1 Non Intrusive Load Monitoring on REDD dataset

Version 0.2 Changelog

- Now uses Pandas for resampling, indexing, and most other Time Series operations.This fixes a bug earlier, where we downsampled based on the number of samples and not on the basis of time
- Added breakdown by time analsyis showing daily variation and 6 hourly variation, also weekday vs weekend
- Added pie-chart breakdown by appliance analysis
- Added dataframe capability, using Pandas whih also gives high level overview of the data

1.1 About the dataset

The datset contains high frequency, low frequency and raw data of 6 households in the USA. We choose House 2 for our analysis as it contains the least number of appliances. Further we choose to do the analysis of **low frequency** data. This house contains the following appliances/circuits:

- Kitchen
- Kitchen 2
- Stove
- Refrigerator
- Dishwasher
- Disposal
- Washer Dryer
- Microwave
- Lighting

These circuits are samppled once every 3-4 seconds. Also the house contains 2 mains which are sampled at 1 Hz.

1.2 Basic imports

In this section we setup the basic imports which shall be required for performing the analysis.

```
import numpy as np
import matplotlib.pyplot as plt
import math
from scipy.cluster.vq import kmeans,vq
import itertools
import matplotlib
```

```
#Setting size of figures as 20*10
plt.figsize(20,10)
#Setting font size to be 16
matplotlib.rcParams.update({'font.size': 16})
import pandas as pd
from pandas import Series,DataFrame
plt.figsize(20,10)
import json
s = json.load( open("/home/nipun/bmh_matplotlibrc.json") )
matplotlib.rcParams.update(s)
matplotlib.rcParams.update({'font.size': 16})
```

1.3 Loading and Plotting of Mains Data

```
mains_1_data=np.loadtxt('/home/nipun/study/datasets/MIT/low_freq/house_2/channel_1.dat')
mains_2_data=np.loadtxt('/home/nipun/study/datasets/MIT/low_freq/house_2/channel_2.dat')
```

We can observe that data is missing towards the end. As a part of the data cleansing process we should eliminate the last indices. Next we find the last valid index for which contiguos data is present.This corresponds to epoch timestamp of 1304282291.

```
upper=np.where(mains_1_data[:,0]==1304282291.0)[0]
lower=np.where(mains_1_data[:,0]>1303084800.0)[0][0]
mains_1_power=mains_1_data[:,1][lower:upper]
mains_2_power=mains_2_data[:,1][lower:upper]
timestamp=mains_1_data[:,0][lower:upper]
timestamp_mains_date=timestamp.astype('datetime64[s]')
```

Overall statistics about the dataset.

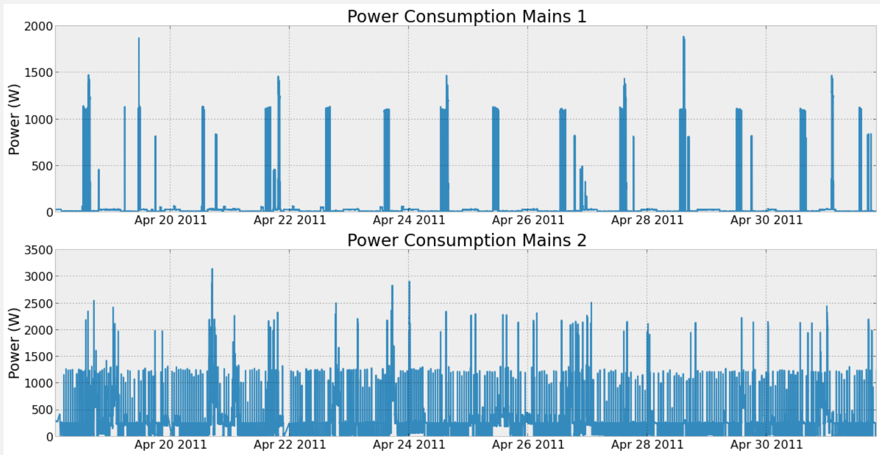
```
df_mains=DataFrame({'Mains_1_Power':mains_1_power,'Mains_2_Power':mains_2_power},index=
    timestamp_mains_date)
df_mains.describe()
```

```
        Mains_1_Power   Mains_2_Power
count  1162980.000000  1162980.000000
mean        43.401942      187.478237
std        148.175308      213.889966
min         12.270000       21.190000
25%         14.830000       22.470000
50%         15.110000      218.380000
75%         33.510000      259.160000
max       1887.420000     3149.020000
```

Plotting overall power consumption for the two main circuits.

```
plt.subplot(2,1,1)
plt.plot(df_mains.index,df_mains.Mains_1_Power);
plt.title('Power Consumption Mains 1');
plt.ylabel('Power (W)');
```

```
plt.subplot(2,1,2)
plt.plot(df_mains.index,df_mains.Mains_2_Power);
plt.ylabel('Power (W)');
plt.title('Power Consumption Mains 2');
```



1.4 Downsampling Mains Data

```
df_1_day=df_mains.resample('1d',how='sum');
df_1_day_energy=DataFrame(index=df_1_day.index);
df_1_day_energy['Mains_1_Energy']=Series(df_1_day.Mains_1_Power/(1000*3600),index=
    df_1_day.index)
df_1_day_energy['Mains_2_Energy']=Series(df_1_day.Mains_2_Power/(1000*3600),index=
    df_1_day.index)
```

Energy consumption (KWh) statistics about data.

```
df_1_day_energy.describe()
```

```
       Mains_1_Energy  Mains_2_Energy
count       14.000000       14.000000
mean         1.001500        4.326060
std          0.284175        0.739165
min          0.739473        3.243120
25%          0.766775        3.733631
50%          0.870461        4.329253
75%          1.264915        4.907687
max          1.516066        5.567054
```

Plotting daily energy consumption.

```
def correct_labels(ax):
    labels = [item.get_text() for item in ax.get_xticklabels()]
    days=[label.split(" ")[0] for label in labels]
    months=["Jan","Feb","Mar","Apr","May","Jun","Jul","Aug","Sep","Oct","Nov","Dec"]
    final_labels=[]
```

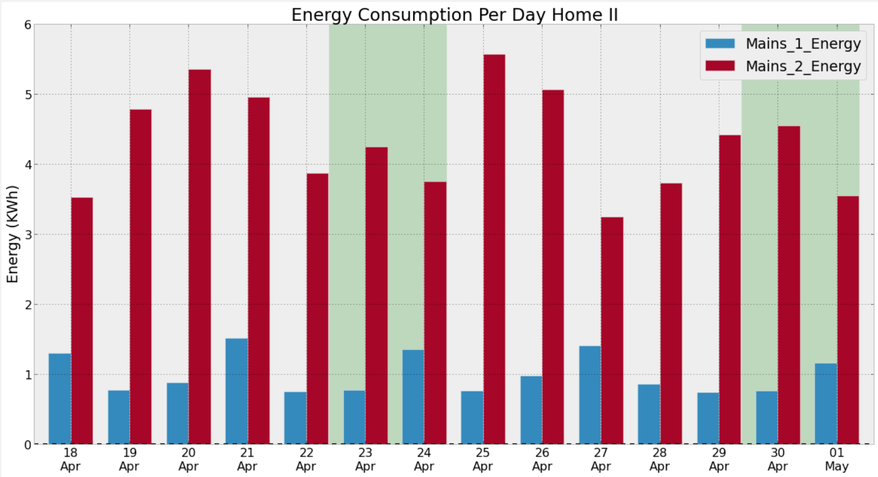
```
    for i in range(len(days)):
        a=days[i].split("-")
        final_labels.append(a[2]+"\n"+months[int(a[1])-1])
    ax.set_xticklabels(final_labels)
```

Function to find which of the days are weekdays and their indices

```
def find_weekend_indices(datetime_array):
    indices=[]
    for i in range(len(datetime_array)):
        if datetime_array[i].weekday()>=5:
            indices.append(i)
    return indices
def highlight_weekend(weekend_indices,ax,ymax):
    i=0
    while i<len(weekend_indices):
        ax.fill_between([weekend_indices[i],weekend_indices[i]+2],ymax,facecolor='green',
             alpha=.2)
        i+=2
```

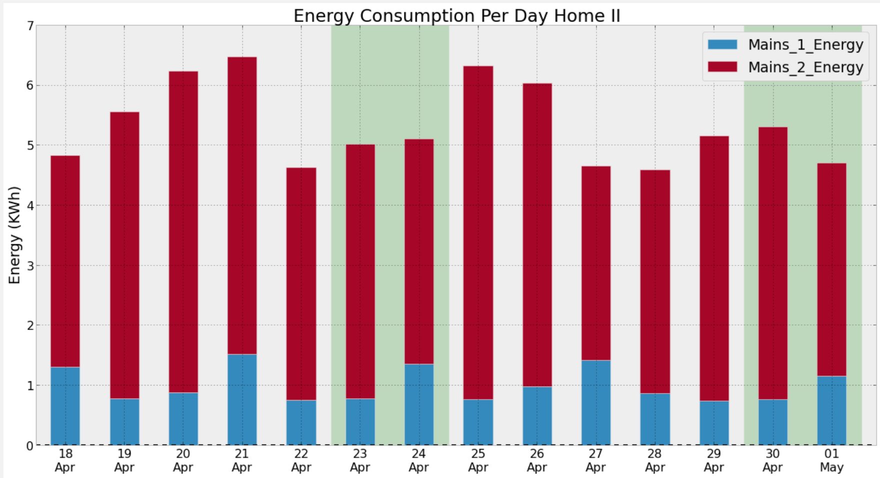
```
date_range=[datetime.datetime(2011,4,18)+datetime.timedelta(days=i) for i in range(14)]
weekend_indices=find_weekend_indices(date_range)
```

```
ax=df_1_day_energy.plot(kind='bar',rot=0);
ax.set_title('Energy Consumption Per Day Home II');
ax.set_ylabel('Energy (KWh)');
correct_labels(ax);
highlight_weekend(weekend_indices,ax,6);
```




```
ax=df_1_day_energy.plot(kind='bar',stacked=True,rot=0);
ax.set_title('Energy Consumption Per Day Home II');
ax.set_ylabel('Energy (KWh)');
correct_labels(ax);
```

```
highlight_weekend(weekend_indices,ax,7);
```



Now we try to break down the energy consumption into 6 hours slot and see if we can see some patterns amongst the same.

```
df_6_hours=df_mains.resample('6h',how='sum');
df_6_hours_energy=DataFrame(index=df_6_hours.index);
df_6_hours_energy['Mains_1_Energy']=Series(df_6_hours.Mains_1_Power/(1000*3600),index=
    df_6_hours.index)
df_6_hours_energy['Mains_2_Energy']=Series(df_6_hours.Mains_2_Power/(1000*3600),index=
    df_6_hours.index)
```

