scenario4

April 22, 2019

```
In [19]: import pandas as pd
         from statsmodels.tsa.stattools import ccf
         import matplotlib.pyplot as plt
         from scipy.signal import correlate
         import numpy as np
         import statsmodels as sm
         from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
         import seaborn as sns
         from sklearn.preprocessing import MinMaxScaler
         from pandas import DataFrame
         from pandas import concat
         from keras.models import Sequential
         from keras.layers import Dense
         from keras.layers import LSTM
         from numpy import concatenate
         from math import sqrt
         from sklearn.metrics import mean_squared_error

         %matplotlib inline
```

```
In [3]: # convert series to supervised learning
        def series_to_supervised(data, n_in=1, n_out=1, dropnan=True):
            n_vars = 1 if type(data) is list else data.shape[1]
            df = DataFrame(data)
            cols, names = list(), list()
            # input sequence (t-n, ... t-1)
            for i in range(n_in, 0, -1):
                cols.append(df.shift(i))
                names += [('var%d(t-%d)' % (j+1, i)) for j in range(n_vars)]
            # forecast sequence (t, t+1, ... t+n)
            for i in range(0, n_out):
                cols.append(df.shift(-i))
                if i == 0:
                    names += [('var%d(t)' % (j+1)) for j in range(n_vars)]
                else:
                    names += [('var%d(t+%d)' % (j+1, i)) for j in range(n_vars)]
            # put it all together
            agg = concat(cols, axis=1)
```

```
        agg.columns = names
        # drop rows with NaN values
        if dropnan:
            agg.dropna(inplace=True)
        return agg
```

In [4]:
```
#define function for ADF test
from statsmodels.tsa.stattools import adfuller
def adf_test(timeseries):
    #Perform Dickey-Fuller test:
    print ('Results of Dickey-Fuller Test:')
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Used','
    for key,value in dftest[4].items():
       dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput)
```

In [36]:
```
def tsplot(y, title, lags=None, figsize=(12, 6)):
    fig = plt.figure(figsize=figsize)
    layout = (2, 2)
    ts_ax = plt.subplot2grid(layout, (0, 0))
    hist_ax = plt.subplot2grid(layout, (0, 1))
    acf_ax = plt.subplot2grid(layout, (1, 0))
    pacf_ax = plt.subplot2grid(layout, (1, 1))
    plt.text(1,-1.4, "Fig. 4.3", size=12, ha="center",weight='bold');
    y.plot(ax=ts_ax)
    ts_ax.set_title(title, fontsize=12, fontweight='bold')
    y.plot(ax=hist_ax, kind='hist', bins=25)
    hist_ax.set_title('Histogram')
    plot_acf(y, lags=lags, ax=acf_ax)
    plot_pacf(y, lags=lags, ax=pacf_ax)
    sns.despine()
    plt.tight_layout()
    plt.show()
    return ts_ax, acf_ax, pacf_ax
```

In [6]:
```
dataset = pd.read_csv('../Scenario3/data_merged_final.csv',index_col=0)
```

In [7]:
```
dataset.head()
```

Out[7]:

Date	Beer	Car	Steel	Gas	Electricity	Temp
1956-01-01	93.2	12700.116925	196.9	1709	1254	25.1
1956-02-01	96.0	12574.354195	192.1	1646	1290	25.3
1956-03-01	95.2	13050.102235	201.8	1794	1379	24.9
1956-04-01	77.1	11604.703762	186.9	1878	1346	23.9
1956-05-01	70.9	13700.668520	218.0	2173	1535	19.4

In [8]:
```
CsI=dataset['Beer']
WLS=dataset['Steel']
```

In [38]:
```
import scipy.signal as ss
import numpy as np
import matplotlib.pyplot as plt

maxlags = 10
result = result = ss.correlate(CsI - np.mean(CsI), WLS - np.mean(WLS), method='direct
lo = (len(result)-1)//2-10 #just get +/- 10 elements around lag 0
hi = (len(result)-1)//2+11

locs = np.arange(lo, hi)
# for loc in locs:
#     print(str(loc)+'\t:\t'+str(result[loc]))

#Make a plot like ccf
f, ax = plt.subplots(figsize=(12,6))
ax.stem(np.arange(-10,11), result[lo:hi], '-.')
ax.set_xticks(np.arange(-10,11))
ax.text(0.5,-0.15, "Fig. 4.1", size=12, ha="center", transform=ax.transAxes,weight='bo

plt.show()
```

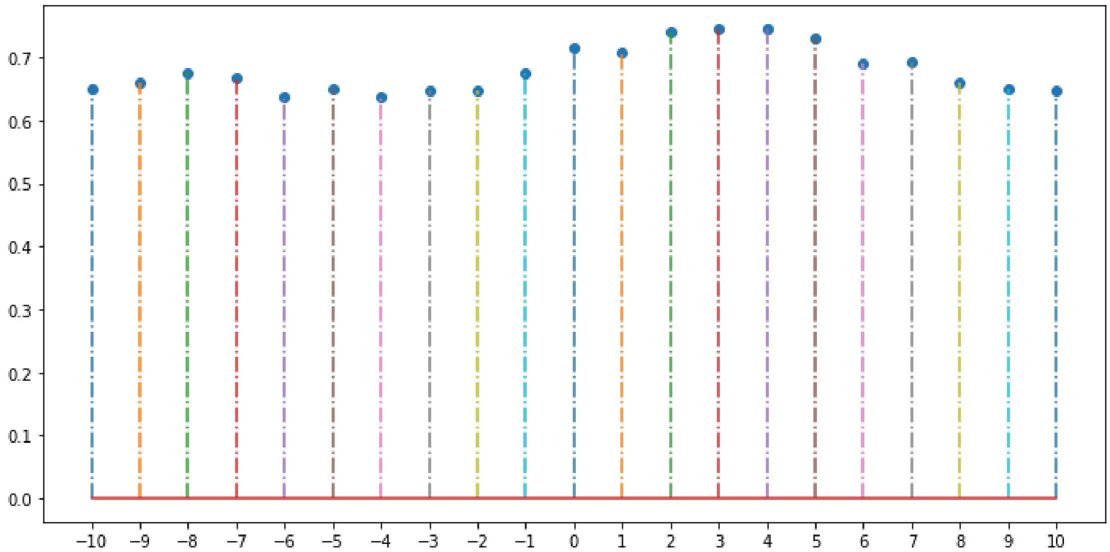


Fig. 4.1

In [29]:
```
dataset.plot(subplots=True,figsize=(12,12))
plt.text(6,-1.4, "Fig. 4.2", size=12, ha="center",weight='bold');
```

