In [1]:
```
#季节性ARIMA展示文件，使用cpc的数据进行实例
#转换为其他数据则修改i值、根据aic修改模型参数、输出文件名称即可


import pandas as pd
import matplotlib.pyplot as plt
import csv
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from datetime import datetime
import scipy as stats
import statsmodels.api as sm
from scipy import stats
from statsmodels.tsa.arima_model import ARIMA
```

In [2]:
```
dataFilePaths = ['../input/timeseries/ec2_cpu_utilization_24ae8d.csv','../input/timeseries/exchange-4_cpc_res
ults.csv',
                 '../input/timeseries/occupancy_t4013.csv','../input/timeseries/TravelTime_387.csv','../inpu
t/timeseries/Twitter_volume_AMZN.csv']
```

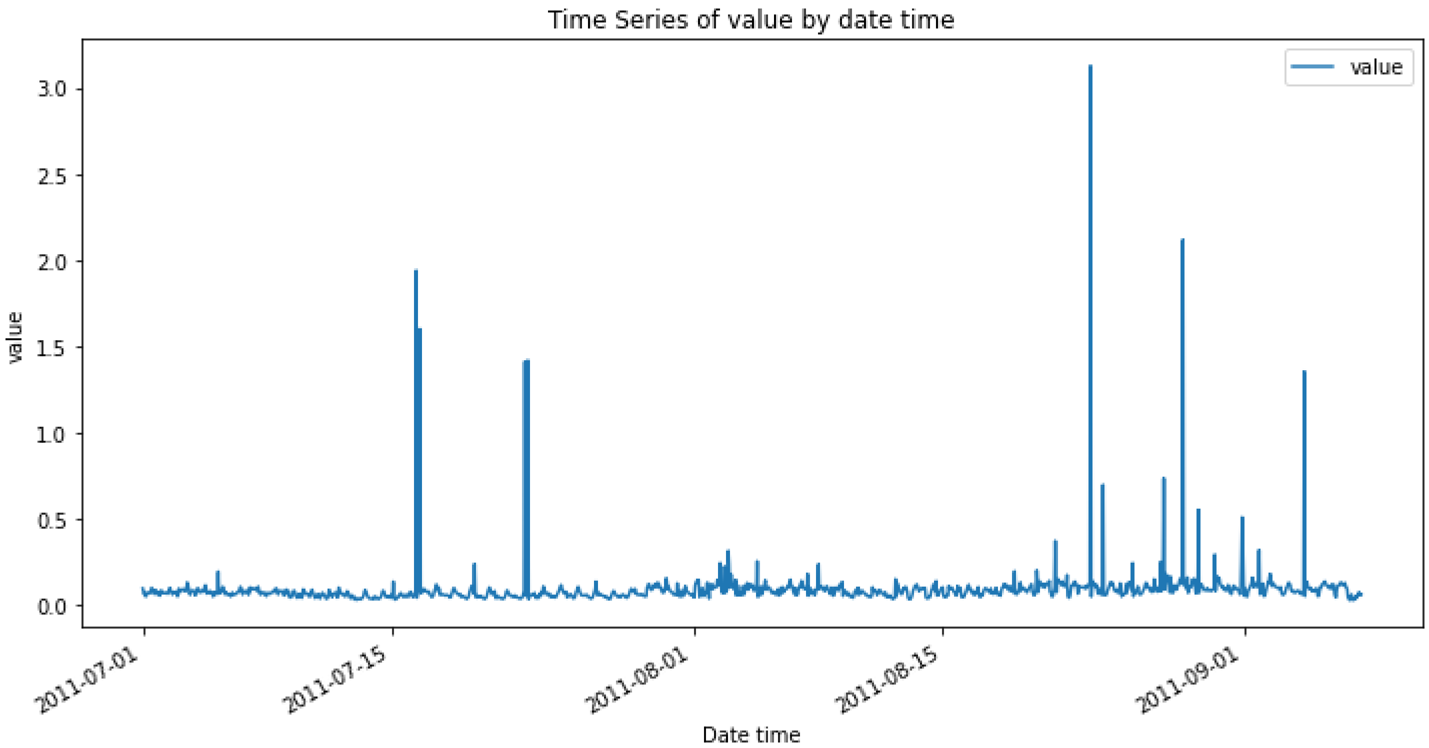
In [3]:
```
i = 1
dataFilePath = dataFilePaths[i]
```