Statistics about Energy data downsampled to 6 hours.

```
df_6_hours_energy.describe()
```

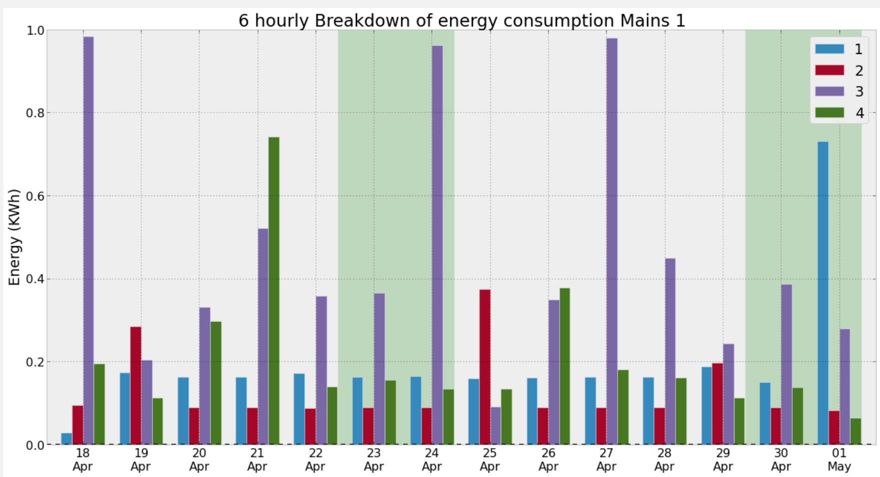
```
       Mains_1_Energy  Mains_2_Energy
count       56.000000       56.000000
mean         0.250375        1.081515
std          0.228078        0.439292
min          0.028911        0.235619
25%          0.107926        0.762373
50%          0.162402        0.964794
75%          0.305203        1.386838
max          0.983501        2.117311
```

```
days_mains_1=[]
dawn_mains_1=[]
morning_mains_1=[]
dusk_mains_1=[]
night_mains_1=[]
dawn_mains_2=[]
morning_mains_2=[]
dusk_mains_2=[]
night_mains_2=[]
```

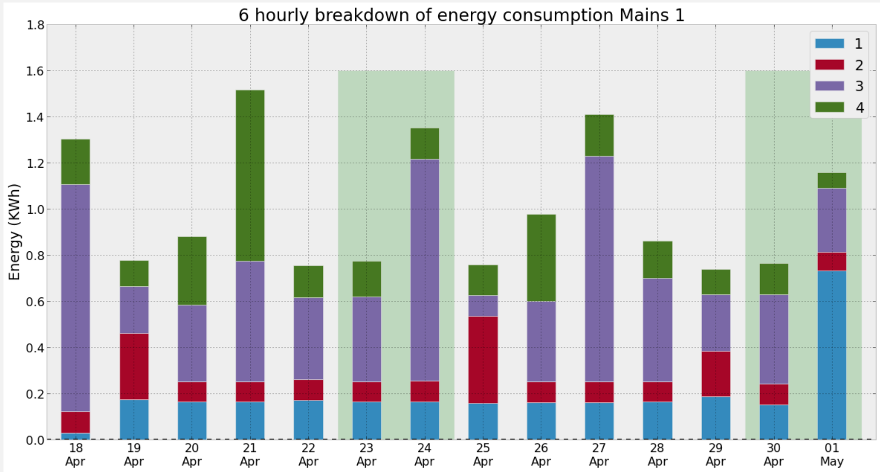
```
for i in range(len(df_6_hours_energy.Mains_1_Energy)/4):
    days_mains_1.append(df_6_hours_energy.index[4*i])
    dawn_mains_1.append(df_6_hours_energy.Mains_1_Energy[4*i])
    morning_mains_1.append(df_6_hours_energy.Mains_1_Energy[4*i+1])
    dusk_mains_1.append(df_6_hours_energy.Mains_1_Energy[4*i+2])
    night_mains_1.append(df_6_hours_energy.Mains_1_Energy[4*i+3])
    dawn_mains_2.append(df_6_hours_energy.Mains_2_Energy[4*i])
    morning_mains_2.append(df_6_hours_energy.Mains_2_Energy[4*i+1])
    dusk_mains_2.append(df_6_hours_energy.Mains_2_Energy[4*i+2])
    night_mains_2.append(df_6_hours_energy.Mains_2_Energy[4*i+3])
```

Plotting 6 hourly breakdown of energy consumption from Mains 1

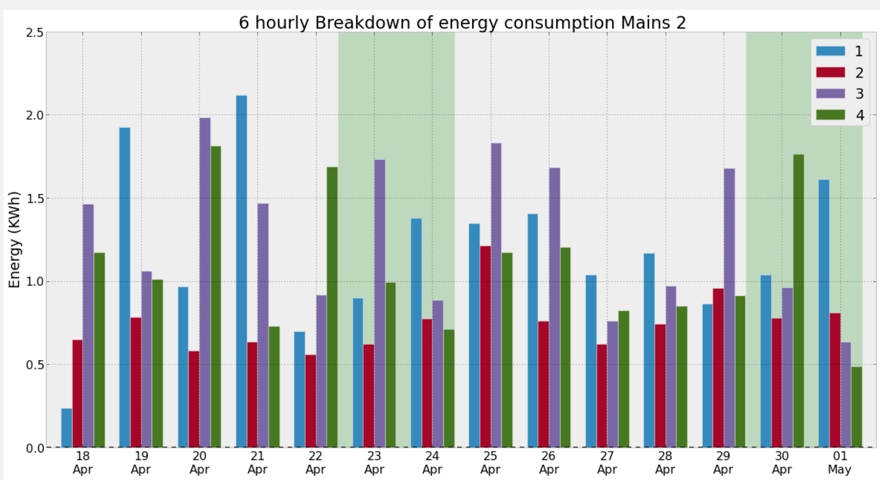
```
df4=DataFrame({'1':dawn_mains_1,'2':morning_mains_1,'3':dusk_mains_1,'4':night_mains_1},
    index=days_mains_1)
ax=df4.plot(kind='bar',stacked=False,legend=False,rot=0);
patches, labels = ax.get_legend_handles_labels();
ax.legend(patches, labels, loc='upper right');
ax.set_title('6 hourly Breakdown of energy consumption Mains 1');
ax.set_ylabel('Energy (KWh)');
correct_labels(ax);
highlight_weekend(weekend_indices,ax,1);
```



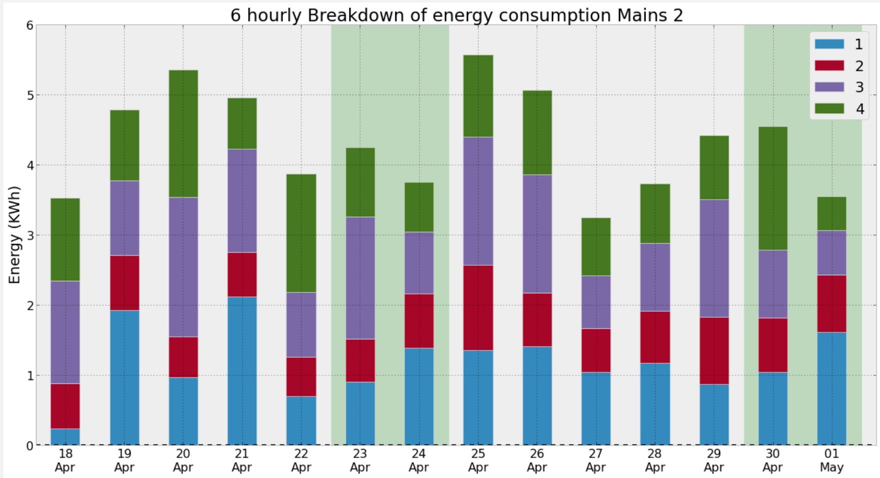

```
#ax.fill_between(pd.date_range("2011-4-18","2011-4-24"),0,20)
df4=DataFrame({'1':dawn_mains_1,'2':morning_mains_1,'3':dusk_mains_1,'4':night_mains_1},
    index=days_mains_1)
ax=df4.plot(kind='bar',stacked=True,legend=False,rot=0);
#ax.fill_between(pd.date_range("2011-4-18","2011-4-24"),0,20);
patches, labels = ax.get_legend_handles_labels();
ax.legend(patches, labels, loc='upper right');
ax.set_title('6 hourly breakdown of energy consumption Mains 1');
ax.set_ylabel('Energy (KWh)');
correct_labels(ax);
highlight_weekend(weekend_indices,ax,1.6);
```




```
df5=DataFrame({'1':dawn_mains_2,'2':morning_mains_2,'3':dusk_mains_2,'4':night_mains_2},
    index=days_mains_1)
ax=df5.plot(kind='bar',stacked=False,legend=False,rot=0);
patches, labels = ax.get_legend_handles_labels();
ax.legend(patches, labels, loc='upper right');
ax.set_title('6 hourly Breakdown of energy consumption Mains 2');
ax.set_ylabel('Energy (KWh)');
correct_labels(ax);
highlight_weekend(weekend_indices,ax,2.5);
```




```
ax=df5.plot(kind='bar',stacked=True,legend=False,rot=0);
patches, labels = ax.get_legend_handles_labels();
ax.legend(patches, labels, loc='upper right');
ax.set_title('6 hourly Breakdown of energy consumption Mains 2');
ax.set_ylabel('Energy (KWh)');
correct_labels(ax);
highlight_weekend(weekend_indices,ax,6);
```




```
kitchen_data=np.loadtxt('house_2/channel_3.dat')
light_data=np.loadtxt('house_2/channel_4.dat')
stove_data=np.loadtxt('house_2/channel_5.dat')
microwave_data=np.loadtxt('house_2/channel_6.dat')
washer_dry_data=np.loadtxt('house_2/channel_7.dat')
kitchen_2_data=np.loadtxt('house_2/channel_8.dat')
refrigerator_data=np.loadtxt('house_2/channel_9.dat')
dishwasher_data=np.loadtxt('house_2/channel_10.dat')
disposal_data=np.loadtxt('house_2/channel_11.dat')
upper=np.where(kitchen_data[:,0]==1304282291.0)[0]
lower=np.where(mains_1_data[:,0]>1303084800.0)[0][0]
kitchen_power=kitchen_data[:,1][lower:upper]
light_power=light_data[:,1][lower:upper]
stove_power=stove_data[:,1][lower:upper]
microwave_power=microwave_data[:,1][lower:upper]
washer_dryer_power=washer_dry_data[:,1][lower:upper]
kitchen_2_power=kitchen_2_data[:,1][lower:upper]
refrigerator_power=refrigerator_data[:,1][lower:upper]
dishwasher_power=dishwasher_data[:,1][lower:upper]
disposal_power=disposal_data[:,1][lower:upper]
timestamp=kitchen_data[:,0][lower:upper]
timestamp_appliance_date=timestamp.astype('datetime64[s]')
```