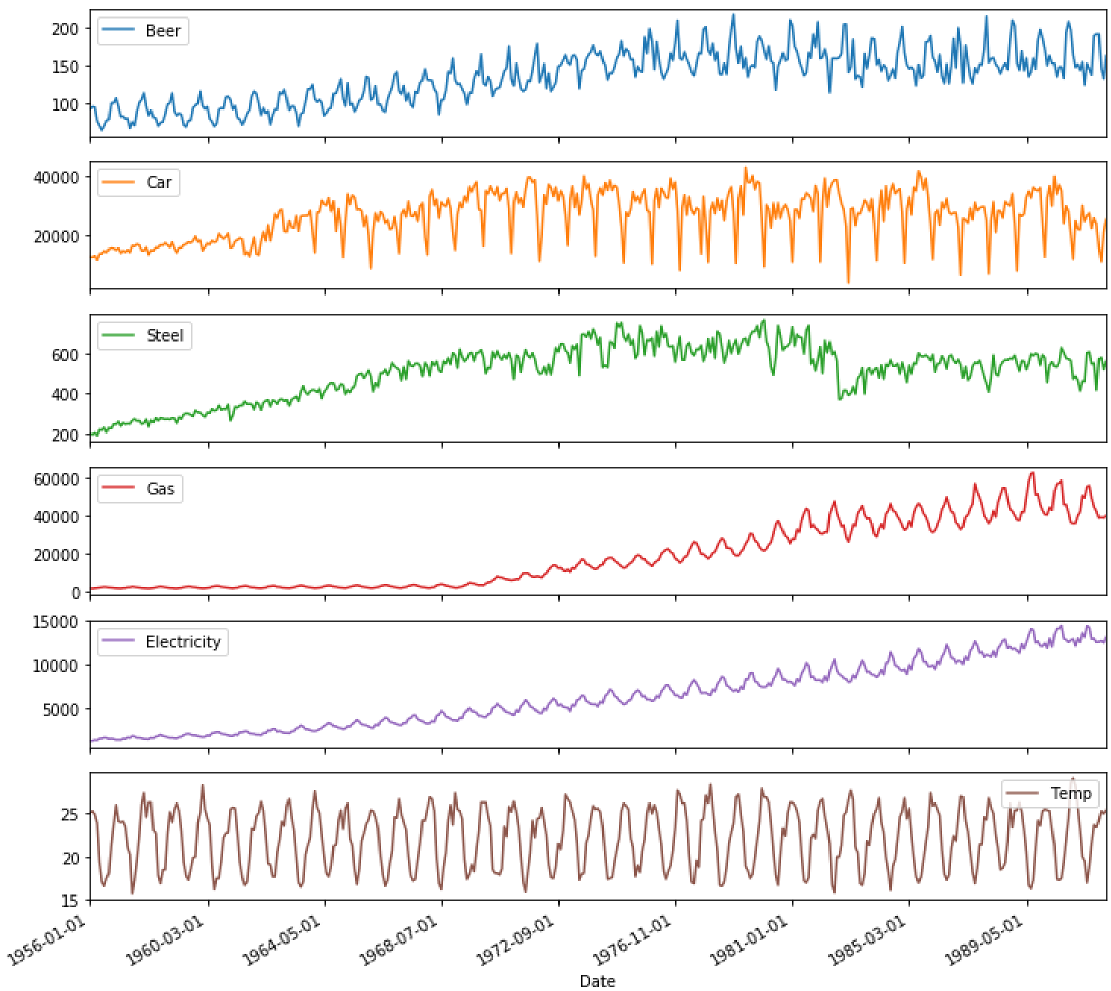


Fig. 4.2

```
In [37]: tsplot(dataset['Gas'],'Gas',lags=np.arange(0,40))
```

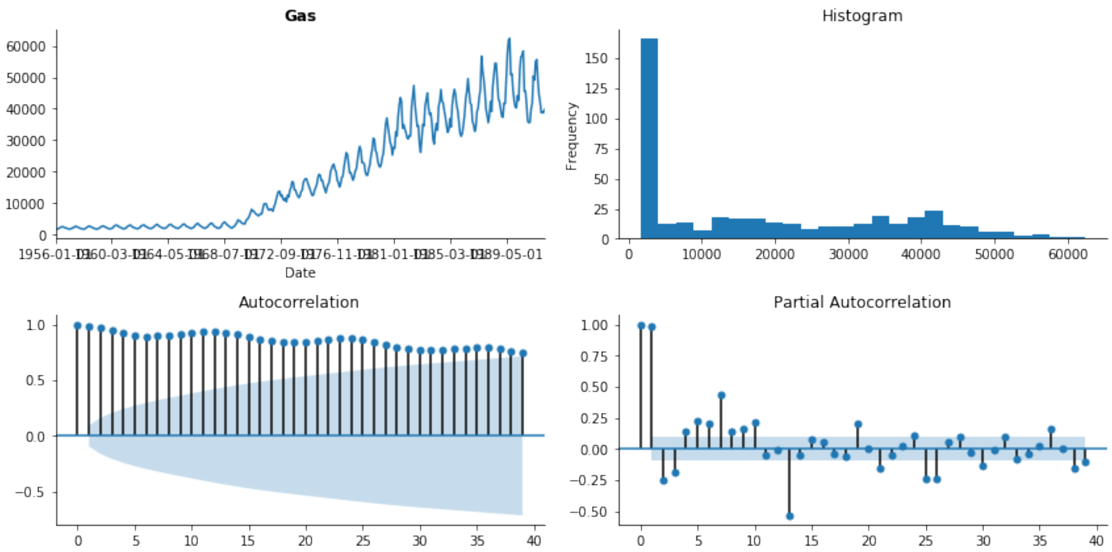


Fig. 4.3

```
Out[37]: (<matplotlib.axes._subplots.AxesSubplot at 0x1dffa719128>,
          <matplotlib.axes._subplots.AxesSubplot at 0x1dff7f155c0>,
          <matplotlib.axes._subplots.AxesSubplot at 0x1dff9e589e8>)
```

```
In [39]: adf_test(dataset['Temp'])
```

```
Results of Dickey-Fuller Test:
Test Statistic                -6.333879e+00
p-value                        2.862096e-08
#Lags Used                     1.800000e+01
Number of Observations Used    4.160000e+02
Critical Value (1%)           -3.446168e+00
Critical Value (5%)           -2.868513e+00
Critical Value (10%)          -2.570484e+00
dtype: float64
```

For temperature, the test statistic < critical value, which implies that the series is stationary.

```
In [40]: adf_test(dataset['Car'])
```

```
Results of Dickey-Fuller Test:
Test Statistic                  -2.737860
p-value                          0.067713
#Lags Used                      13.000000
Number of Observations Used    421.000000
Critical Value (1%)             -3.445979
```

```
Critical Value (5%)            -2.868430
Critical Value (10%)           -2.570440
dtype: float64
```

For car, the test statistic < critical value in 10% significance level, which implies that the series is stationary. The cas has growth in the beginning but tends to stationay later.

```
In [41]: adf_test(dataset['Steel'])
```

```
Results of Dickey-Fuller Test:
Test Statistic                 -2.252618
p-value                         0.187705
#Lags Used                     12.000000
Number of Observations Used   422.000000
Critical Value (1%)            -3.445941
Critical Value (5%)            -2.868413
Critical Value (10%)           -2.570431
dtype: float64
```

```
In [42]: adf_test(dataset['Gas'])
```

```
Results of Dickey-Fuller Test:
Test Statistic                  0.205778
p-value                         0.972584
#Lags Used                     17.000000
Number of Observations Used   417.000000
Critical Value (1%)            -3.446129
Critical Value (5%)            -2.868496
Critical Value (10%)           -2.570475
dtype: float64
```

```
In [43]: adf_test(dataset['Electricity'])
```

```
Results of Dickey-Fuller Test:
Test Statistic                  1.563761
p-value                         0.997745
#Lags Used                     17.000000
Number of Observations Used   417.000000
Critical Value (1%)            -3.446129
Critical Value (5%)            -2.868496
Critical Value (10%)           -2.570475
dtype: float64
```

For the above three, transformation to stationary is needed.

```
In [44]: dataset['Steel_log'] = np.log(dataset['Steel'])