In [4]:
```
data = pd.read_csv(dataFilePath, parse_dates=['timestamp'], index_col='timestamp')


# df = pd.read_csv(filepath_or_buffer = dataFilePath, header = 0)
print('shape:', data.shape[0])
print('head:')
print(data.head(5))
```

```
shape: 1643
head:
                        value
timestamp
2011-07-01 00:15:01  0.091795
2011-07-01 01:15:01  0.074414
2011-07-01 02:15:01  0.056984
2011-07-01 03:15:01  0.071225
2011-07-01 04:15:01  0.045466
```

In [5]:
```
# data['Datetime'] = pd.to_datetime(data['timestamp'])#利用时间戳生成df列

data.plot(figsize=(12,6))
plt.xlabel('Date time')
plt.ylabel('value')
plt.title('Time Series of value by date time')
```

Out[5]:
```
Text(0.5, 1.0, 'Time Series of value by date time')
```



In [6]:
```
import itertools

# Define the p, d and q parameters to take any value between 0 and 2
p = d = q = range(0, 2)
# Generate all different combinations of p, q and q triplets
pdq = list(itertools.product(p, d, q))
print(pdq)
# Generate all different combinations of seasonal p, q and q triplets
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]
print(seasonal_pdq)
```

```
[(0, 0, 0), (0, 0, 1), (0, 1, 0), (0, 1, 1), (1, 0, 0), (1, 0, 1), (1, 1, 0), (1, 1, 1)]
[(0, 0, 0, 12), (0, 0, 1, 12), (0, 1, 0, 12), (0, 1, 1, 12), (1, 0, 0, 12), (1, 0, 1, 12), (1, 1, 0, 12),
(1, 1, 1, 12)]
```

