```
In [2]:
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
import itertools
from statsmodels.tsa.stattools import adfuller
from sklearn.metrics import mean squared error
from statsmodels.graphics.tsaplots import plot acf
from statsmodels.graphics.tsaplots import plot pacf
from statsmodels.tsa.seasonal import seasonal decompose
import statsmodels.api as sm
In [3]:
def check stationarity(series):
   result = adfuller(series)
   print('ADF Statistic: %f' % result[0])
    print('p-value: %f' % result[1])
    if result[1]<0.05:</pre>
       print('Time Series is stationary')
    else:
       print('Time Series is not stationary')
In [4]:
def series decomposition(series, method='additive'):
    result = seasonal decompose(series, model=method)
    result.plot()
    plt.show()
In [5]:
def plot acf pacf graphs (series):
    fig, ax = plt.subplots(2,1)
    fig = sm.graphics.tsa.plot acf(series, lags=25, ax=ax[0])
    fig = sm.graphics.tsa.plot pacf(series, lags=25, ax=ax[1])
    plt.tight layout()
    plt.show()
In [6]:
def arima modeling(series, params):
   mod = sm.tsa.arima.ARIMA(series, order=params)
   results = mod.fit()
   print('ARIMA{} - AIC:{}'.format(params, results.aic))
   print(results.summary())
    results.plot_diagnostics(figsize=(18, 8))
    plt.show()
In [7]:
def arima prediction(series, params, start point):
   model = sm.tsa.arima.ARIMA(series, order=params).fit()
   pred = model.get prediction(start=start point, dynamic=False)
   pred ci = pred.conf int()
    ax = series.plot(label='observed')
   pred.predicted mean.plot(ax=ax, label='One-step ahead Forecast', alpha=.7, figsize=(
14, 4))
    ax.fill between (pred ci.index, pred ci.iloc[:, 0], pred ci.iloc[:, 1], color='k', al
pha=.2)
    ax.set xlabel('Date')
    ax.set ylabel('Quantity')
```

plt.legend()

```
In [8]:
def arima walk forward validation(series, params, test size):
    n train = int(len(series) * (1-test size))
    train, test = series.values[0:n train], series.values[n train:len(series)]
    history = [x for x in train]
    predictions = list()
    # walk-forward validation
    for t in range(len(test)):
        model = sm.tsa.arima.ARIMA(history, order=params)
       model fit = model.fit()
        output = model fit.forecast()
       yhat = output[0]
       predictions.append(yhat)
       obs = test[t]
       history.append(obs)
    # evaluate forecasts
    rmse = np.sqrt(mean squared error(test, predictions))
    print('Test RMSE: %.3f' % rmse)
    # plot forecasts against actual outcomes
    plt.plot(test)
    plt.plot(predictions, color='red')
    plt.show()
In [9]:
def arima walk forward forecast(series, params, steps=5):
   history = series.copy()
   predictions = [history.iloc[-1]]
   predictions ci min = [history.iloc[-1]]
   predictions_ci_max = [history.iloc[-1]]
    predictions ci index = [history.index[-1]]
    for t in range(steps):
        model = sm.tsa.arima.ARIMA(history, order=params)
        model fit = model.fit()
        predictions.append(model fit.get forecast().predicted mean[0])
        predictions_ci_min.append(model_fit.get_forecast().conf_int().values[0,0])
        predictions ci max.append(model fit.get forecast().conf int().values[0,1])
        predictions ci index.append(model fit.get forecast().conf int().index.tolist()[0
1)
        history = history.append(model fit.get forecast().predicted mean)
   plt.figure(figsize=(14, 4))
   plt.plot(predictions ci index, predictions, label='Walk-Forward ahead Forecast', alp
ha=.7, color='red')
   plt.plot(series, label='observed', color='blue')
   plt.fill between (predictions ci index, predictions ci min, predictions ci max, color=
'k', alpha=.2)
   plt.xlabel('Date')
   plt.ylabel('Quantity')
    plt.legend()
   plt.show()
In [10]:
def sarimax modeling(series, params, s params):
   model = sm.tsa.statespace.SARIMAX(series, order=params,
                                      seasonal order=s params).fit(max iter=50, method='
powell')
   print('SARIMAX{}x{} - AIC:{}'.format(params, s_params, model.aic))
   print (model.summary())
   model.plot diagnostics(figsize=(18, 8))
    plt.show()
```

def sarimax_prediction(series, params, s_params, start_point):
 model = sm.tsa.statespace.SARIMAX(series, order=params,

seasonal order=s params).fit(max iter=50, method='

plt.show()