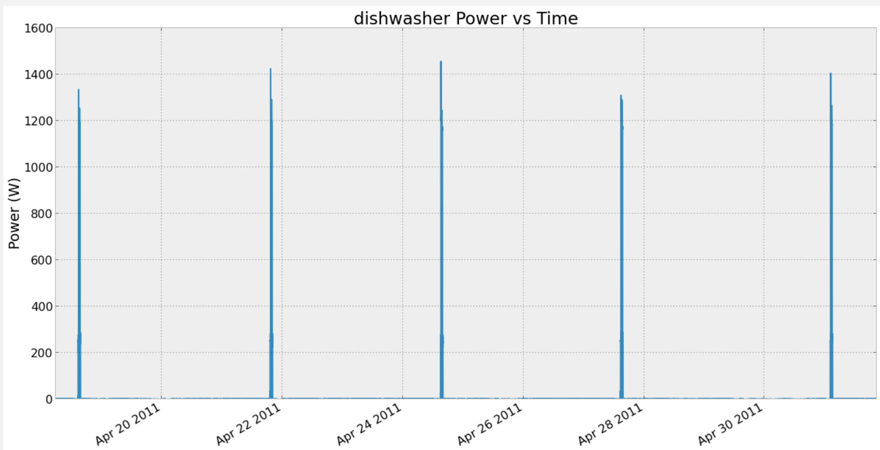
```
df_appliances=DataFrame({'kitchen':kitchen_power,'light':light_power,'stove':stove_power
    ,'microwave':microwave_power,\
'washer_dryer':washer_dryer_power,'kitchen_2':kitchen_2_power,'refrigerator':
    refrigerator_power,'dishwasher':dishwasher_power,\
'disposal':disposal_power},index=timestamp_appliance_date)
pd.set_option('display.precision', 2)
print df_appliances.describe().to_string()
```

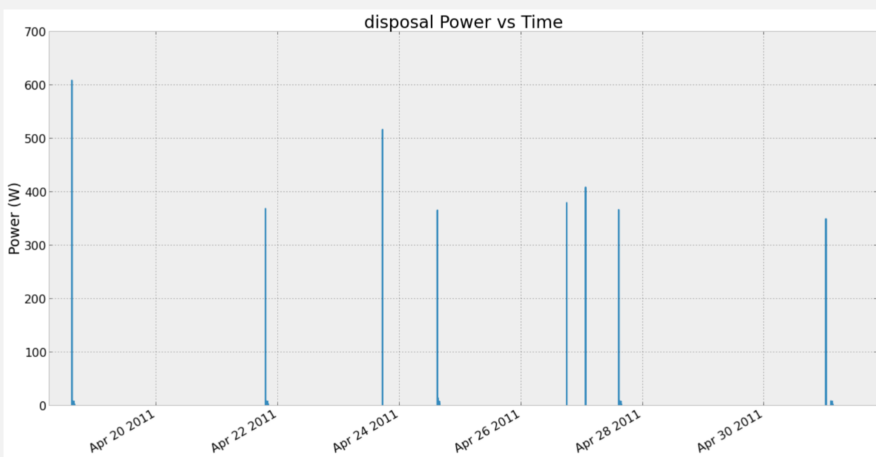
```
dishwasher  disposal   kitchen  kitchen_2     light  microwave  refrigerator     stove  washer_dryer
count     308612.0  308612.0  308612.0    308612.0  308612.0   308612.0       308612.0  308612.0       3086
mean           9.2       0.1       6.1        10.5      26.9       14.4           79.6       1.5
```

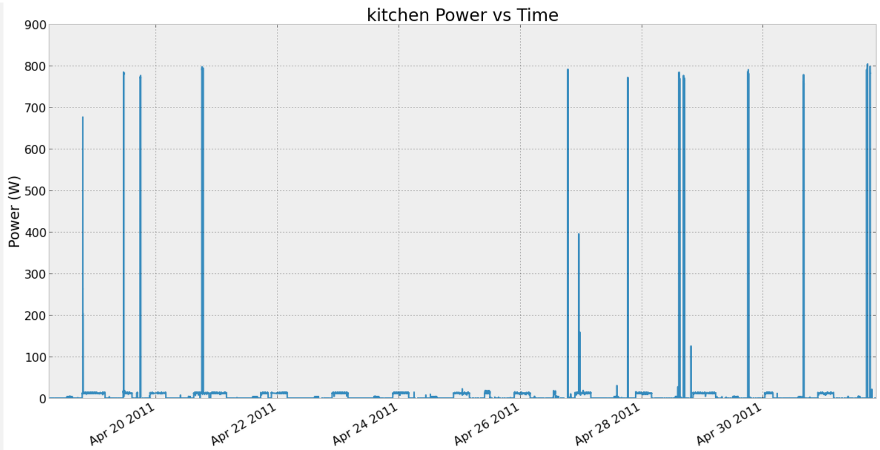
std	97.2	3.4	38.3	99.0	46.2	104.5	87.7	19.2	
min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
25%	0.0	0.0	0.0	1.0	8.0	4.0	6.0	0.0	
50%	0.0	0.0	0.0	1.0	8.0	5.0	7.0	0.0	
75%	0.0	0.0	13.0	1.0	9.0	5.0	161.0	1.0	
max	1457.0	609.0	805.0	1119.0	289.0	1986.0	2246.0	457.0	5

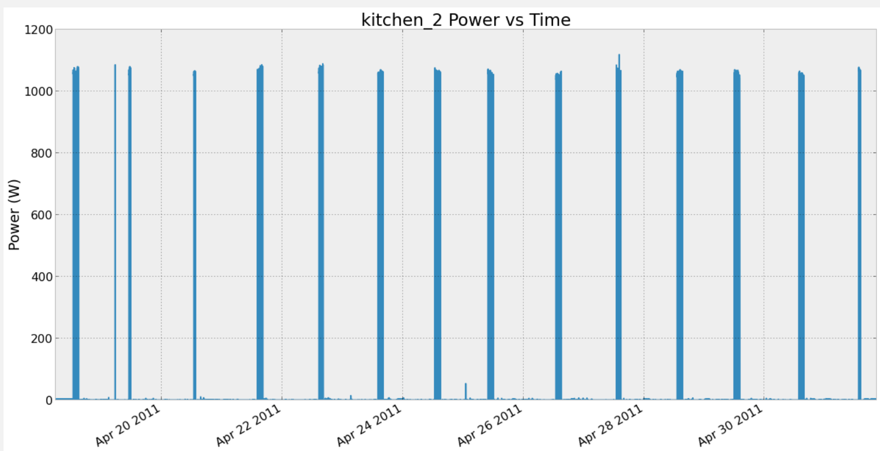
Now we plot all the channels and desctibe their statistics

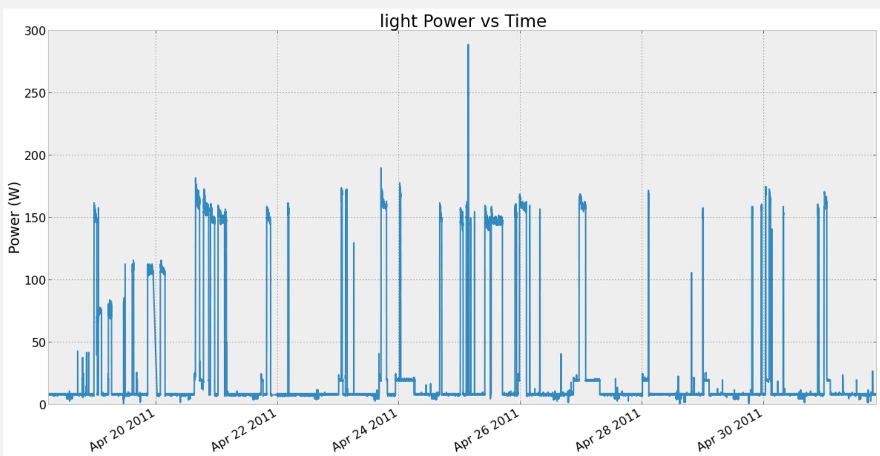
```
for key in df_appliances:
    plt.figure()
    ax=df_appliances[key].plot(title=key+" Power vs Time")
    ax.set_ylabel("Power (W)")
```