         dataset['Steel_log_diff'] = dataset['Steel_log'] - dataset['Steel_log'].shift(1)
         adfuller(dataset['Steel_log_diff'].dropna())
```

```
Out[44]: (-6.287739626234377,
          3.662730800933948e-08,
          13,
          420,
          {'1%': -3.4460159927788574,
           '10%': -2.570448781179138,
           '5%': -2.868446209372638},
          -897.0581197796027)
```

Use log transform for steel.

```
In [45]: dataset['Gas_diff_seas'] = dataset['Gas'] - dataset['Gas'].shift(12)
         dataset['Gas_diff'] = dataset['Gas_diff_seas'] - dataset['Gas_diff_seas'].shift(1)
```

```
In [46]: adfuller(dataset['Gas_diff'].dropna())
```

```
Out[46]: (-7.423805825441933,
          6.629388763872179e-11,
          18,
          403,
          {'1%': -3.4466811208382437,
           '10%': -2.5706046655665635,
           '5%': -2.8687386420385494},
          6970.282319837302)
```

For gas, first seasonal difference. then difference by 1.

```
In [47]: dataset['Electricity_diff_seas'] = dataset['Electricity'] - dataset['Electricity'].sh
         dataset['Electricity_diff'] = dataset['Electricity_diff_seas'] - dataset['Electricity_
```

```
In [48]: adfuller(dataset['Electricity_diff'].dropna())
```

```
Out[48]: (-6.32664313158624,
          2.9751670322101644e-08,
          17,
          404,
          {'1%': -3.44664043608676,
           '10%': -2.5705951311145965,
           '5%': -2.868720756230461},
          5275.094116151984)
```

```
In [49]: dataset_stationary=dataset.drop(['Steel','Gas','Electricity',\
                                          'Steel_log','Gas_diff_seas','Electricity_diff_seas']
```

```
In [50]: dataset_stationary.head()
```

Out[50]:
```
             Beer          Car  Temp  Steel_log_diff  Gas_diff  \
Date
1957-02-01  82.8  13985.911224  24.0       -0.092787       0.0
1957-03-01  83.3  14767.651312  24.1        0.069590      84.0
1957-04-01  80.0  14270.452770  23.5       -0.030697     -63.0
1957-05-01  80.4  15046.366905  21.1        0.014658      75.0
1957-06-01  67.5  14187.495032  20.3       -0.008525    -180.0

            Electricity_diff
Date
1957-02-01             -58.0
1957-03-01              67.0
1957-04-01              -8.0
1957-05-01               2.0
1957-06-01             -97.0
```

In [51]:
```
values = dataset_stationary.values
# normalize features
scaler = MinMaxScaler(feature_range=(0, 1))
scaled = scaler.fit_transform(values)
```

In [451]:
```
# specify the number of lag hours
n_days = 24
n_features = 6

# frame as supervised learning
reframed = series_to_supervised(scaled, n_days, n_days)

reframed.to_csv('input_LSTM.csv')
```

In [428]:
```
# split into train and test sets
values = reframed.values
n_train_days = 330
train = values[:n_train_days, :]
test = values[n_train_days:, :]
```

