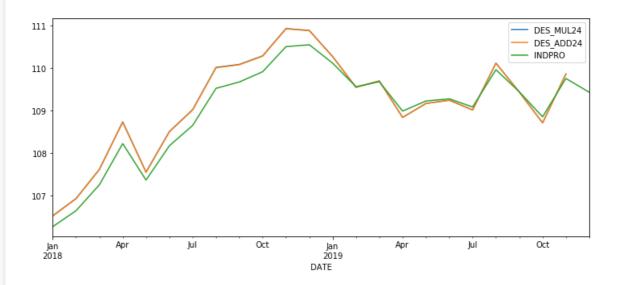


In [39]:

```
df[['DES_MUL24', 'DES_ADD24','INDPRO']]['2018-01-01':].plot()
```

Out[39]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e1536a108>



In [42]:

#Implementing Triple Exponential Smoothing, supporting trend and seasonality that is alpha, beta and
gamma.
df['TES_MUL24']=ExponentialSmoothing(df['INDPRO'], trend='mul', seasonal='mul', seasonal_periods=24).f
it().fittedvalues
df['TES_ADD24']=ExponentialSmoothing(df['INDPRO'], trend='add', seasonal='add', seasonal_periods=24).f
it().fittedvalues

C:\Users\chumj\Anaconda3\Ben\lib\site-packages\statsmodels\tsa\holtwinters.py:725: RuntimeWarning:
invalid value encountered in less_equal
 loc = initial_p <= lb

C:\Users\chumj\Anaconda3\Ben\lib\site-packages\statsmodels\tsa\holtwinters.py:731: RuntimeWarning:
invalid value encountered in greater_equal
 loc = initial_p >= ub

In [43]:

df

Out[43]:

	INDPRO	Trend	ma50	EWA24	SES24	DES_MUL24	DES_ADD24	TES_MUL24	TES_ADD24
DATE									
1919-01-01	5.0124	-0.040006	NaN	5.012400	5.012400	4.979524	5.010177	4.989045	5.277892
1919-02-01	4.7908	-0.286230	NaN	4.994672	4.994672	4.716834	4.736807	4.754877	4.936286
1919-03-01	4.6524	-0.449230	NaN	4.967290	4.967290	4.565812	4.578488	4.609886	4.680236
1919-04-01	4.7355	-0.390501	NaN	4.948747	4.948747	4.688103	4.698641	4.688182	4.473652
1919-05-01	4.7632	-0.386458	NaN	4.933903	4.933903	4.733341	4.741576	4.713969	4.695956
2019-08-01	109.9634	0.139045	105.545012	108.269967	108.269967	110.118578	110.116475	109.292725	109.054745
2019-09-01	109.4437	-0.428749	105.647400	108.363866	108.363866	109.439723	109.438010	109.845289	110.073773

2019-10-01	10008582	-1.0 65660	105.7 41250	108. EV&Q23	108.4 5/2924	DESS_MU624	DESS_A00524	TES)_696924	TES9_A9DID22
2019 :DA-70 E	109.7573	-0.206481	105.860832	108.511356	108.511356	109.863250	109.860868	110.086742	108.747264
2019-12-01	109.4330	-0.575664	105.981540	108.585087	NaN	NaN	NaN	109.990222	109.888814

1212 rows × 9 columns

In [44]:

df.columns

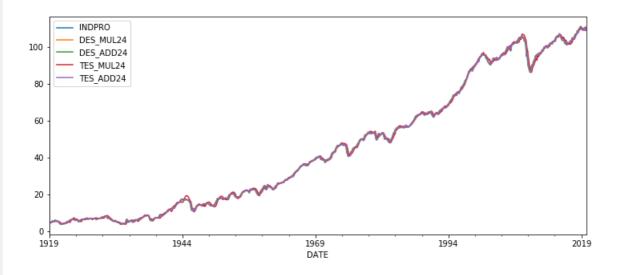
Out[44]:

In [45]:

```
df[['INDPRO','DES_MUL24', 'DES_ADD24','TES_MUL24', 'TES_ADD24']].plot()
```

Out[45]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e173fe788>

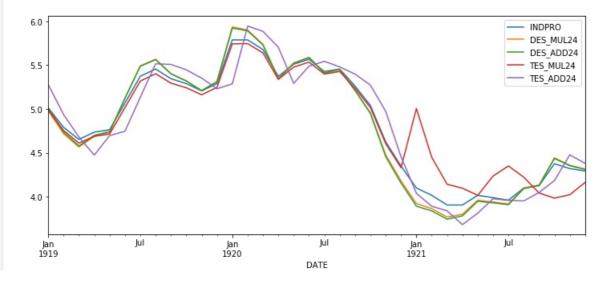


In [50]:

```
df[['INDPRO','DES_MUL24', 'DES_ADD24','TES_MUL24', 'TES_ADD24']].iloc[:36].plot()
```

Out[50]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e16db5fc8>

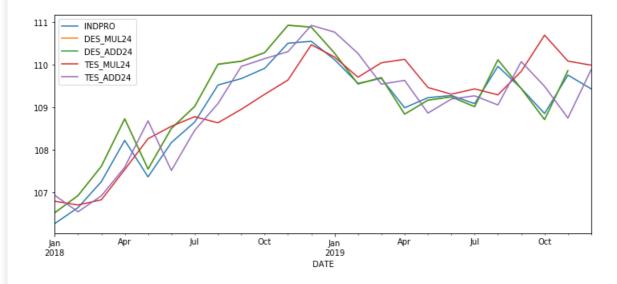


In [49]:

```
df[['INDPRO','DES_MUL24', 'DES_ADD24','TES_MUL24', 'TES_ADD24']].iloc[-24:].plot()
```

Out[49]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e164c8848>

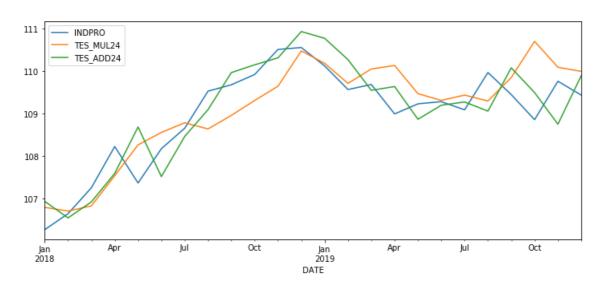


In [51]:

```
df[['INDPRO','TES_MUL24', 'TES_ADD24']].iloc[-24:].plot()
```

Out[51]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e1723c348>



Base on our analysis, it seems DES does well or fits well more than TES,but the main aspect that comes in to clarify us is the forecasting evaluation,from there we can make our conclusions.

In [54]:

```
df.info()
```

```
Freq: MS
Data columns (total 9 columns):
 # Column
                Non-Null Count Dtype
                1212 non-null
                               float64
float64
    INDPRO
   Trend
               1212 non-null
 1
               1163 non-null float64
 2 ma50
               1212 non-null float64
 3 EWA24
 4 SES24
               1211 non-null
                                float64
   DES_MUL24 1211 non-null float64
DES_ADD24 1211 non-null float64
   TES MUL24 1212 non-null float64
 8 TES ADD24 1212 non-null float64
dtypes: float64(9)
memory usage: 134.7 KB
In [55]:
#Lets split our data into train and test set and make 3years forecast. That is train=1212-36 and te
st=36
#train=1176
\#test=36
In [84]:
train=df.iloc[:973]
test=df.iloc[972:]
In [85]:
from statsmodels.tsa.holtwinters import ExponentialSmoothing
In [94]:
TES model=ExponentialSmoothing(train['INDPRO'], trend='mul', seasonal='mul', seasonal periods=12).fit
C:\Users\chumj\Anaconda3\Ben\lib\site-packages\statsmodels\tsa\holtwinters.py:725: RuntimeWarning:
invalid value encountered in less_equal
 loc = initial p <= lb</pre>
C:\Users\chumj\Anaconda3\Ben\lib\site-packages\statsmodels\tsa\holtwinters.py:731: RuntimeWarning:
invalid value encountered in greater_equal
 loc = initial_p >= ub
In [109]:
test prediction=TES model.forecast(240)
In [110]:
train['INDPRO'].plot(legend=True, label='training', figsize=(12,8))
test['INDPRO'].plot(legend=True, label='testing');

    training

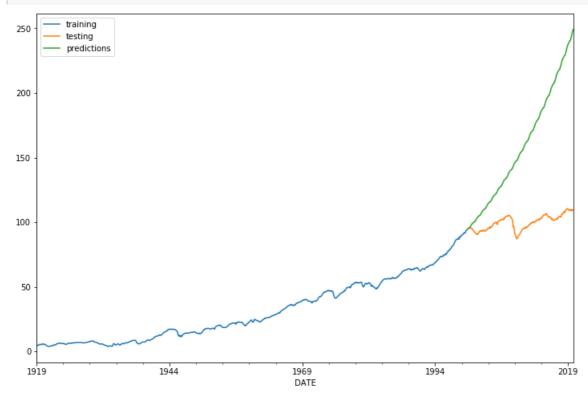
    testina

 100
  80
  60
```