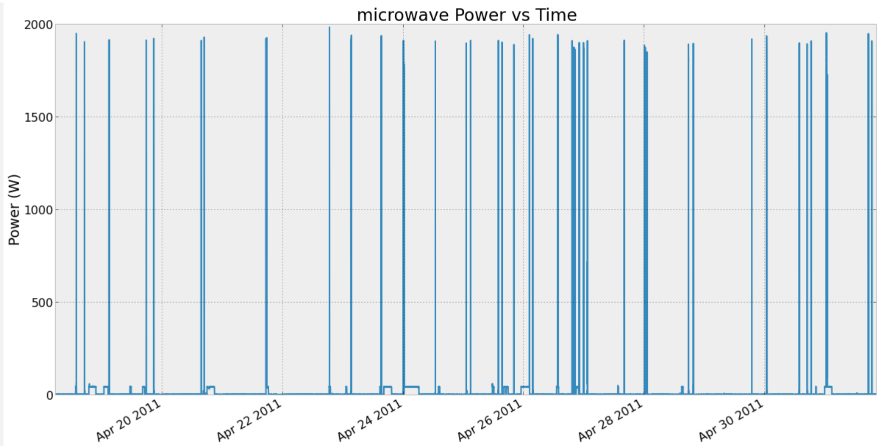


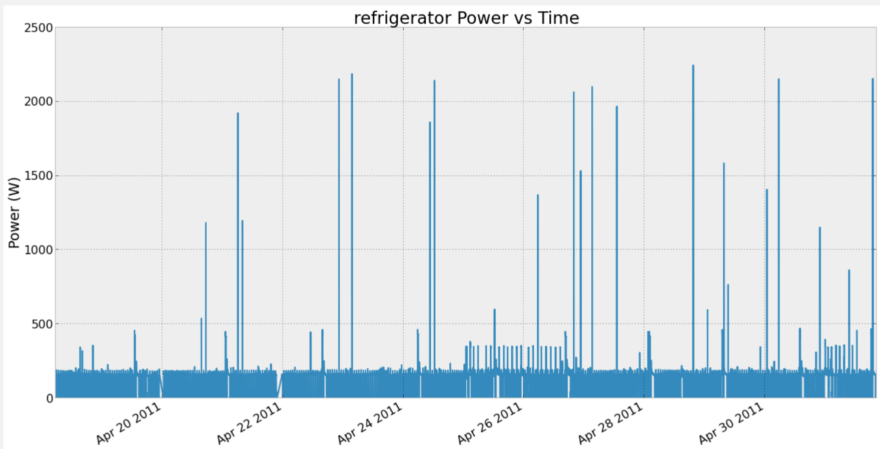


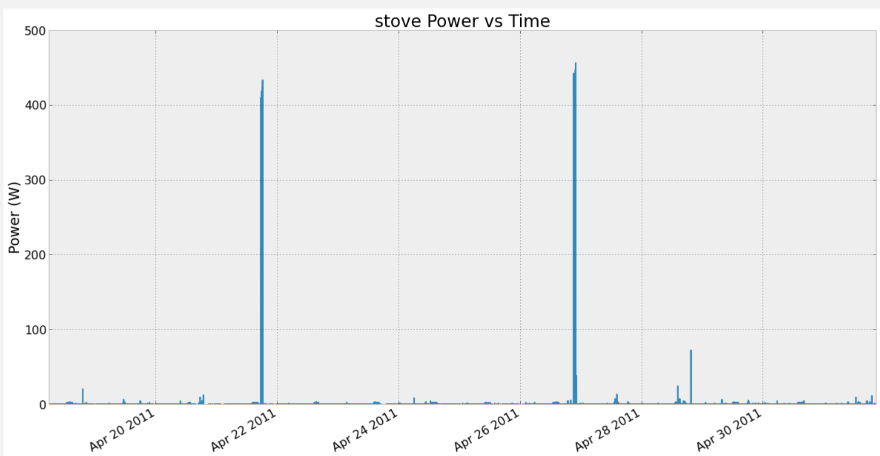

kitchen Power vs Time
Power (W)
0
100
200
300
400
500
600
700
800
900
Apr 20 2011
Apr 22 2011
Apr 24 2011
Apr 26 2011
Apr 28 2011
Apr 30 2011

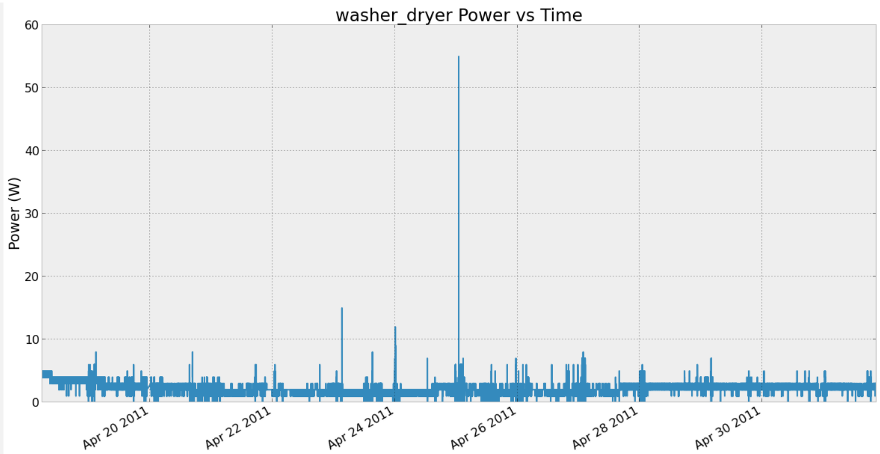

kitchen_2 Power vs Time
Power (W)
0
200
400
600
800
1000
1200
Apr 20 2011
Apr 22 2011
Apr 24 2011
Apr 26 2011
Apr 28 2011
Apr 30 2011


light Power vs Time
Power (W)
0
50
100
150
200
250
300
Apr 20 2011
Apr 22 2011
Apr 24 2011
Apr 26 2011
Apr 28 2011
Apr 30 2011


microwave Power vs Time
Power (W)
0
500
1000
1500
2000
Apr 20 2011
Apr 22 2011
Apr 24 2011
Apr 26 2011
Apr 28 2011
Apr 30 2011


refrigerator Power vs Time
Power (W)
0
500
1000
1500
2000
2500
Apr 20 2011
Apr 22 2011
Apr 24 2011
Apr 26 2011
Apr 28 2011
Apr 30 2011


stove Power vs Time
Power (W)
0
100
200
300
400
500
Apr 20 2011
Apr 22 2011
Apr 24 2011
Apr 26 2011
Apr 28 2011
Apr 30 2011



Similarly we load data correspding to different channels (appliances/circuits) and plot them.

1.5 Assigning loads to different mains circuits

Since there are two mains in the home we need to break down the individual appliance into different mains. Clearly,

- Kitchen_2 belongs to Mains1
- Kitchen belongs to Mains1
- Refrigerator belongs to Mains 2

Beyond this it is difficult to visually find the mains corresponding to different appliances. We thus decide to iteratively remove the known components. It must be noted that Mains is at 1 Hz and appliance are at lower resolution. Thus we need to align the two. This we do by aligning higher frequency mains to lower resolution appliance resolution. Thus, we downsample both the mains and all the appliances to a minute resolution, taking mean of the values contained within the minute.

```
df_appliances_minute=df_appliances.resample('1Min',how='mean')
pd.set_option('display.precision', 2)
print df_appliances_minute.describe().to_string()
```

```
dishwasher  disposal  kitchen  kitchen_2    light  microwave  refrigerator    stove  washer_dryer
count     19398.0   19398.0  19398.0    19398.0  19398.0    19398.0       19398.0  19398.0       19398.
mean          9.3       0.1      6.1       10.6     26.9       14.4          79.6      1.5           2.2
std          96.5       1.6     35.0       74.5     46.1       89.7          85.5     18.1           0.6
min           0.0       0.0      0.0        0.0      2.0        1.6           1.6      0.0           0.0
25%           0.0       0.0      0.0        1.0      8.0        4.1           6.1      0.1           2.0
50%           0.1       0.0      0.4        1.0      8.6        4.6           7.0      0.5           2.0
75%           0.1       0.0     13.0        1.0      9.0        5.0         160.8      0.9           2.2
max        1255.6     115.8    794.6     1071.8    185.4     1926.0         598.2    411.0           8.8
```

As a sanity check, we confirm that 19400 minutes correspond to about 14 days, thus our resampling was correct. We next align mains and appliance time series.

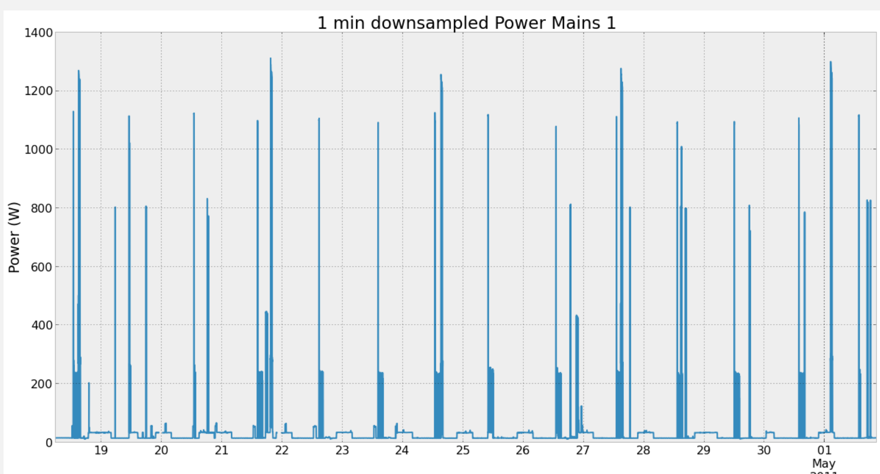
```
df_mains_minute=df_mains.resample('1Min',how='mean')
df_mains_minute.describe()
print df_mains_minute.index
print np.where(df_mains_minute.index==df_appliances_minute.index[0])
df_mains_minute=df_mains_minute[236:]

print df_mains_minute.index
df_mains_minute.describe()
```

```
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-04-18 01:45:00, ..., 2011-05-01 20:38:00]
Length: 19854, Freq: T, Timezone: None
(array([236]),)
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-04-18 05:41:00, ..., 2011-05-01 20:38:00]
Length: 19618, Freq: T, Timezone: None
```

	Mains_1_Power	Mains_2_Power
count	19397.0	19397.0
mean	43.5	187.7
std	130.4	204.1
min	13.4	21.4
25%	14.9	22.5
50%	15.1	214.4
75%	33.7	259.1
max	1312.0	2612.5

We now plot the lower resolution mains 1 and iteratively attempt to take out appliances.

```
ax=df_mains_minute.Mains_1_Power.plot(title='1 min downsampled Power Mains 1');
ax.set_ylabel("Power (W)");
```