In [429]:
```
# split into input and outputs
n_obs = n_days * n_features
train_X, train_y = train[:, :n_obs], train[:,n_obs::n_features]
test_X, test_y = test[:, :n_obs], test[:,n_obs::n_features]
print(train_X.shape, len(train_X), train_y.shape)
```

```
(330, 144) 330 (330, 24)
```

In [430]:
```
# reshape input to be 3D [samples, timesteps, features]
train_X = train_X.reshape((train_X.shape[0], n_days, n_features))
test_X = test_X.reshape((test_X.shape[0], n_days, n_features))
print(train_X.shape, train_y.shape, test_X.shape, test_y.shape)
```

```
(330, 24, 6) (330, 24) (45, 24, 6) (45, 24)
```

In [473]:
```
train_X_all, train_y_all = values[:, :n_obs], values[:,n_obs::n_features]
train_X_all = train_X_all.reshape((train_X_all.shape[0], n_days, n_features))
```

In [476]:
```
train_X_all.shape,train_y_all.shape
```

Out[476]:
```
((375, 24, 6), (375, 24))
```

In [477]:
```
# design network
model = Sequential()
model.add(LSTM(50, input_shape=(train_X.shape[1], train_X.shape[2])))
model.add(Dense(n_days))
model.compile(loss='mae', optimizer='adam')
# fit network
history = model.fit(train_X_all, train_y_all, epochs=200, batch_size=10, validation_d
```

```
Train on 375 samples, validate on 45 samples
Epoch 1/200
 - 1s - loss: 0.2063 - val_loss: 0.1217
Epoch 2/200
 - 0s - loss: 0.1881 - val_loss: 0.1194
Epoch 3/200
 - 0s - loss: 0.1904 - val_loss: 0.1199
Epoch 4/200
 - 0s - loss: 0.1815 - val_loss: 0.1178
Epoch 5/200
 - 0s - loss: 0.1710 - val_loss: 0.1160
Epoch 6/200
 - 0s - loss: 0.1624 - val_loss: 0.1159
Epoch 7/200
 - 0s - loss: 0.1547 - val_loss: 0.1150
Epoch 8/200
 - 0s - loss: 0.1457 - val_loss: 0.1145
Epoch 9/200
 - 0s - loss: 0.1368 - val_loss: 0.1129
Epoch 10/200
 - 0s - loss: 0.1256 - val_loss: 0.1078
Epoch 11/200
 - 0s - loss: 0.1072 - val_loss: 0.0992
Epoch 12/200
 - 0s - loss: 0.0930 - val_loss: 0.0921
Epoch 13/200
 - 0s - loss: 0.1019 - val_loss: 0.0898
Epoch 14/200
 - 0s - loss: 0.0808 - val_loss: 0.0882
Epoch 15/200
 - 0s - loss: 0.0887 - val_loss: 0.0859
```

```
Epoch 16/200
 - 0s - loss: 0.0778 - val_loss: 0.0869
Epoch 17/200
 - 0s - loss: 0.0768 - val_loss: 0.0864
Epoch 18/200
 - 0s - loss: 0.0747 - val_loss: 0.0869
Epoch 19/200
 - 0s - loss: 0.0738 - val_loss: 0.0871
Epoch 20/200
 - 0s - loss: 0.0729 - val_loss: 0.0875
Epoch 21/200
 - 0s - loss: 0.0726 - val_loss: 0.0870
Epoch 22/200
 - 0s - loss: 0.0720 - val_loss: 0.0862
Epoch 23/200
 - 0s - loss: 0.0714 - val_loss: 0.0860
Epoch 24/200
 - 0s - loss: 0.0708 - val_loss: 0.0852
Epoch 25/200
 - 0s - loss: 0.0704 - val_loss: 0.0850
Epoch 26/200
 - 1s - loss: 0.0705 - val_loss: 0.0846
Epoch 27/200
 - 1s - loss: 0.0703 - val_loss: 0.0841
Epoch 28/200
 - 1s - loss: 0.0701 - val_loss: 0.0842
Epoch 29/200
 - 0s - loss: 0.0698 - val_loss: 0.0841
Epoch 30/200
 - 0s - loss: 0.0699 - val_loss: 0.0838
Epoch 31/200
 - 0s - loss: 0.0699 - val_loss: 0.0836
Epoch 32/200
 - 0s - loss: 0.0693 - val_loss: 0.0834
Epoch 33/200
 - 1s - loss: 0.0693 - val_loss: 0.0835
Epoch 34/200
 - 1s - loss: 0.0694 - val_loss: 0.0832
Epoch 35/200
 - 1s - loss: 0.0693 - val_loss: 0.0829
Epoch 36/200
 - 1s - loss: 0.0688 - val_loss: 0.0829
Epoch 37/200
 - 1s - loss: 0.0688 - val_loss: 0.0824
Epoch 38/200
 - 1s - loss: 0.0685 - val_loss: 0.0830
Epoch 39/200
 - 1s - loss: 0.0682 - val_loss: 0.0828
```

```
Epoch 40/200
 - 1s - loss: 0.0684 - val_loss: 0.0826
Epoch 41/200
 - 0s - loss: 0.0679 - val_loss: 0.0825
Epoch 42/200
 - 0s - loss: 0.0679 - val_loss: 0.0824
Epoch 43/200
 - 0s - loss: 0.0674 - val_loss: 0.0821
Epoch 44/200
 - 0s - loss: 0.0671 - val_loss: 0.0817
Epoch 45/200
 - 0s - loss: 0.0671 - val_loss: 0.0816
Epoch 46/200
 - 0s - loss: 0.0672 - val_loss: 0.0816
Epoch 47/200
 - 0s - loss: 0.0672 - val_loss: 0.0812
Epoch 48/200
 - 0s - loss: 0.0669 - val_loss: 0.0806
Epoch 49/200
 - 1s - loss: 0.0667 - val_loss: 0.0803
Epoch 50/200
 - 1s - loss: 0.0662 - val_loss: 0.0802
Epoch 51/200
 - 1s - loss: 0.0659 - val_loss: 0.0796
Epoch 52/200
 - 1s - loss: 0.0664 - val_loss: 0.0799
Epoch 53/200
 - 1s - loss: 0.0658 - val_loss: 0.0796
Epoch 54/200
 - 1s - loss: 0.0659 - val_loss: 0.0795
Epoch 55/200
 - 1s - loss: 0.0662 - val_loss: 0.0789
Epoch 56/200
 - 1s - loss: 0.0663 - val_loss: 0.0786
Epoch 57/200