In [11]:

powell', disp=False)

```
pred = model.get_prediction(start=start_point, dynamic=False)
pred_ci = pred.conf_int()
ax = series.plot(label='observed')
pred.predicted_mean.plot(ax=ax, label='One-step ahead Forecast', alpha=.7, figsize=(
14, 4))
ax.fill_between(pred_ci.index, pred_ci.iloc[:, 0], pred_ci.iloc[:, 1], color='k', al
pha=.2)
ax.set_xlabel('Date')
ax.set_ylabel('Quantity')
plt.legend()
plt.show()
```

In [12]:

```
def sarimax walk forward validation (series, params, s params, test size):
   n train = int(len(series) * (1-test size))
   train, test = series.values[0:n train], series.values[n train:len(series)]
   history = [x for x in train]
   predictions = list()
    # walk-forward validation
    for t in range(len(test)):
        model = sm.tsa.statespace.SARIMAX(history, order=params, seasonal_order=s_params
        model fit = model.fit(max iter=50, method='powell', disp=False)
        output = model fit.forecast()
        yhat = output[0]
        predictions.append(yhat)
        obs = test[t]
       history.append(obs)
    # evaluate forecasts
    rmse = np.sqrt(mean_squared_error(test, predictions))
   print('Test RMSE: %.3f' % rmse)
    # plot forecasts against actual outcomes
   plt.plot(test)
   plt.plot(predictions, color='red')
   plt.show()
```

In [13]:

```
def sarimax walk forward forecast(series, params, s params, steps=5):
   history = series.copy()
   predictions = [history.iloc[-1]]
   predictions ci min = [history.iloc[-1]]
   predictions ci max = [history.iloc[-1]]
   predictions ci index = [history.index[-1]]
    for t in range(steps):
       model = sm.tsa.statespace.SARIMAX(history, order=params, seasonal order=s params
       model fit = model.fit(max iter=50, method='powell', disp=False)
       predictions.append(model fit.get forecast().predicted mean[0])
       predictions_ci_min.append(model_fit.get_forecast().conf_int().values[0,0])
       predictions ci max.append(model fit.get forecast().conf int().values[0,1])
       predictions ci index.append(model fit.get forecast().conf int().index.tolist()[0
])
       history = history.append(model fit.get forecast().predicted mean)
   plt.figure(figsize=(14, 4))
   plt.plot(predictions ci index, predictions, label='Walk-Forward ahead Forecast', alp
ha=.7, color='red')
   plt.plot(series, label='observed', color='blue')
   plt.fill between (predictions ci index, predictions ci min, predictions ci max, color=
'k', alpha=.2)
   plt.xlabel('Date')
   plt.ylabel('Quantity')
    plt.legend()
    plt.show()
```

(ARIMA) when dealing with non-seasonal time series data without a repeating pattern at fixed intervals.

```
In [14]:
```

```
df = pd.read csv('Annual changes in the earths rotation day length sec105 18211970.csv')
```

df.head()

Out[14]:

	Unnamed: 0	X
0	1	-217
1	2	-177
2	3	-166
3	4	-136
4	5	-110

In [15]:

```
df.drop(columns=['Unnamed: 0'], inplace=True)
```

In [16]:

```
len(pd.date_range('1821-01-01','1971-01-01' , freq='1Y')), len(df)
```

Out[16]:

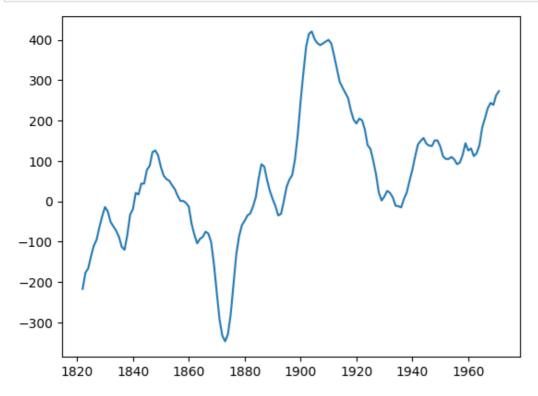
(150, 150)