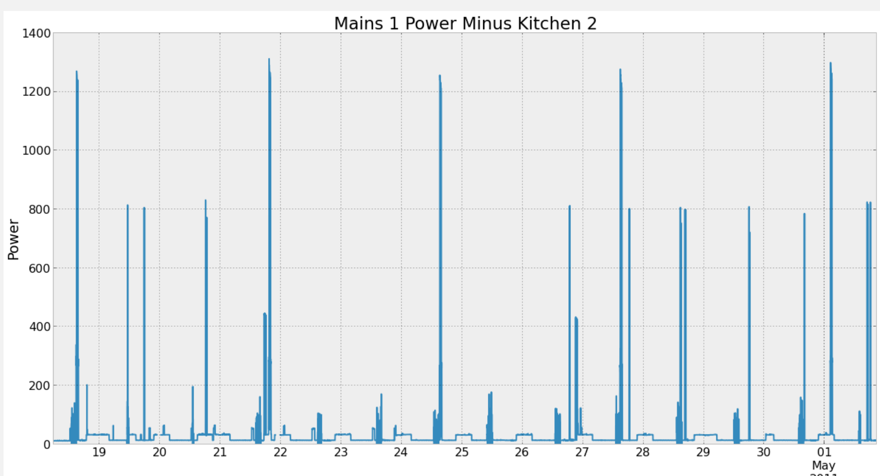


Removing kitchen_2 from Mains 1

```python
temp_1=df_mains_minute.Mains_1_Power-df_appliances_minute.kitchen_2
temp_1[temp_1<0.0]=0.0
```

```python
df_mains_minute_minus_kitchen_2=df_mains_minute.copy()
df_mains_minute_minus_kitchen_2.Mains_1_Power=temp_1
print "Before\n\n",df_mains_minute.describe()
print "\nAfter\n\n",df_mains_minute_minus_kitchen_2.describe()
ax=df_mains_minute_minus_kitchen_2.Mains_1_Power.plot(title='Mains 1 Power Minus Kitchen
     2')
ax.set_ylabel('Power');
```

```
Before

       Mains_1_Power  Mains_2_Power
count        19397.0        19397.0
mean            43.5          187.7
std            130.4          204.1
min             13.4           21.4
25%             14.9           22.5
50%             15.1          214.4
75%             33.7          259.1
max           1312.0         2612.5

After

       Mains_1_Power  Mains_2_Power
count        19395.0        19397.0
mean            33.2          187.7
std            107.0          204.1
min              0.0           21.4
25%             13.7           22.5
50%             14.1          214.4
75%             32.4          259.1
max           1312.0         2612.5
```

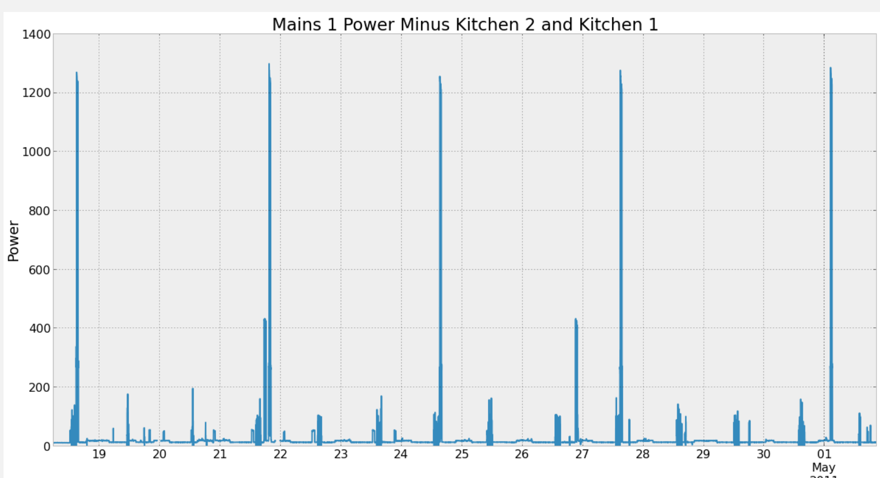


Now removing Kitchen 1 from mains 1

```
temp_2=df_mains_minute_minus_kitchen_2.Mains_1_Power-df_appliances_minute.kitchen
temp_2[temp_2<0.0]=0.0
```

```
df_mains_minute_minus_kitchen_2_1=df_mains_minute_minus_kitchen_2.copy()
df_mains_minute_minus_kitchen_2_1.Mains_1_Power=temp_2
print "Before\n\n",df_mains_minute_minus_kitchen_2.describe()
print "\nAfter\n\n",df_mains_minute_minus_kitchen_2_1.describe()
ax=df_mains_minute_minus_kitchen_2_1.Mains_1_Power.plot(title='Mains 1 Power Minus
    Kitchen 2 and Kitchen 1')
ax.set_ylabel('Power');
```

```
Before

       Mains_1_Power  Mains_2_Power
count        19395.0        19397.0
mean            33.2          187.7
std            107.0          204.1
min              0.0           21.4
25%             13.7           22.5
50%             14.1          214.4
75%             32.4          259.1
max           1312.0         2612.5

After

       Mains_1_Power  Mains_2_Power
count        19395.0        19397.0
mean            27.1          187.7
std            100.7          204.1
min              0.0           21.4
25%             13.5           22.5
50%             13.7          214.4
75%             18.6          259.1
max           1299.0         2612.5
```

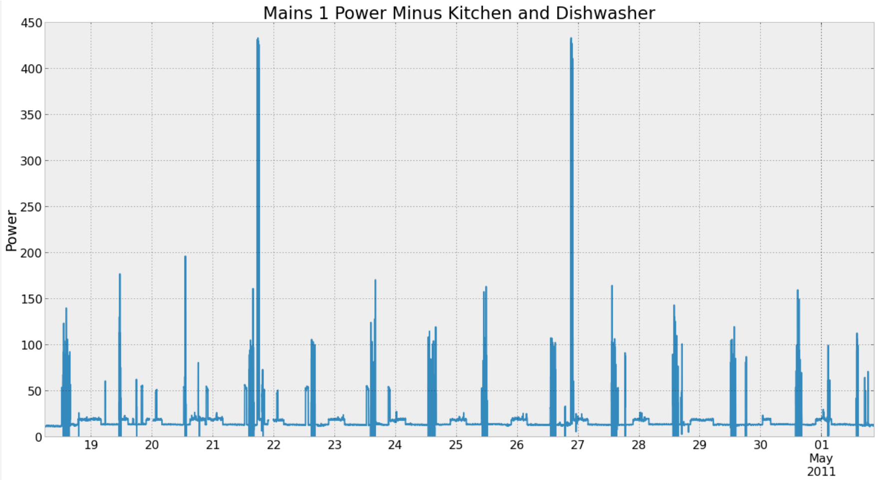


Now we observe that Dishwasher was used every 3rd day starting from 19th and power consumption was about 1200+ W. Thus, we next remove the dishwasher component from mains 1

```
temp_3=df_mains_minute_minus_kitchen_2_1.Mains_1_Power-df_appliances_minute.dishwasher
temp_3[temp_3<0.0]=0.0
```

```
df_mains_minute_minus_kitchen_dishwasher=df_mains_minute_minus_kitchen_2_1.copy()
df_mains_minute_minus_kitchen_dishwasher.Mains_1_Power=temp_3
print "Before\n\n",df_mains_minute_minus_kitchen_2_1.describe()
print "\nAfter\n\n",df_mains_minute_minus_kitchen_dishwasher.describe()
ax=df_mains_minute_minus_kitchen_dishwasher.Mains_1_Power.plot(title='Mains 1 Power
    Minus Kitchen and Dishwasher')
ax.set_ylabel('Power');
```

```
Before

       Mains_1_Power  Mains_2_Power
count        19395.0        19397.0
mean            27.1          187.7
std            100.7          204.1
min              0.0           21.4
25%             13.5           22.5
50%             13.7          214.4
75%             18.6          259.1
max           1299.0         2612.5

After

       Mains_1_Power  Mains_2_Power
count        19395.0        19397.0
mean            17.8          187.7
std             20.9          204.1
min              0.0           21.4
25%             13.5           22.5
50%             13.7          214.4
75%             18.5          259.1
max            433.4         2612.5
```



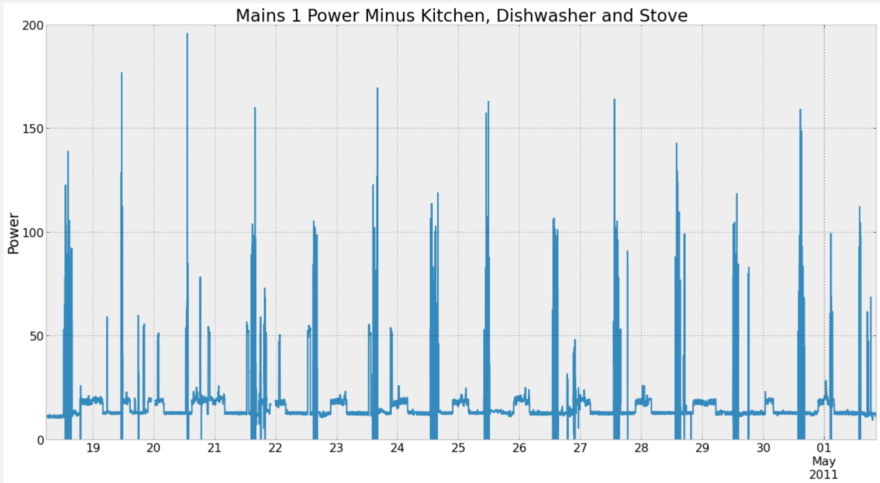
Removing stove from Mains 1

```
temp_4=df_mains_minute_minus_kitchen_dishwasher.Mains_1_Power-df_appliances_minute.stove
temp_4[temp_4<0.0]=0.0
```

```
df_mains_minute_minus_kitchen_dishwasher_stove=df_mains_minute_minus_kitchen_dishwasher.
    copy()
df_mains_minute_minus_kitchen_dishwasher_stove.Mains_1_Power=temp_4
print "Before\n\n",df_mains_minute_minus_kitchen_dishwasher.describe()
print "\nAfter\n\n",df_mains_minute_minus_kitchen_dishwasher_stove.describe()
ax=df_mains_minute_minus_kitchen_dishwasher_stove.Mains_1_Power.plot(title='Mains 1
    Power Minus Kitchen, Dishwasher and Stove')
ax.set_ylabel('Power');
```

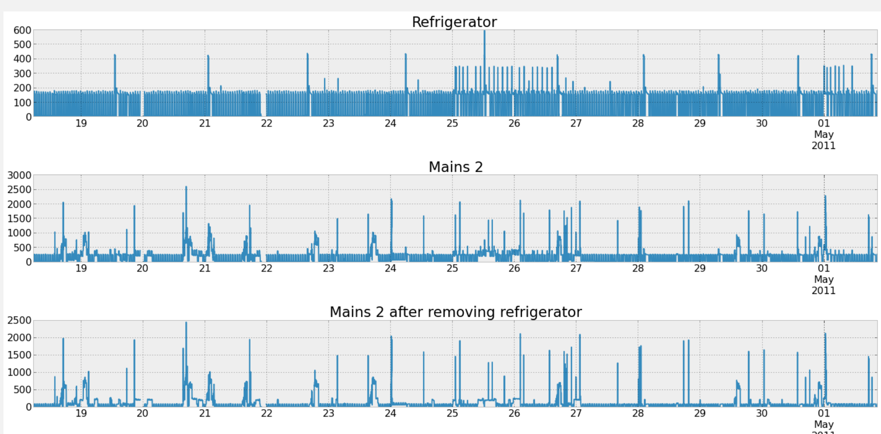
```
Before

       Mains_1_Power  Mains_2_Power
count        19395.0        19397.0
mean            17.8          187.7
std             20.9          204.1
min              0.0           21.4
25%             13.5           22.5
50%             13.7          214.4
75%             18.5          259.1
max            433.4         2612.5

After

       Mains_1_Power  Mains_2_Power
count        19395.0        19397.0
mean            16.3          187.7
std              9.9          204.1
min              0.0           21.4
25%             12.7           22.5
50%             13.4          214.4
```

```
75%                17.7            259.1
max               196.0           2612.5
```