 - 1s - loss: 0.0655 - val_loss: 0.0783
Epoch 58/200
 - 1s - loss: 0.0654 - val_loss: 0.0778
Epoch 59/200
 - 0s - loss: 0.0650 - val_loss: 0.0779
Epoch 60/200
 - 1s - loss: 0.0649 - val_loss: 0.0782
Epoch 61/200
 - 1s - loss: 0.0649 - val_loss: 0.0778
Epoch 62/200
 - 1s - loss: 0.0646 - val_loss: 0.0775
Epoch 63/200
 - 1s - loss: 0.0645 - val_loss: 0.0776
```

```
Epoch 64/200
 - 1s - loss: 0.0645 - val_loss: 0.0777
Epoch 65/200
 - 0s - loss: 0.0651 - val_loss: 0.0764
Epoch 66/200
 - 0s - loss: 0.0644 - val_loss: 0.0759
Epoch 67/200
 - 0s - loss: 0.0644 - val_loss: 0.0760
Epoch 68/200
 - 0s - loss: 0.0641 - val_loss: 0.0762
Epoch 69/200
 - 0s - loss: 0.0656 - val_loss: 0.0763
Epoch 70/200
 - 0s - loss: 0.0651 - val_loss: 0.0752
Epoch 71/200
 - 0s - loss: 0.0659 - val_loss: 0.0757
Epoch 72/200
 - 0s - loss: 0.0648 - val_loss: 0.0755
Epoch 73/200
 - 0s - loss: 0.0636 - val_loss: 0.0756
Epoch 74/200
 - 0s - loss: 0.0658 - val_loss: 0.0737
Epoch 75/200
 - 0s - loss: 0.0637 - val_loss: 0.0739
Epoch 76/200
 - 0s - loss: 0.0639 - val_loss: 0.0738
Epoch 77/200
 - 0s - loss: 0.0629 - val_loss: 0.0751
Epoch 78/200
 - 0s - loss: 0.0644 - val_loss: 0.0751
Epoch 79/200
 - 0s - loss: 0.0634 - val_loss: 0.0747
Epoch 80/200
 - 0s - loss: 0.0637 - val_loss: 0.0760
Epoch 81/200
 - 0s - loss: 0.0638 - val_loss: 0.0730
Epoch 82/200
 - 1s - loss: 0.0622 - val_loss: 0.0737
Epoch 83/200
 - 1s - loss: 0.0637 - val_loss: 0.0728
Epoch 84/200
 - 0s - loss: 0.0628 - val_loss: 0.0726
Epoch 85/200
 - 0s - loss: 0.0623 - val_loss: 0.0735
Epoch 86/200
 - 1s - loss: 0.0629 - val_loss: 0.0734
Epoch 87/200
 - 0s - loss: 0.0625 - val_loss: 0.0721
```

```
Epoch 88/200
 - 0s - loss: 0.0619 - val_loss: 0.0715
Epoch 89/200
 - 0s - loss: 0.0617 - val_loss: 0.0705
Epoch 90/200
 - 0s - loss: 0.0616 - val_loss: 0.0702
Epoch 91/200
 - 0s - loss: 0.0618 - val_loss: 0.0699
Epoch 92/200
 - 0s - loss: 0.0611 - val_loss: 0.0697
Epoch 93/200
 - 0s - loss: 0.0608 - val_loss: 0.0692
Epoch 94/200
 - 0s - loss: 0.0614 - val_loss: 0.0690
Epoch 95/200
 - 0s - loss: 0.0608 - val_loss: 0.0681
Epoch 96/200
 - 0s - loss: 0.0602 - val_loss: 0.0677
Epoch 97/200
 - 0s - loss: 0.0611 - val_loss: 0.0676
Epoch 98/200
 - 1s - loss: 0.0599 - val_loss: 0.0668
Epoch 99/200
 - 1s - loss: 0.0614 - val_loss: 0.0664
Epoch 100/200
 - 1s - loss: 0.0600 - val_loss: 0.0661
Epoch 101/200
 - 1s - loss: 0.0615 - val_loss: 0.0660
Epoch 102/200
 - 1s - loss: 0.0601 - val_loss: 0.0658
Epoch 103/200
 - 1s - loss: 0.0614 - val_loss: 0.0654
Epoch 104/200
 - 1s - loss: 0.0616 - val_loss: 0.0644
Epoch 105/200
 - 1s - loss: 0.0588 - val_loss: 0.0645
Epoch 106/200
 - 1s - loss: 0.0617 - val_loss: 0.0637
Epoch 107/200
 - 1s - loss: 0.0609 - val_loss: 0.0632
Epoch 108/200
 - 0s - loss: 0.0634 - val_loss: 0.0630
Epoch 109/200
 - 0s - loss: 0.0615 - val_loss: 0.0627
Epoch 110/200
 - 0s - loss: 0.0598 - val_loss: 0.0624
Epoch 111/200
 - 0s - loss: 0.0586 - val_loss: 0.0626
```

```
Epoch 112/200
 - 0s - loss: 0.0599 - val_loss: 0.0620
Epoch 113/200
 - 0s - loss: 0.0583 - val_loss: 0.0620
Epoch 114/200
 - 0s - loss: 0.0593 - val_loss: 0.0614
Epoch 115/200
 - 1s - loss: 0.0581 - val_loss: 0.0622
Epoch 116/200
 - 0s - loss: 0.0569 - val_loss: 0.0624
Epoch 117/200
 - 0s - loss: 0.0579 - val_loss: 0.0618
Epoch 118/200
 - 0s - loss: 0.0572 - val_loss: 0.0615
Epoch 119/200
 - 0s - loss: 0.0575 - val_loss: 0.0613
Epoch 120/200
 - 0s - loss: 0.0572 - val_loss: 0.0614
Epoch 121/200
 - 0s - loss: 0.0563 - val_loss: 0.0612
Epoch 122/200
 - 0s - loss: 0.0568 - val_loss: 0.0613
Epoch 123/200
 - 0s - loss: 0.0577 - val_loss: 0.0611
Epoch 124/200
 - 0s - loss: 0.0564 - val_loss: 0.0609
Epoch 125/200
 - 0s - loss: 0.0576 - val_loss: 0.0608
Epoch 126/200
 - 0s - loss: 0.0569 - val_loss: 0.0610
Epoch 127/200
 - 0s - loss: 0.0565 - val_loss: 0.0606
Epoch 128/200
 - 0s - loss: 0.0574 - val_loss: 0.0613
Epoch 129/200
 - 0s - loss: 0.0595 - val_loss: 0.0615
Epoch 130/200
 - 0s - loss: 0.0581 - val_loss: 0.0613
Epoch 131/200
 - 1s - loss: 0.0588 - val_loss: 0.0616
Epoch 132/200
 - 1s - loss: 0.0577 - val_loss: 0.0609
Epoch 133/200
 - 0s - loss: 0.0577 - val_loss: 0.0603
Epoch 134/200
 - 0s - loss: 0.0596 - val_loss: 0.0618
Epoch 135/200
 - 0s - loss: 0.0615 - val_loss: 0.0619
```