In [17]:

```
df['date'] = pd.date_range('1821-01-01','1971-01-01', freq='1Y')
df = df.set_index('date')
df.index = pd.DatetimeIndex(df.index.values, freq=df.index.inferred_freq)
```

In [18]:

```
plt.plot(df['x'])
plt.show()
```



In [19]:

```
check_stationarity(df['x'])
```

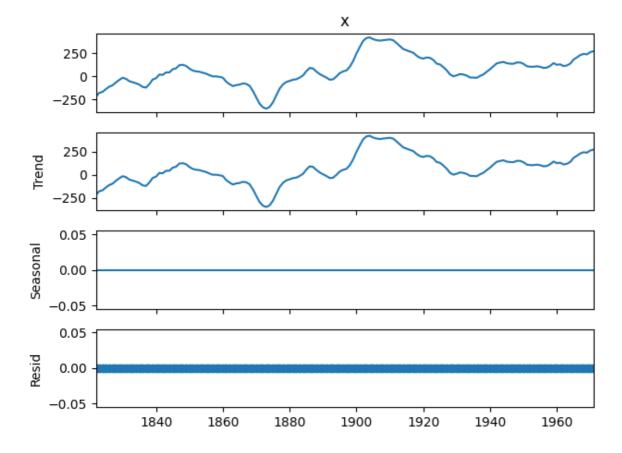
ADF Statistic: -2.033183

p-value: 0.272215

Time Series is not stationary

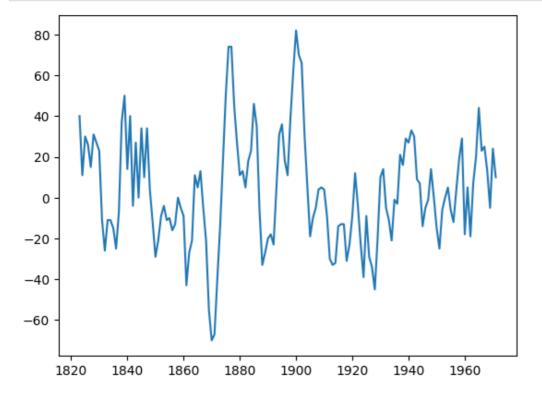
In [20]:

```
series_decomposition(df['x'])
```



In [21]:

```
plt.plot(df['x'].diff(1))
plt.show()
```



In [22]:

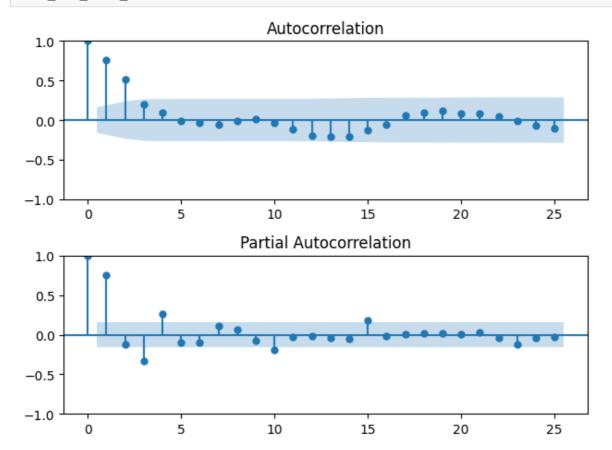
```
check_stationarity(df['x'].diff(1).dropna())
```

ADF Statistic: -3.835409

p-value: 0.002565

Time Series is stationary

plot_acf_pacf_graphs(df['x'].diff(1).dropna())



In [24]:

 $arima_modeling(df['x'], (4,1,2))$

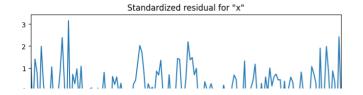
ARIMA(4, 1, 2) - AIC:1254.8485263818966

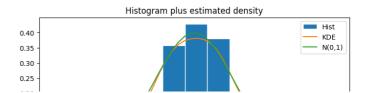
SARIMAX Results

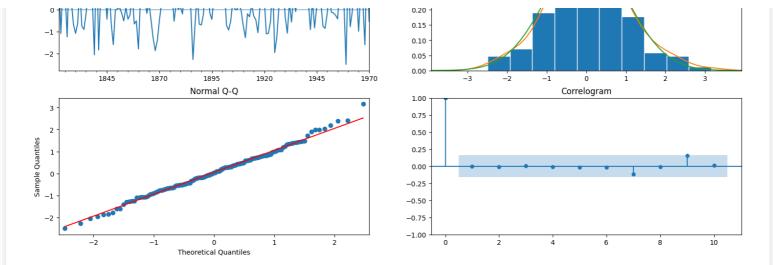
========		=======					
Dep. Varia		X		Observations:			
Model:		ARIMA(4, 1, 2)		Likelihood	-620.42		
Date:	Мс	n, 13 Nov 20			1254.84		76
Time:		15:32:15 12-31-1821 - 12-31-1970				1275.876	
Sample:					1263.392		
Covariance	e Type:		obà				
========	coef	std err	z	P> z	[0.025	0.975]	
ar.L1	0.3924	0.256	1.531	0.126	-0.110	0.895	
ar.L2	0.2000	0.166	1.208	0.227	-0.124	0.524	
ar.L3	-0.2344	0.216	-1.083	0.279	-0.659	0.190	
ar.L4	0.1313	0.153	0.860	0.390	-0.168	0.431	
ma.L1	0.5572	0.241	2.315	0.021	0.085	1.029	
ma.L2	0.4518	0.206	2.196	0.028	0.049	0.855	
sigma2	239.3068	29.110	8.221	0.000	182.252	296.362	
Ljung-Box	(L1) (Q):		0.00	Jarque-Bera	(JB):		0.94
Prob(Q):			0.97	Prob(JB):			0.63
Heteroskedasticity (H):			0.80	Skew:			0.16
Prob(H) (t	two-sided):		0.43	Kurtosis:			3.22

Warnings:

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

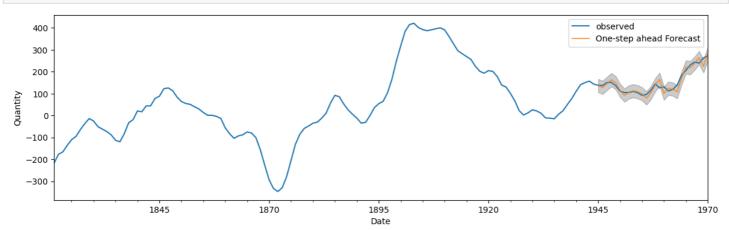






In [25]:

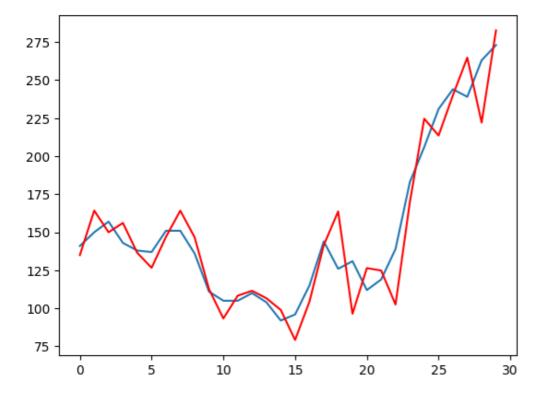
arima_prediction(df['x'], (4,1,2), start_point=pd.to_datetime('1945-12-31'))



In [26]:

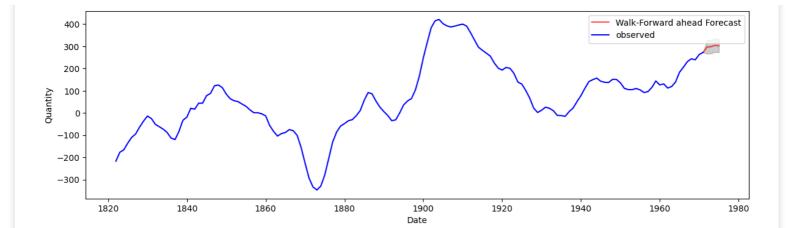
arima_walk_forward_validation(df['x'], (4,1,2), test_size=0.2)

Test RMSE: 17.260



In [27]:

arima_walk_forward_forecast(df['x'], (4,1,2), steps=4)



SARIMA(when dealing with time series data that exhibits a repeating pattern at fixed intervals, indicating a seasonal influence)

```
In [28]:
```

```
beer = pd.read_csv('BeerWineLiquor.csv')
beer.head()
```