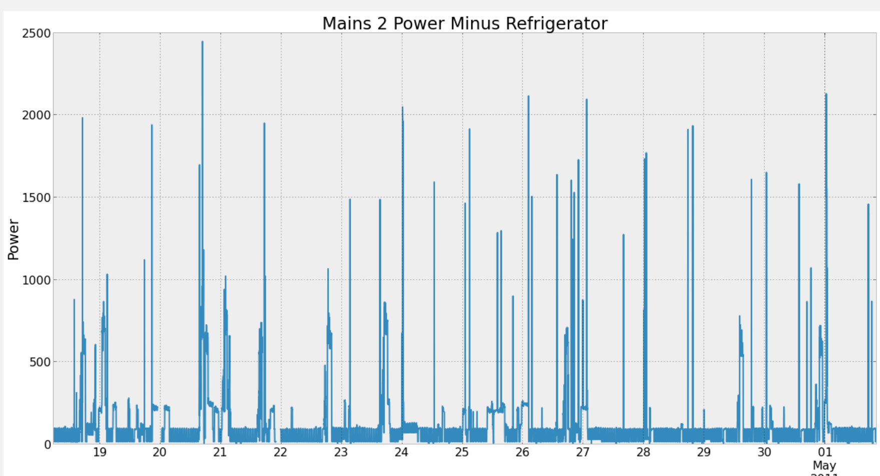
We next observe that none of the other appliance can be extracted visually from Mains 1. So we start removing appliances iteratively from Mains 2. **From the next plot we can see that there is a slight difference in power seen by the mains and the appliance level monitor, hence there seems to be a need to do this calibration to ensure that we have better results. Moreover, this is an aspect i think no one has yet highlighted in their work**.

```
temp_5=df_mains_minute_minus_kitchen_dishwasher_stove.Mains_2_Power-df_appliances_minute
    .refrigerator
temp_5[temp_5<0.0]=0.0
plt.subplot(3,1,1)
df_appliances_minute.refrigerator.plot(title='Refrigerator')
plt.subplot(3,1,2)
df_mains_minute.Mains_2_Power.plot(title='Mains 2')
plt.subplot(3,1,3)
temp_5.plot(title='Mains 2 after removing refrigerator');
plt.tight_layout()
```



```
df_mains_minute_minus_kitchen_dishwasher_stove_ref=
    df_mains_minute_minus_kitchen_dishwasher_stove.copy()
df_mains_minute_minus_kitchen_dishwasher_stove_ref.Mains_2_Power=temp_5
print "Before\n\n",df_mains_minute_minus_kitchen_dishwasher_stove.describe()
print "\nAfter\n\n",df_mains_minute_minus_kitchen_dishwasher_stove_ref.describe()
ax=df_mains_minute_minus_kitchen_dishwasher_stove_ref.Mains_2_Power.plot(title='Mains 2
    Power Minus Refrigerator')
ax.set_ylabel('Power');
```

```
Before

       Mains_1_Power  Mains_2_Power
count        19395.0        19397.0
mean            16.3          187.7
std              9.9          204.1
min              0.0           21.4
25%             12.7           22.5
50%             13.4          214.4
75%             17.7          259.1
max            196.0         2612.5

After

       Mains_1_Power  Mains_2_Power
count        19395.0        19395.0
mean            16.3          108.1
std              9.9          168.1
min              0.0            0.0
25%             12.7           16.3
50%             13.4           89.3
75%             17.7           97.5
max            196.0         2448.5
```

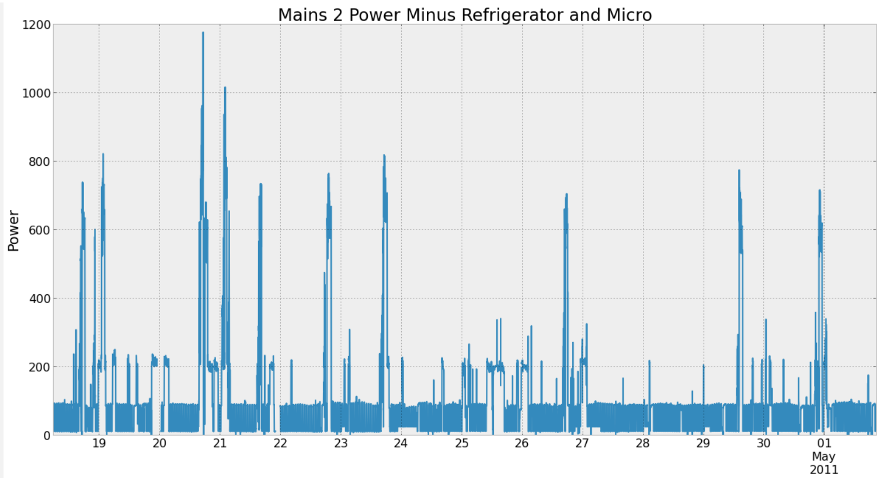


Since microwave is taking more power than residual power in Mains 1, it has to belong to Mains 2. Next, removing Microwave from Mains 2.

```
temp_6=df_mains_minute_minus_kitchen_dishwasher_stove_ref.Mains_2_Power-
    df_appliances_minute.microwave
temp_6[temp_6<0.0]=0.0
```

```
df_mains_minute_minus_kitchen_dishwasher_stove_ref_micro=
    df_mains_minute_minus_kitchen_dishwasher_stove_ref.copy()
df_mains_minute_minus_kitchen_dishwasher_stove_ref_micro.Mains_2_Power=temp_6
print "Before\n\n",df_mains_minute_minus_kitchen_dishwasher_stove_ref.describe()
print "\nAfter\n\n",df_mains_minute_minus_kitchen_dishwasher_stove_ref_micro.describe()
ax=df_mains_minute_minus_kitchen_dishwasher_stove_ref_micro.Mains_2_Power.plot(title='
    Mains 2 Power Minus Refrigerator and Micro')
ax.set_ylabel('Power');
```

```
Before

       Mains_1_Power  Mains_2_Power
count        19395.0        19395.0
mean            16.3          108.1
std              9.9          168.1
min              0.0            0.0
25%             12.7           16.3
50%             13.4           89.3
75%             17.7           97.5
max            196.0         2448.5

After

       Mains_1_Power  Mains_2_Power
count        19395.0        19395.0
mean            16.3           93.6
std              9.9          136.0
min              0.0            0.0
25%             12.7           12.2
50%             13.4           80.0
75%             17.7           91.6
max            196.0         1177.5
```



An interesting thing to note is the correlation between **Disposal** and **Dishwasher** both of which occur on the same days. Next, we iteratively start extracting out appliances from Mains 2.

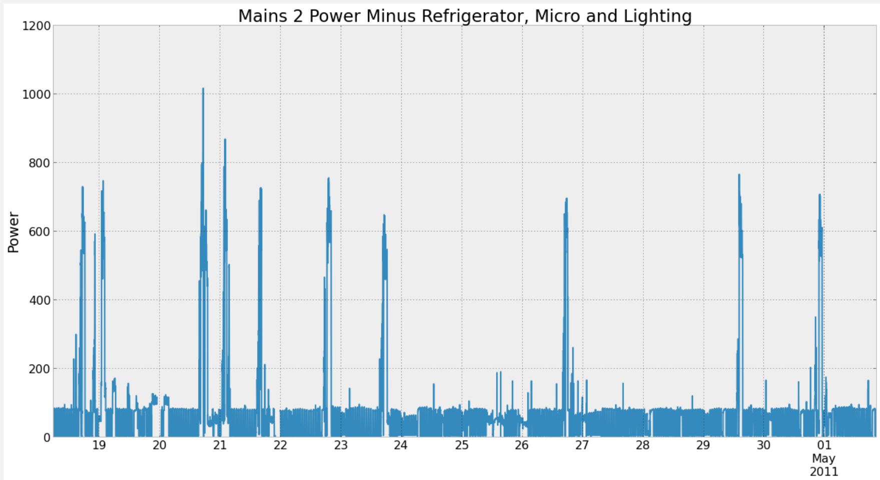
Removing lighting from Mains 2.

```
temp_7=df_mains_minute_minus_kitchen_dishwasher_stove_ref_micro.Mains_2_Power-
    df_appliances_minute.light
temp_7[temp_7<0.0]=0.0
```

```
df_mains_minute_minus_kitchen_dishwasher_stove_ref_micro_light=
    df_mains_minute_minus_kitchen_dishwasher_stove_ref_micro.copy()
df_mains_minute_minus_kitchen_dishwasher_stove_ref_micro_light.Mains_2_Power=temp_7
print "Before\n\n",df_mains_minute_minus_kitchen_dishwasher_stove_ref_micro.describe()
print "\nAfter\n\n",df_mains_minute_minus_kitchen_dishwasher_stove_ref_micro_light.
    describe()
ax=df_mains_minute_minus_kitchen_dishwasher_stove_ref_micro_light.Mains_2_Power.plot(
    title='Mains 2 Power Minus Refrigerator, Micro and Lighting')
ax.set_ylabel('Power');
```

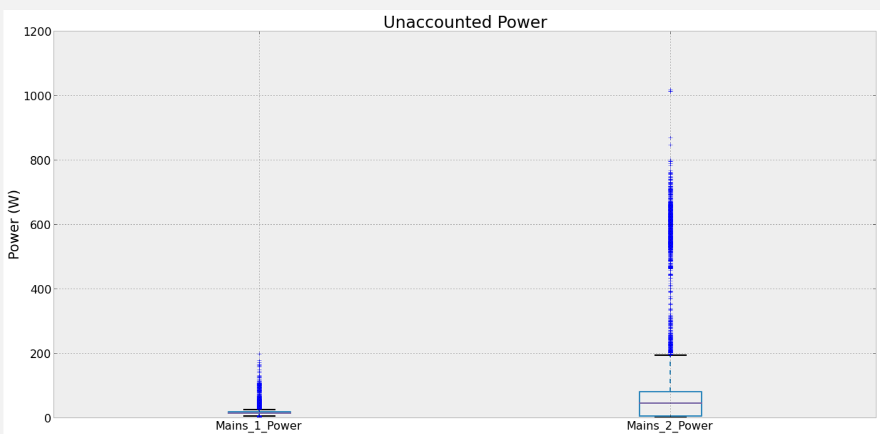
```
Before

       Mains_1_Power  Mains_2_Power
count        19395.0        19395.0
mean            16.3           93.6
std              9.9          136.0
min              0.0            0.0
25%             12.7           12.2
50%             13.4           80.0
75%             17.7           91.6
max            196.0         1177.5

After

       Mains_1_Power  Mains_2_Power
count        19395.0        19395.0
```

```
mean             16.3          66.7
std               9.9         120.2
min               0.0           0.0
25%              12.7           4.2
50%              13.4          45.7
75%              17.7          80.3
max             196.0        1017.3
```



Thus, we can see that both for Mains 1 and Mains 2 there is still a lot of unaccounted power. This is due to mis calibration between the appliance level loads and also due to absence of complete information. This is an important aspect to address. Next, we draw the boxplot showing unaccounted power.