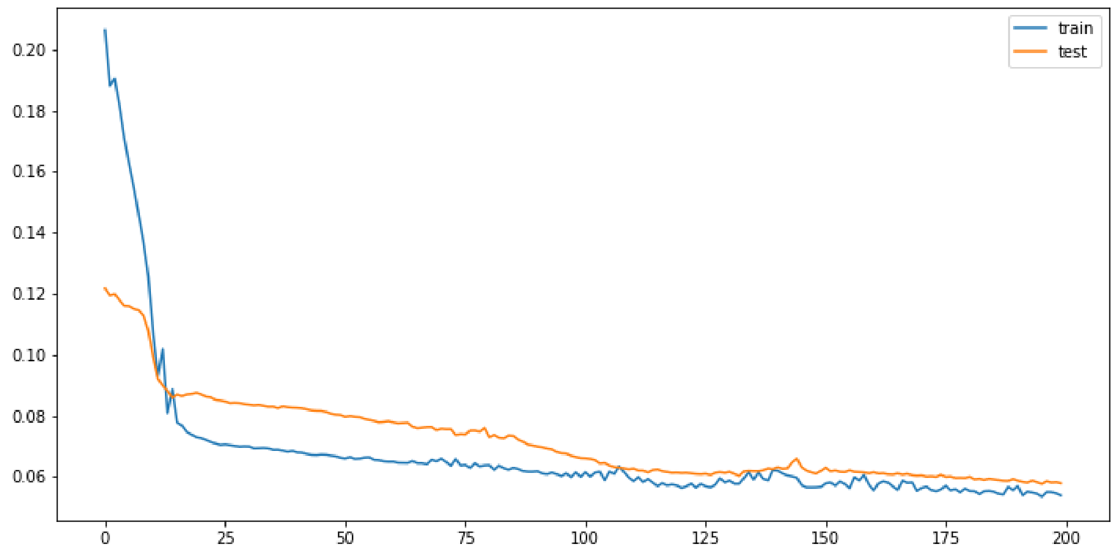
```
Epoch 136/200
 - 0s - loss: 0.0591 - val_loss: 0.0618
Epoch 137/200
 - 1s - loss: 0.0614 - val_loss: 0.0618
Epoch 138/200
 - 0s - loss: 0.0593 - val_loss: 0.0621
Epoch 139/200
 - 0s - loss: 0.0588 - val_loss: 0.0627
Epoch 140/200
 - 1s - loss: 0.0621 - val_loss: 0.0625
Epoch 141/200
 - 1s - loss: 0.0620 - val_loss: 0.0631
Epoch 142/200
 - 1s - loss: 0.0611 - val_loss: 0.0626
Epoch 143/200
 - 1s - loss: 0.0604 - val_loss: 0.0627
Epoch 144/200
 - 1s - loss: 0.0601 - val_loss: 0.0647
Epoch 145/200
 - 0s - loss: 0.0597 - val_loss: 0.0659
Epoch 146/200
 - 0s - loss: 0.0572 - val_loss: 0.0631
Epoch 147/200
 - 1s - loss: 0.0565 - val_loss: 0.0620
Epoch 148/200
 - 1s - loss: 0.0565 - val_loss: 0.0614
Epoch 149/200
 - 1s - loss: 0.0565 - val_loss: 0.0610
Epoch 150/200
 - 1s - loss: 0.0567 - val_loss: 0.0619
Epoch 151/200
 - 0s - loss: 0.0578 - val_loss: 0.0630
Epoch 152/200
 - 0s - loss: 0.0581 - val_loss: 0.0618
Epoch 153/200
 - 1s - loss: 0.0571 - val_loss: 0.0621
Epoch 154/200
 - 0s - loss: 0.0585 - val_loss: 0.0616
Epoch 155/200
 - 1s - loss: 0.0576 - val_loss: 0.0616
Epoch 156/200
 - 0s - loss: 0.0562 - val_loss: 0.0621
Epoch 157/200
 - 0s - loss: 0.0598 - val_loss: 0.0616
Epoch 158/200
 - 0s - loss: 0.0587 - val_loss: 0.0615
Epoch 159/200
 - 1s - loss: 0.0606 - val_loss: 0.0614
```

```
Epoch 160/200
 - 1s - loss: 0.0574 - val_loss: 0.0611
Epoch 161/200
 - 1s - loss: 0.0555 - val_loss: 0.0615
Epoch 162/200
 - 1s - loss: 0.0578 - val_loss: 0.0610
Epoch 163/200
 - 0s - loss: 0.0585 - val_loss: 0.0611
Epoch 164/200
 - 0s - loss: 0.0581 - val_loss: 0.0608
Epoch 165/200
 - 0s - loss: 0.0568 - val_loss: 0.0607
Epoch 166/200
 - 0s - loss: 0.0557 - val_loss: 0.0611
Epoch 167/200
 - 0s - loss: 0.0587 - val_loss: 0.0607
Epoch 168/200
 - 0s - loss: 0.0580 - val_loss: 0.0610
Epoch 169/200
 - 0s - loss: 0.0581 - val_loss: 0.0605
Epoch 170/200
 - 0s - loss: 0.0554 - val_loss: 0.0603
Epoch 171/200
 - 0s - loss: 0.0563 - val_loss: 0.0604
Epoch 172/200
 - 0s - loss: 0.0568 - val_loss: 0.0600
Epoch 173/200
 - 0s - loss: 0.0556 - val_loss: 0.0601
Epoch 174/200
 - 0s - loss: 0.0552 - val_loss: 0.0599
Epoch 175/200
 - 0s - loss: 0.0558 - val_loss: 0.0606
Epoch 176/200
 - 0s - loss: 0.0571 - val_loss: 0.0599
Epoch 177/200
 - 0s - loss: 0.0555 - val_loss: 0.0601
Epoch 178/200
 - 0s - loss: 0.0559 - val_loss: 0.0596
Epoch 179/200
 - 1s - loss: 0.0549 - val_loss: 0.0596
Epoch 180/200
 - 0s - loss: 0.0561 - val_loss: 0.0596
Epoch 181/200
 - 1s - loss: 0.0553 - val_loss: 0.0600
Epoch 182/200
 - 1s - loss: 0.0553 - val_loss: 0.0591
Epoch 183/200
 - 1s - loss: 0.0543 - val_loss: 0.0593
```

```
Epoch 184/200
 - 1s - loss: 0.0552 - val_loss: 0.0589
Epoch 185/200
 - 1s - loss: 0.0554 - val_loss: 0.0593
Epoch 186/200
 - 1s - loss: 0.0551 - val_loss: 0.0591
Epoch 187/200
 - 1s - loss: 0.0544 - val_loss: 0.0589
Epoch 188/200
 - 1s - loss: 0.0541 - val_loss: 0.0587
Epoch 189/200
 - 1s - loss: 0.0567 - val_loss: 0.0586
Epoch 190/200
 - 1s - loss: 0.0556 - val_loss: 0.0592
Epoch 191/200
 - 1s - loss: 0.0570 - val_loss: 0.0587
Epoch 192/200
 - 1s - loss: 0.0539 - val_loss: 0.0583
Epoch 193/200
 - 1s - loss: 0.0551 - val_loss: 0.0581
Epoch 194/200
 - 0s - loss: 0.0548 - val_loss: 0.0587
Epoch 195/200
 - 0s - loss: 0.0544 - val_loss: 0.0582
Epoch 196/200
 - 0s - loss: 0.0535 - val_loss: 0.0577
Epoch 197/200
 - 0s - loss: 0.0550 - val_loss: 0.0585
Epoch 198/200
 - 0s - loss: 0.0550 - val_loss: 0.0581
Epoch 199/200
 - 0s - loss: 0.0545 - val_loss: 0.0582
Epoch 200/200
 - 0s - loss: 0.0539 - val_loss: 0.0579
```

```
In [478]: # plot history
          fig=plt.figure(figsize=(12,6))
          plt.plot(history.history['loss'], label='train')
          plt.plot(history.history['val_loss'], label='test')
          plt.text(6,-1.4, "Fig. 4.3", size=12, ha="center",weight='bold');
          plt.legend()
```

```
Out[478]: <matplotlib.legend.Legend at 0x1cb69ba8438>
```