In [7]:
```
import warnings
warnings.filterwarnings('ignore')
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            model = sm.tsa.statespace.SARIMAX(data, order=param, seasonal_order=param_seasonal, enforce_stati
onarity=False, enforce_invertibility=False)
            results = model.fit()
            print('ARIMA{}x{} - AIC:{}'.format(param, param_seasonal, results.aic))
        except:
            continue
```

```
ARIMA(0, 0, 0)x(0, 0, 0, 12) - AIC:-1455.118002123923
ARIMA(0, 0, 0)x(0, 0, 1, 12) - AIC:-1547.2690531281069
ARIMA(0, 0, 0)x(0, 1, 0, 12) - AIC:-934.1686717280904
ARIMA(0, 0, 0)x(0, 1, 1, 12) - AIC:-1984.1298495748515
ARIMA(0, 0, 0)x(1, 0, 0, 12) - AIC:-1611.2259247236302
ARIMA(0, 0, 0)x(1, 0, 1, 12) - AIC:-2004.9802995862983
ARIMA(0, 0, 0)x(1, 1, 0, 12) - AIC:-1411.5978702820237
ARIMA(0, 0, 0)x(1, 1, 1, 12) - AIC:-1975.4305384780505
ARIMA(0, 0, 1)x(0, 0, 0, 12) - AIC:-1582.3241797438707
ARIMA(0, 0, 1)x(0, 0, 1, 12) - AIC:-1623.6456913295463
ARIMA(0, 0, 1)x(0, 1, 0, 12) - AIC:-931.7415904604477
ARIMA(0, 0, 1)x(0, 1, 1, 12) - AIC:-1981.1368808638372
ARIMA(0, 0, 1)x(1, 0, 0, 12) - AIC:-1659.3191298816655
ARIMA(0, 0, 1)x(1, 0, 1, 12) - AIC:-2001.755287171092
ARIMA(0, 0, 1)x(1, 1, 0, 12) - AIC:-1409.791322349534
ARIMA(0, 0, 1)x(1, 1, 1, 12) - AIC:-1973.0701548250709
ARIMA(0, 1, 0)x(0, 0, 0, 12) - AIC:-992.3105708621838
ARIMA(0, 1, 0)x(0, 0, 1, 12) - AIC:-971.1591986335164
ARIMA(0, 1, 0)x(0, 1, 0, 12) - AIC:150.9768219539865
ARIMA(0, 1, 0)x(0, 1, 1, 12) - AIC:-913.7535708892465
ARIMA(0, 1, 0)x(1, 0, 0, 12) - AIC:-972.7544929431032
ARIMA(0, 1, 0)x(1, 0, 1, 12) - AIC:-969.1593830933978
ARIMA(0, 1, 0)x(1, 1, 0, 12) - AIC:-306.51575413744064
ARIMA(0, 1, 0)x(1, 1, 1, 12) - AIC:-911.7429412792922
ARIMA(0, 1, 1)x(0, 0, 0, 12) - AIC:-2075.249063625263
ARIMA(0, 1, 1)x(0, 0, 1, 12) - AIC:-2046.3227990477699
ARIMA(0, 1, 1)x(0, 1, 0, 12) - AIC:-922.725715614447
ARIMA(0, 1, 1)x(0, 1, 1, 12) - AIC:-1980.4294545552798
ARIMA(0, 1, 1)x(1, 0, 0, 12) - AIC:-2050.154768269864
ARIMA(0, 1, 1)x(1, 0, 1, 12) - AIC:-2044.4694679296244
ARIMA(0, 1, 1)x(1, 1, 0, 12) - AIC:-1400.3362902687913
ARIMA(0, 1, 1)x(1, 1, 1, 12) - AIC:-1971.332122384299
ARIMA(1, 0, 0)x(0, 0, 0, 12) - AIC:-1652.1828745556259
ARIMA(1, 0, 0)x(0, 0, 1, 12) - AIC:-1664.7894343592116
ARIMA(1, 0, 0)x(0, 1, 0, 12) - AIC:-933.408536880095
ARIMA(1, 0, 0)x(0, 1, 1, 12) - AIC:-1983.4806374150098
ARIMA(1, 0, 0)x(1, 0, 0, 12) - AIC:-1681.9796363490136
ARIMA(1, 0, 0)x(1, 0, 1, 12) - AIC:-2004.0763826875113
ARIMA(1, 0, 0)x(1, 1, 0, 12) - AIC:-1407.940988515801
ARIMA(1, 0, 0)x(1, 1, 1, 12) - AIC:-1974.74725234681
ARIMA(1, 0, 1)x(0, 0, 0, 12) - AIC:-2074.866124293798
```