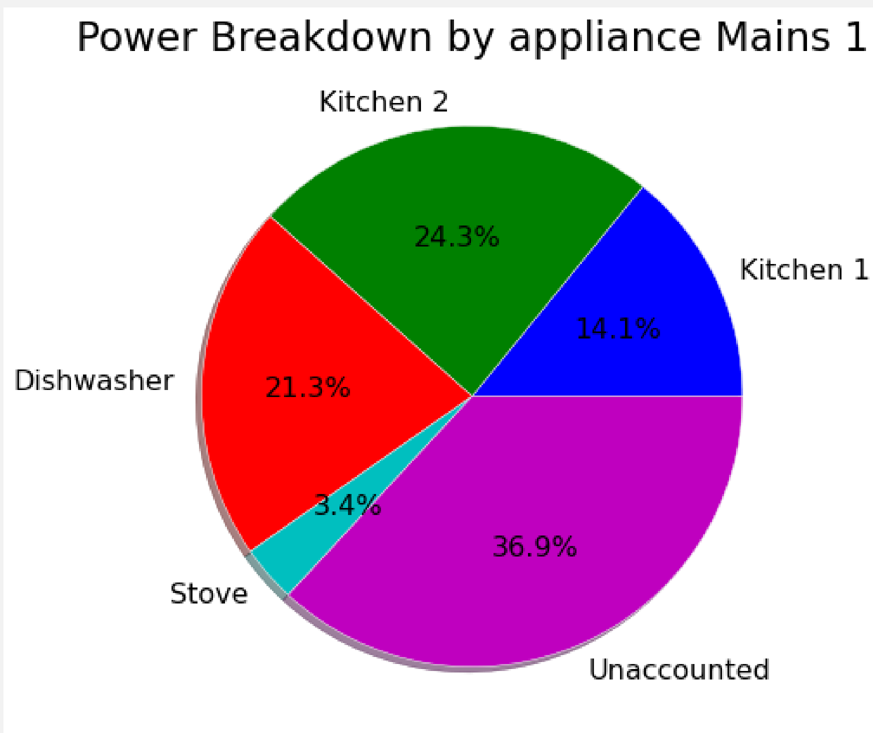
```
plt.figure()
plt.title("Unaccounted Power")
plt.ylabel("Power (W)")
df_mains_minute_minus_kitchen_dishwasher_stove_ref_micro_light.boxplot();
```



1.5.1 Breakdown by appliance

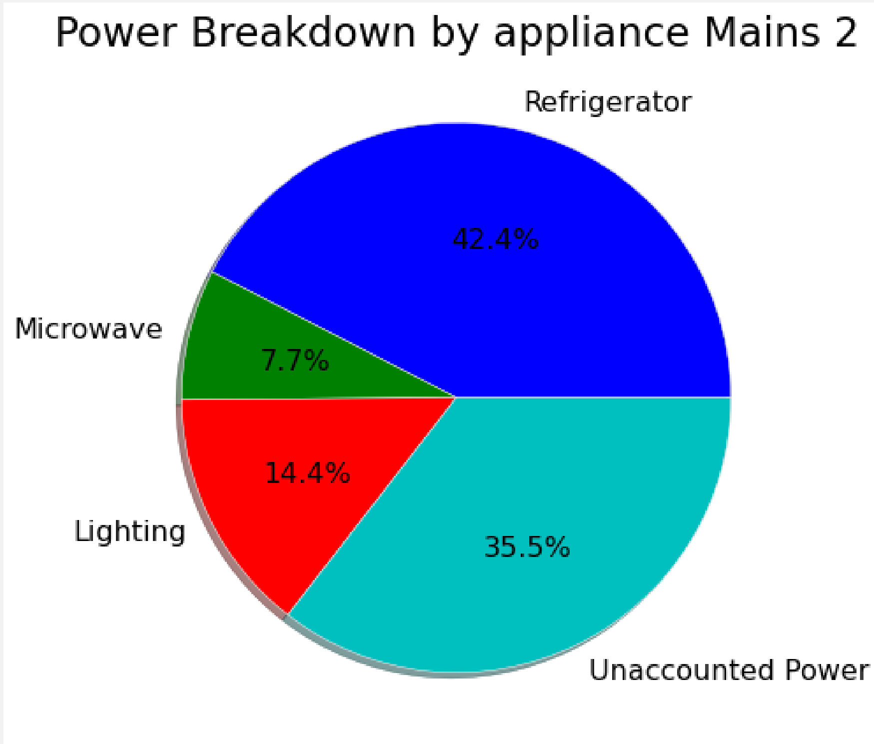
Mains 1

```
labels = 'Kitchen 1', 'Kitchen 2', 'Dishwasher', 'Stove','Unaccounted'
kitchen_mean,kitchen_2_mean,dishwasher_mean,stove_mean=df_appliances_minute.kitchen.mean
    (),\
df_appliances_minute.kitchen_2.mean(),df_appliances_minute.dishwasher.mean(),
    df_appliances_minute.stove.mean()
unaccounted_mean=df_mains_minute.Mains_1_Power.mean()-(kitchen_mean+kitchen_2_mean+
    dishwasher_mean+stove_mean)

fracs = [kitchen_mean,kitchen_2_mean,dishwasher_mean,stove_mean,unaccounted_mean]
explode=(0, 0, 0, 0,0)
plt.figsize(7,7)
plt.title('Power Breakdown by appliance Mains 1');
plt.pie(fracs, explode=explode, labels=labels,autopct='%1.1f%%', shadow=True);
```



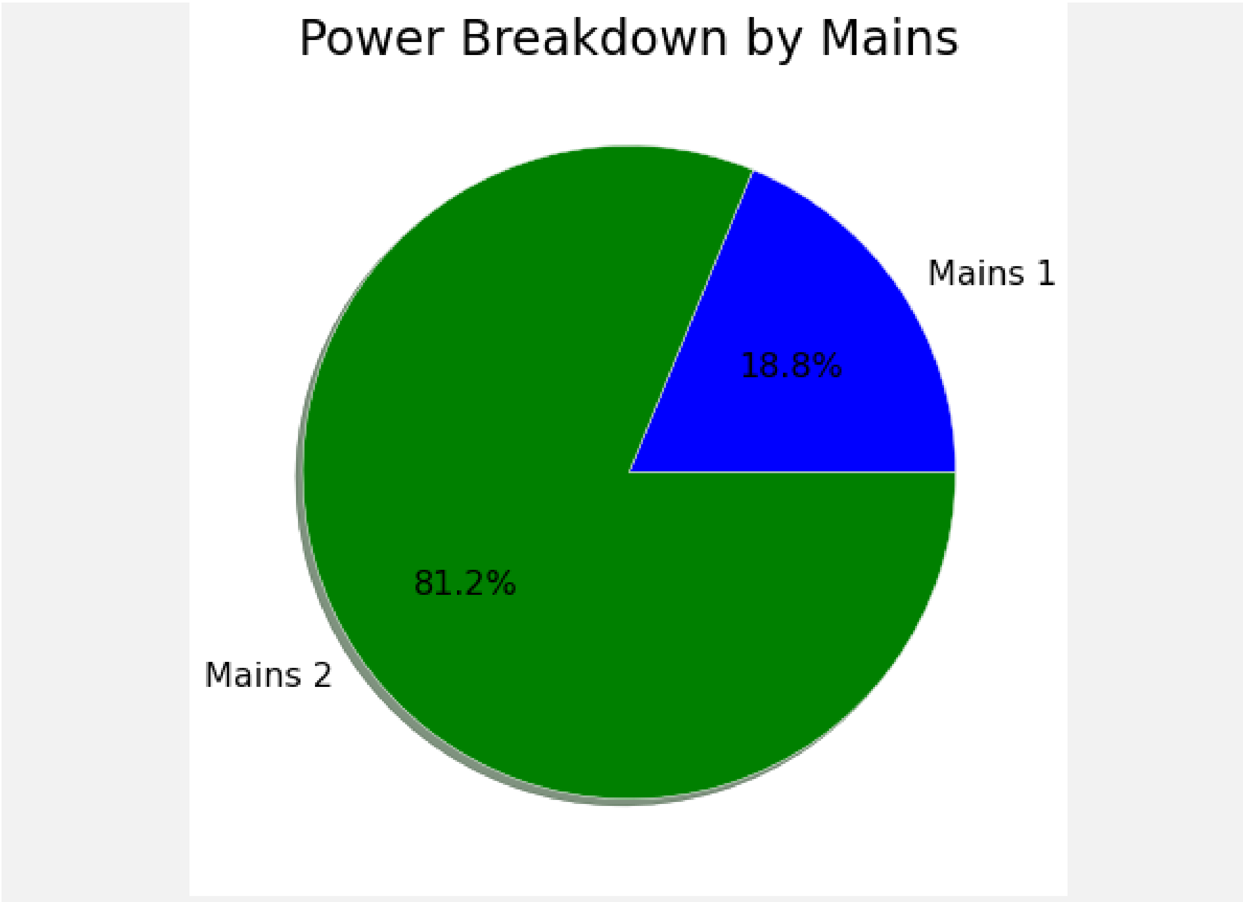

```
labels = 'Refrigerator', 'Microwave', 'Lighting','Unaccounted Power'
refrigerator_mean,microwave_mean,lighting_mean=df_appliances_minute.refrigerator.mean()
    ,\
df_appliances_minute.microwave.mean(),df_appliances_minute.light.mean()
unaccounted_mean=df_mains_minute.Mains_2_Power.mean()-(refrigerator_mean+microwave_mean+
    lighting_mean)

fracs = [refrigerator_mean,microwave_mean,lighting_mean,unaccounted_mean]
explode=(0, 0, 0,0)
```

```
plt.figsize(7,7)
plt.title('Power Breakdown by appliance Mains 2');
plt.pie(fracs, explode=explode, labels=labels,autopct='%1.1f%%', shadow=True);
```