In [479]:
```
test_y[-1:]
```

Out[479]:
```
array([[0.57351963, 0.56819694, 0.45242848, 0.53892216, 0.53825682,
        0.43978709, 0.84231537, 0.93878909, 0.86360612, 0.64471058,
        0.53626081, 0.56220892, 0.50964737, 0.582169  , 0.37924152,
        0.56886228, 0.52228876, 0.46906188, 0.81503659, 0.82834331,
        0.82834331, 0.52894212, 0.43579508, 0.63539587]])
```

In [480]:
```
test_X.shape,yhat.shape,test_X_res.shape,test_y.shape
```

Out[480]:
```
((45, 24, 6), (1, 24), (45, 144), (45, 24))
```

In [481]:
```
yhat=model.predict(test_X[-1:])
test_X_res = test_X.reshape((test_X.shape[0], n_days*n_features))

# invert scaling for forecast

yhat_last24=[]
ytrue_last24=[]

for i in np.arange(n_days):
    inv_yhat = concatenate((yhat[-1:,[i]], test_X_res[-1:, -5:]), axis=1)
    inv_yhat = scaler.inverse_transform(inv_yhat)
    inv_yhat = inv_yhat[:,0]
    yhat_last24.append(inv_yhat)

for i in np.arange(n_days):
    inv_y = concatenate((test_y[-1:,[i]], test_X_res[-1:, -5:]), axis=1)
    inv_y = scaler.inverse_transform(inv_y)
```

```
    inv_y = inv_y[:,0]
    ytrue_last24.append(inv_y)
```

In [482]:
```
yhat=model.predict(np.reshape(test[-1,n_obs:],newshape=(1,n_days,n_features)))
test_X_res = test_X.reshape((test_X.shape[0], n_days*n_features))

# invert scaling for forecast

yhat_future=[]

for i in np.arange(n_days):
    inv_yhat = concatenate((yhat[-1:,[i]], test_X_res[-1:, -5:]), axis=1)
    inv_yhat = scaler.inverse_transform(inv_yhat)
    inv_yhat = inv_yhat[:,0]
    yhat_future.append(inv_yhat)
```