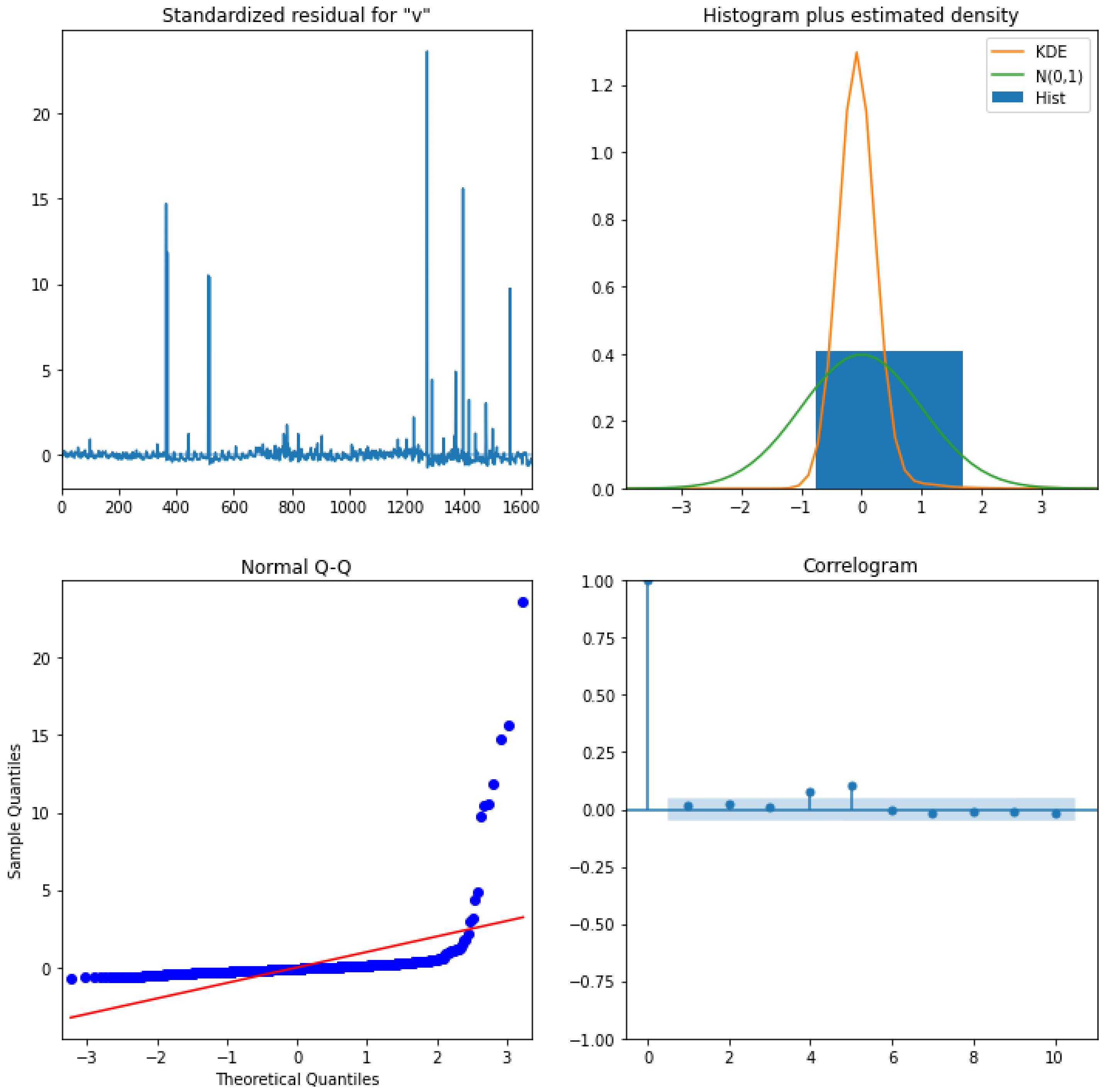
```
ARIMA(1, 0, 1)x(0, 0, 1, 12) - AIC:-2045.9544091465236
ARIMA(1, 0, 1)x(0, 1, 0, 12) - AIC:-966.8548064519013
ARIMA(1, 0, 1)x(0, 1, 1, 12) - AIC:-1995.1533476501672
ARIMA(1, 0, 1)x(1, 0, 0, 12) - AIC:-2048.2086211977785
ARIMA(1, 0, 1)x(1, 0, 1, 12) - AIC:-2044.0894747489306
ARIMA(1, 0, 1)x(1, 1, 0, 12) - AIC:-1420.935602284691
ARIMA(1, 0, 1)x(1, 1, 1, 12) - AIC:-1986.790183418564
ARIMA(1, 1, 0)x(0, 0, 0, 12) - AIC:-1472.6710531561662
ARIMA(1, 1, 0)x(0, 0, 1, 12) - AIC:-1448.0934036236472
ARIMA(1, 1, 0)x(0, 1, 0, 12) - AIC:-332.71884135348836
ARIMA(1, 1, 0)x(0, 1, 1, 12) - AIC:-1386.2154212425824
ARIMA(1, 1, 0)x(1, 0, 0, 12) - AIC:-1448.0931295296828
ARIMA(1, 1, 0)x(1, 0, 1, 12) - AIC:-1446.0920842864462
ARIMA(1, 1, 0)x(1, 1, 0, 12) - AIC:-768.2902214425849
ARIMA(1, 1, 0)x(1, 1, 1, 12) - AIC:-1384.2136464291916
ARIMA(1, 1, 1)x(0, 0, 0, 12) - AIC:-2073.6092880395313
ARIMA(1, 1, 1)x(0, 0, 1, 12) - AIC:-2044.647644568609
ARIMA(1, 1, 1)x(0, 1, 0, 12) - AIC:-921.9827558485025
ARIMA(1, 1, 1)x(0, 1, 1, 12) - AIC:-1978.6443693251329
ARIMA(1, 1, 1)x(1, 0, 0, 12) - AIC:-2046.819234220844
ARIMA(1, 1, 1)x(1, 0, 1, 12) - AIC:-2042.7860570709445
ARIMA(1, 1, 1)x(1, 1, 0, 12) - AIC:-1397.376484088382
ARIMA(1, 1, 1)x(1, 1, 1, 12) - AIC:-1969.4538580785347
```