Out[28]:

date beer

0 1/1/1992 1509

1 2/1/1992 1541

2 3/1/1992 1597

3 4/1/1992 1675

4 5/1/1992 1822

In [29]:

```
beer['date'] = pd.to_datetime(beer['date'])
beer = beer.set_index('date')
beer.index = pd.DatetimeIndex(beer.index.values, freq=beer.index.inferred_freq)
```

In [30]:

beer.head()

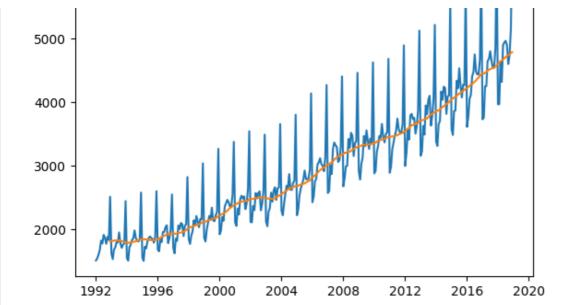
Out[30]:

1992-01-01 1509 1992-02-01 1541 1992-03-01 1597 1992-04-01 1675 1992-05-01 1822

In [31]:

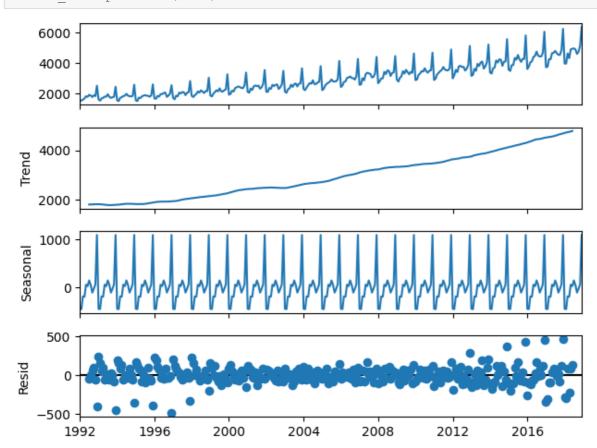
```
plt.plot(beer)
plt.plot(beer.rolling(window=12).mean())
plt.show()
```

6000 -



In [32]:

series_decomposition(beer)



In [33]:

check_stationarity(beer)

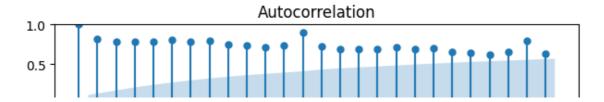
ADF Statistic: 2.864309

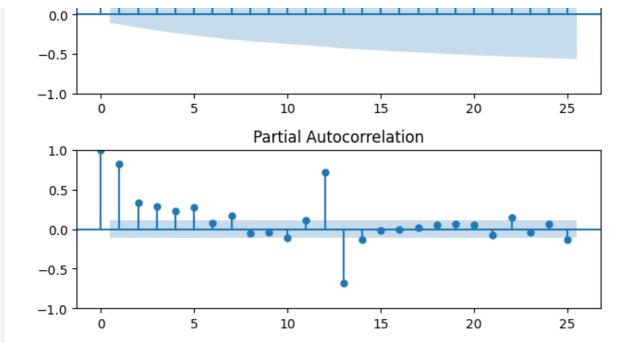
p-value: 1.000000

Time Series is not stationary

In [34]:

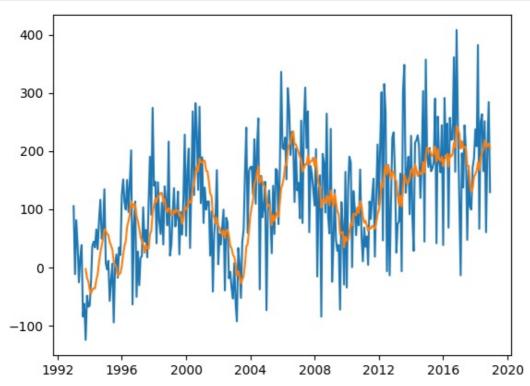
plot_acf_pacf_graphs(beer)





In [35]:

```
plt.plot(beer.diff(12))
plt.plot(beer.diff(12).rolling(window=10).mean())
plt.show()
```