In [483]:
```
yhat_future
```

Out[483]:
```
[array([152.51552664]),
 array([138.85869391]),
 array([134.16951433]),
 array([144.89787746]),
 array([148.69925299]),
 array([151.05538591]),
 array([163.66366187]),
 array([196.96757017]),
 array([185.83429722]),
 array([156.73270562]),
 array([149.34777342]),
 array([161.02483206]),
 array([146.99964051]),
 array([142.90194209]),
 array([133.63986527]),
 array([148.69771212]),
 array([151.19717333]),
 array([146.61835447]),
 array([175.58979585]),
 array([198.8434158]),
 array([192.79560513]),
 array([155.76620046]),
 array([150.37765156]),
 array([162.13171813])]
```

In [485]:
```
np.savetxt('../Result in CSV/Li_Scenario4.csv', yhat_future, delimiter=',')
```

0.0.1 Prediction Interval

In [52]:
```
import csv
import itertools
```

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
import statsmodels.api as sm
```

```
In [53]: Beer=pd.read_csv('../Scenario3/data_merged_final.csv',sep=',',index_col=0,usecols=[0,
```

```
In [55]: mod = sm.tsa.statespace.SARIMAX(Beer,
                                         order=(1, 0, 1),
                                         enforce_stationarity=False,
                                         enforce_invertibility=False,)


         results = mod.fit()
         print(results.summary())
```

```
                           Statespace Model Results
==============================================================================
Dep. Variable:                   Beer   No. Observations:                  435
Model:               SARIMAX(1, 0, 1)   Log Likelihood               -1872.418
Date:                Mon, 22 Apr 2019   AIC                           3750.837
Time:                        22:36:31   BIC                           3763.049
Sample:                    01-01-1956   HQIC                          3755.658
                         - 03-01-1992
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9968      0.004    237.065      0.000       0.989       1.005
ma.L1         -0.3107      0.044     -7.066      0.000      -0.397      -0.225
sigma2       335.4263     21.510     15.594      0.000     293.267     377.585
===================================================================================
Ljung-Box (Q):                      824.88   Jarque-Bera (JB):                 3.08
Prob(Q):                              0.00   Prob(JB):                         0.21
Heteroskedasticity (H):               3.70   Skew:                             0.04
Prob(H) (two-sided):                  0.00   Kurtosis:                         3.41
===================================================================================

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


C:\Users\Jackie Li\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:171: ValueWarn
  % freq, ValueWarning)
C:\Users\Jackie Li\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:191: FutureWa
  start=index[0], end=index[-1], freq=freq)
```

```
In [57]: # Get forecast 24 steps ahead in future
         pred_uc = results.get_forecast(steps=24)

         # Get 95% confidence intervals of forecasts
         pred_ci = pred_uc.conf_int(alpha=0.05)
```

```
C:\Users\Jackie Li\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:320: FutureWa
  freq=base_index.freq)
```

```
In [58]: s=pd.DataFrame(pred_uc.predicted_mean)
         s.columns=['Beer']
         s.set_index(s.columns[0])
         s.index.name='Date'
         s.index=s.index.to_period('D')

In [59]: Beer.index = pd.to_datetime(Beer.index)
         Beer.index=Beer.index.to_period('D')

In [64]: fig, ax = plt.subplots(figsize=(10,6))
         Beer.append(s)[300:].plot(ax=ax)
         ax.fill_between(pred_ci.index,
                         pred_ci.iloc[:, 0],
                         pred_ci.iloc[:, 1], color='k', alpha=.25)
         ax.text(0.5,-0.15, "Fig. 4.5", size=12, ha="center", transform=ax.transAxes,weight='bo
         plt.legend(['Forcast','Prediction Interval'],loc=2)
         plt.show()
```

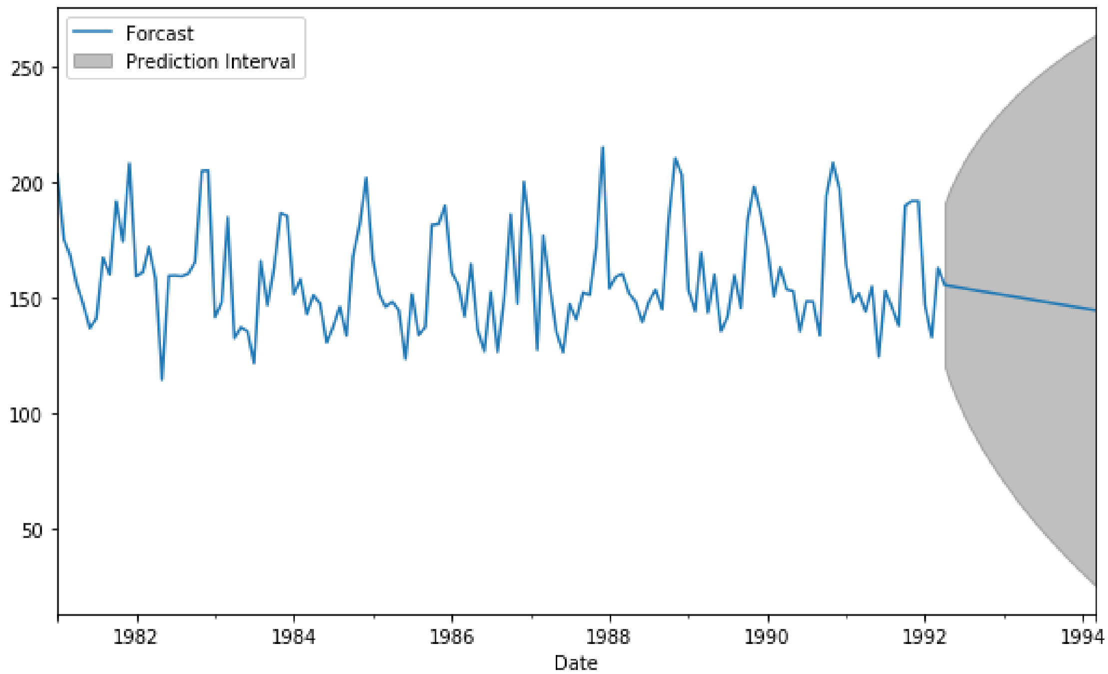


Fig. 4.5