找值最小的AIC ARIMA(0, 1, 1)x(0, 0, 0, 12) =-2075.249063625087 通过“网格搜索”我们找到了最佳拟合模型的参数，接下里我们将最佳参数值输入到一个新的SARIMAX 模型：

In [8]:
```
model = sm.tsa.statespace.SARIMAX(data, order=(0, 1, 1), seasonal_order=(0, 0, 0, 12), enforce_stationarity=False, enforce_invertibility=False)
results = model.fit()
print(results.summary().tables[1])
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -1.0146      0.005   -214.976      0.000      -1.024      -1.005
sigma2         0.0160      0.000     88.064      0.000       0.016       0.016
==============================================================================
```

In [9]:
```
results.plot_diagnostics(figsize=(12, 12))
plt.show()
```


Standardized residual for "v"
Histogram plus estimated density
KDE
N(0,1)
Hist
Normal Q-Q
Sample Quantiles
Theoretical Quantiles
Correlogram

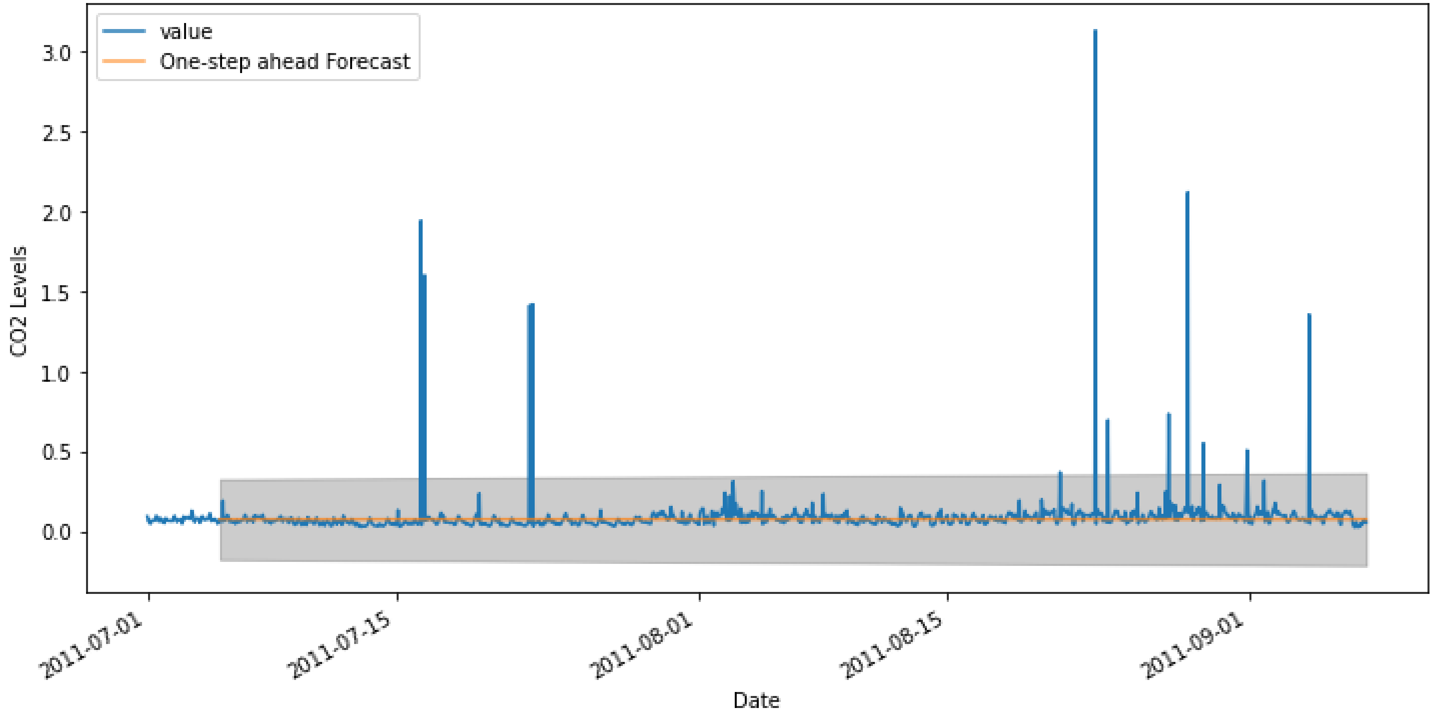
我们主要要确保残差稳定，且平均分布为0。上面的模型诊断表明：

右上角的红色KDE线和黄色N(0,1)线不接近，因此残差不是正太分布，但是其关于x=0对称，因此满足平均分布为0的特性。

随着时间的推移（左上图）残差不会显示任何明显的季节性，似乎是白噪声。这通过右下角的自相关（即相关图）证实了这一点，它表明时间序列的残差与其自身的滞后版本有很低的相关性。

In [10]:
```
pred = results.get_prediction(start=pd.to_datetime('2011-07-05 02:15:01'), dynamic=True)
pred_ci = pred.conf_int()
```

In [11]:
```
ax = data['2011':].plot(label='Observed',figsize=(12, 6))
pred.predicted_mean.plot(ax=ax, label='One-step ahead Forecast', alpha=.7)
ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k', alpha=.2)
ax.set_xlabel('Date')