Datectmethoev. ISIS entites, ISIS of of CO SOLS IS OF

In [111]:

```
train['INDPRO'].plot(legend=True, label='training', figsize=(12,8))
test['INDPRO'].plot(legend=True, label='testing')
test_prediction.plot(legend=True, label='predictions');
```



In [101]:

```
model=ExponentialSmoothing(df['INDPRO'], trend='mul', seasonal='mul', seasonal_periods=12).fit()
C:\Users\chumj\Anaconda3\Ben\lib\site-packages\statsmodels\tsa\holtwinters.py:725: RuntimeWarning:
invalid value encountered in less_equal
  loc = initial_p <= lb
C:\Users\chumj\Anaconda3\Ben\lib\site-packages\statsmodels\tsa\holtwinters.py:731: RuntimeWarning:
invalid value encountered in greater_equal
  loc = initial_p >= ub
```

In [102]:

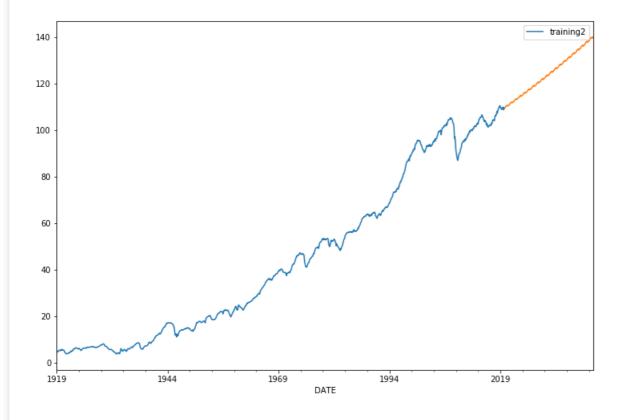
```
ft=model.forecast(240)
```

In [104]:

```
df['INDPRO'].plot(legend=True,label='training2',figsize=(12,8))
ft.plot()
```

Out[104]:

<matplotlib.axes._subplots.AxesSubplot at 0x12e1aee4088>



In [105]:

from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score,

In [125]:

mean_absolute_error(test['INDPRO'], test_prediction)

Out[125]:

59.626285583773026

In [126]:

```
r2_score(test['INDPRO'],test_prediction)
```

Out[126]:

-162.82233127970912

In [127]:

```
mean_squared_error(test['INDPRO'],test_prediction)
```

Out[127]:

5186.955060712123

In [128]:

```
np.sqrt (mean_squared_error(test['INDPRO'], test_prediction))
```

Out[128]:

72.02051833132086

In [129]:

```
test['INDPRO'].describe()
```

```
Out[129]:
count 240.000000
mean 99.665681
std 5.638666
min 87.074200
25% 95.110300
25%
              95.110300
50% 100.328500
75% 104.056200
max 110.551600
50%
Name: INDPRO, dtype: float64
In [130]:
test prediction.describe()
Out[130]:
count 240.000000
mean 159.290858
           44.482849
std
min
             94.693537
min 94.693537
25% 120.612138
50% 153.624691
75% 195.672755
max 249.229257
dtype: float64
In [ ]:
```