In [38]:

```
check_stationarity(beer.diff(12).diff(1).dropna())
```

ADF Statistic: -8.639802

p-value: 0.000000

Time Series is stationary

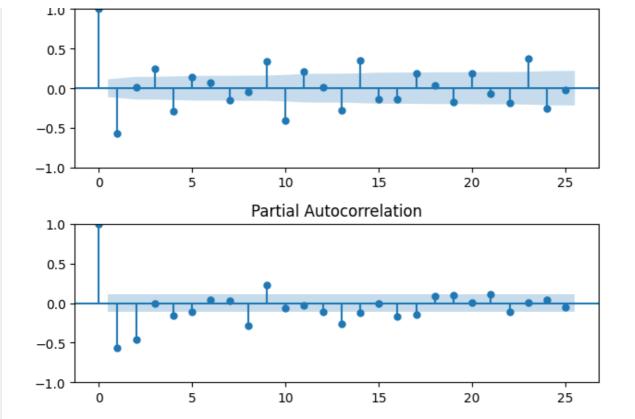
In [39]:

```
diff_beer = beer.diff(12).diff(1).dropna()
```

In [40]:

```
plot_acf_pacf_graphs(diff_beer)
```

Autocorrelation



In [41]:

sarimax_modeling(beer, params=(2,1,3), s_params=(0,1,0,12))

Optimization terminated successfully.

Current function value: 5.511796

Iterations: 11

Function evaluations: 725

SARIMAX(2, 1, 3) \times (0, 1, 0, 12) - AIC:3583.643916978222 SARIMAX Results

SARIMAX RESULT

______ No. Observations: Dep. Variable: beer 324 Model: SARIMAX(2, 1, 3) \times (0, 1, [], 12) Log Likelihood -1785. 822 Mon, 13 Nov 2023 AIC 3583. Date: 644 Time: 15:40:52 BIC 3606 .083 01-01-1992 3592. Sample: HOIC 613

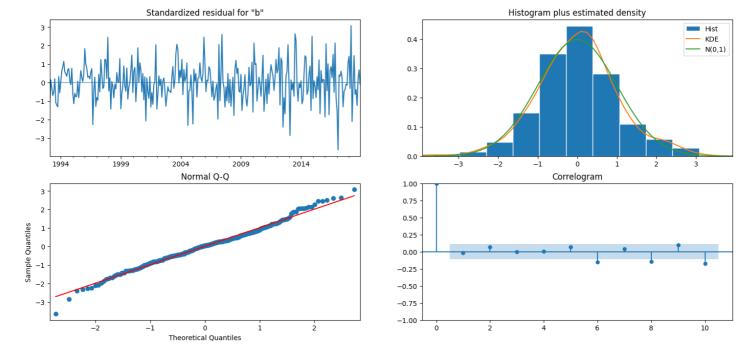
- 12-01-2018

Covariance Type: opg

=======	coef	std err	========= Z	P> z	[0.025	0.975]
ar.L1	-1.1547	0.008	-150.100	0.000	-1.170	-1.140
ar.L2	-0.9923	0.006	-153.065	0.000	-1.005	-0.980
ma.L1	0.3964	0.042	9.392	0.000	0.314	0.479
ma.L2	0.2243	0.049	4.612	0.000	0.129	0.320
ma.L3	-0.6791	0.049	-13.873	0.000	-0.775	-0.583
sigma2	5576.6337	400.281	13.932	0.000	4792.098	6361.170
Ljung-Box	======================================	:======:	 0.10	Jarque-Bera	======== (JB):	6.0
Prob(Q):			0.75	Prob(JB):		0.0
Heteroske	dasticity (H):		1.93	Skew:		0.0
Prob(H) (two-sided):		0.00	Kurtosis:		3.6

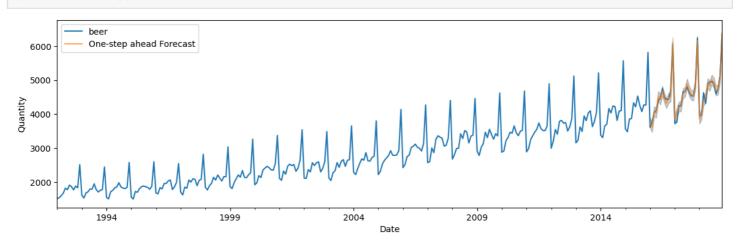
Warnings:

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



In [44]:

 $sarimax_prediction(beer, params=(2,1,3), s_params=(0,1,0,12), start_point=pd.to_datetime('2016-01-01'))$



In [45]:

sarimax_walk_forward_validation(beer,params=(2,1,3), s_params=(0,1,0,12), test_size=0.3)

Test RMSE: 91.535