ax.set_ylabel('CO2 Levels')
plt.legend()
plt.show()
```



In [12]:
```
# Extract the predicted and true values of our time series
data_forecasted = pred.predicted_mean
data_truth = data['2011-07-05 02:15:01':]
# Compute the mean square error
# mse = ((data_forecasted - data_truth) ** 2).mean()
# print('The Mean Squared Error of our forecasts is {}'.format(round(mse, 2)))

print(pred.predicted_mean)
```

```
timestamp
2011-07-05 02:15:01    0.073975
2011-07-05 03:15:01    0.073975
2011-07-05 04:15:01    0.073975
2011-07-05 05:15:01    0.073975
2011-07-05 06:15:01    0.073975
                         ...
2011-09-07 10:15:01    0.073975
2011-09-07 11:15:01    0.073975
2011-09-07 12:15:01    0.073975
2011-09-07 13:15:01    0.073975
2011-09-07 14:15:01    0.073975
Name: predicted_mean, Length: 1545, dtype: float64
```

In [13]:
```
print(data_truth)
```

```
                        value
timestamp
2011-07-05 02:15:01  0.059788
2011-07-05 03:15:01  0.061842
2011-07-05 04:15:01  0.061810
2011-07-05 05:15:01  0.059676
2011-07-05 06:15:01  0.190325
...                       ...
2011-09-07 10:15:01  0.054275
2011-09-07 11:15:01  0.070650
2011-09-07 12:15:01  0.056339
2011-09-07 13:15:01  0.050782
2011-09-07 14:15:01  0.056232

[1545 rows x 1 columns]
```

In [14]:
```
res = data_truth
res['value_predicted'] = data_forecasted
res['dist'] = abs(res['value_predicted']-res['value'])
res.to_csv('./02Arima.csv')
```