Thus, we can see that in both the mains circuits about 1/3 of total power cannot be attributed to any appliance.

```
labels = 'Mains 1','Mains 2'

fracs = [df_mains_minute.Mains_1_Power.mean(),df_mains_minute.Mains_2_Power.mean()]
explode=(0, 0)
plt.figsize(7,7)
plt.title('Power Breakdown by Mains');
plt.pie(fracs, explode=explode, labels=labels,autopct='%1.1f%%', shadow=True);
```



Remaining load is unaccounted for in the analysis. We now have 2 options:

- To continue with this data as such and not process further
- To filter out data about which not information has been provided

Option 1 is more realistic and Option 2 is more ideal. We shall be considering the ideal case through the remaining analysis. Thus, we need to filter out the remaining data.

```
filtered_mains_1_power=df_appliances_minute.kitchen+df_appliances_minute.kitchen_2+
    df_appliances_minute.stove+\
df_appliances_minute.dishwasher

filtered_mains_2_power=df_appliances_minute.refrigerator+df_appliances_minute.light+
    df_appliances_minute.microwave
```

```
df_filtered_mains=pd.DataFrame({'Mains_1_Power':filtered_mains_1_power,'Mains_2_Power':
    filtered_mains_2_power},\
index=df_mains_minute_minus_kitchen_dishwasher_stove_ref_micro_light.index)
```

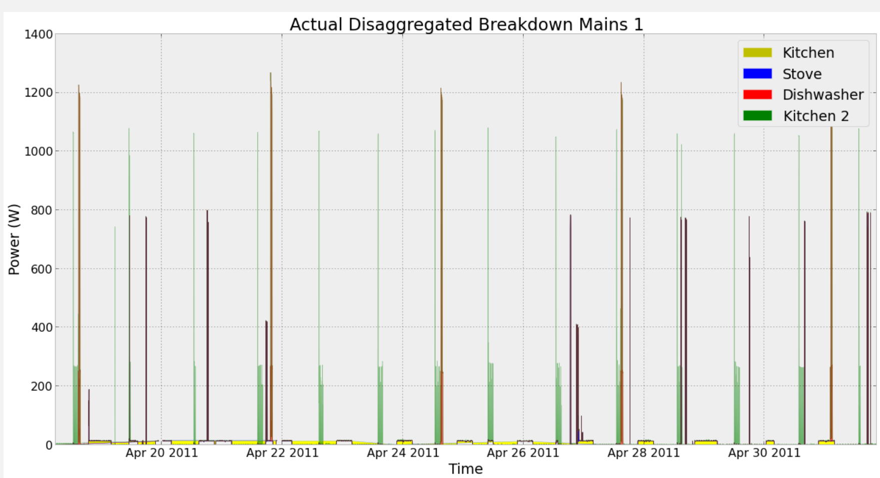
```
df_filtered_mains.describe()
```

```
       Mains_1_Power  Mains_2_Power
count        19398.0        19398.0
mean            27.4          121.0
std            127.4          139.6
min              0.2            9.6
25%              1.5           18.3
50%              2.5          121.3
75%             14.4          177.8
max           1268.6         2252.2
```

Plotting Disaggregated consumption Mains 1

```
python_datetime=df_filtered_mains.index.to_pydatetime()
```

```
plt.title('Actual Disaggregated Breakdown Mains 1');
plt.xlabel('Time');
plt.ylabel('Power (W)');
y_1=df_appliances_minute.kitchen+df_appliances_minute.stove
y_2=y_1+df_appliances_minute.dishwasher
plt.fill_between(python_datetime,df_appliances_minute.kitchen,np.zeros(len(
    df_appliances_minute.kitchen)),color="yellow")
plt.fill_between(python_datetime,y_1,df_appliances_minute.kitchen,color='blue',label='
    Test')
plt.fill_between(python_datetime,y_2,y_1,color='red',alpha=.6)
plt.fill_between(python_datetime,y_2,df_filtered_mains.Mains_1_Power,color='green',alpha
    =0.4)
p = Rectangle((0, 0), 1, 1, fc="y")
p1=Rectangle((0, 0), 1, 1, fc="b")
p2=Rectangle((0, 0), 1, 1, fc="r")
p3=Rectangle((0, 0), 1, 1, fc="g")
legend([p,p1,p2,p3], ["Kitchen","Stove","Dishwasher","Kitchen 2"]);
```



1.6 State Space

Finding different states for each appliance and the corresponding power consumption using various clustering techniques. Firstly, we start with stove. There are several reasons behind choosing a clustering algorithm, some of them are mentioned at http://scikit-learn.org/stable/modules/clustering.html

```
from sklearn.cluster import MiniBatchKMeans, KMeans
import time
plt.figsize(15,8)
```

Filling missing data (currently NaN) with previous value (commonly known as forward filling). **CONFIRM: If this is the right thing to do**.

```
df_appliances_minute.fillna(method='pad',inplace=True)
times=df_appliances_minute.index.to_pydatetime()
raw_data={}
for key in df_appliances_minute:
    raw_data[key]=df_appliances_minute[key].values
    length=len(raw_data[key])
    raw_data[key]=raw_data[key].reshape(length,1)
```

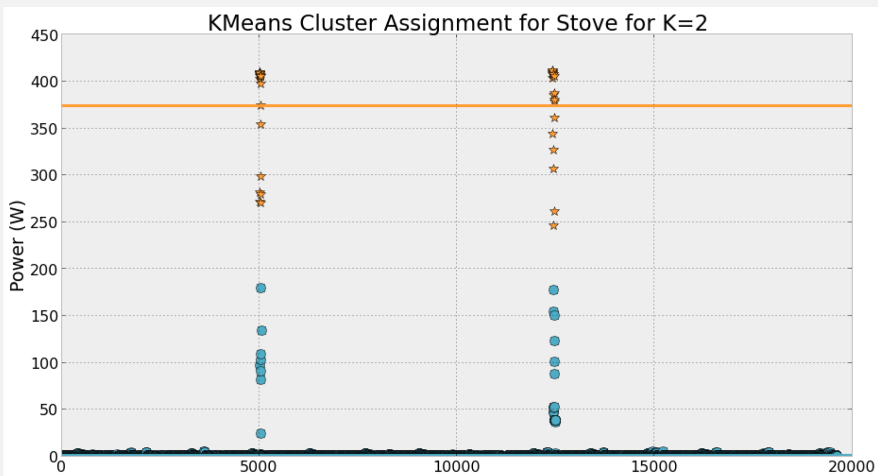
```
def apply_kmeans(n_clusters, n_init,X,init=None):
    if init is None:
        k_means = KMeans(n_clusters=n_clusters, n_init=n_init)
    else:
        k_means=KMeans(init='k-means++',n_clusters=n_clusters, n_init=n_init)
    t0 = time.time()
    k_means.fit(X)
    t_batch = time.time() - t0
    k_means_labels = k_means.labels_
    k_means_cluster_centers = k_means.cluster_centers_
    k_means_labels_unique = np.unique(k_means_labels)
    inertia=k_means.inertia_
    return [t_batch, k_means_labels, k_means_cluster_centers, k_means_labels_unique,
        inertia]
```

```
def plot_cluster_assignments(X,k_means_labels, k_means_cluster_centers,n_clusters,
    appliance_name):
    colors = ['#4EACC5', '#FF9C34', '#4E9A06']
    markers=['o','*','.']
    x_temp=np.arange(len(X))
    for k, col in zip(range(n_clusters), colors):
        my_members = k_means_labels == k
        cluster_center = k_means_cluster_centers[k]
        plt.ylabel('Power (W)');
        plt.plot(x_temp[my_members],X[my_members, 0],markers[k],markersize=10,
            markerfacecolor=col)
        plt.axhline(k_means_cluster_centers[k],linewidth=3,color=col)
        print "State %d Centroid= %0.4f, Fraction of datapoints= %0.4f" %(k,
```

```
            cluster_center,sum(my_members)*1.0/np.size(X))
        plt.title('KMeans Cluster Assignment for '+appliance_name+' for K='+str(
            n_clusters))
```

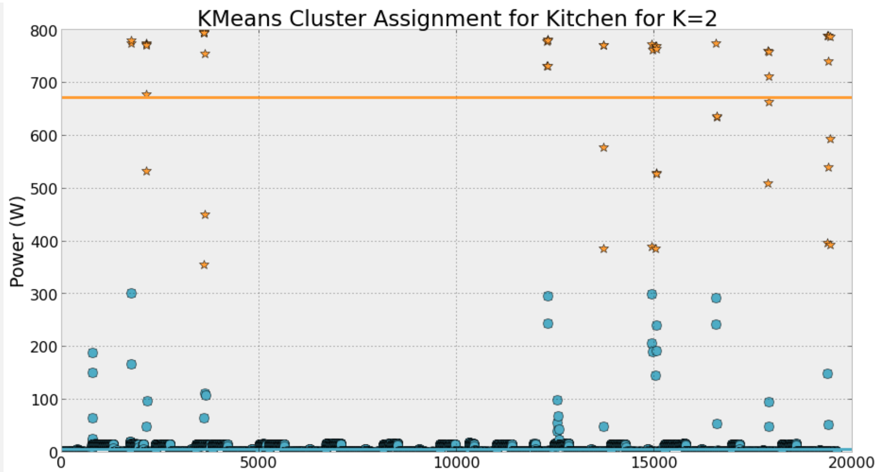
```
[t_batch_stove, k_means_labels_stove, k_means_cluster_centers_stove,
    k_means_labels_unique_stove, inertia_stove]=\
apply_kmeans(2,10,raw_data["stove"],"kmeans++")
plot_cluster_assignments(raw_data["stove"],k_means_labels_stove,
    k_means_cluster_centers_stove,len(k_means_labels_unique_stove),"Stove")
print "Time taken for clustering : ",t_batch_stove
print "Inertia of cluster assignment: ",inertia_stove
```

```
State 0 Centroid= 0.6480, Fraction of datapoints= 0.9978
State 1 Centroid= 374.0394, Fraction of datapoints= 0.0022
Time taken for clustering    :      0.0534088611603
Inertia of cluster assignment:      361045.705434
```



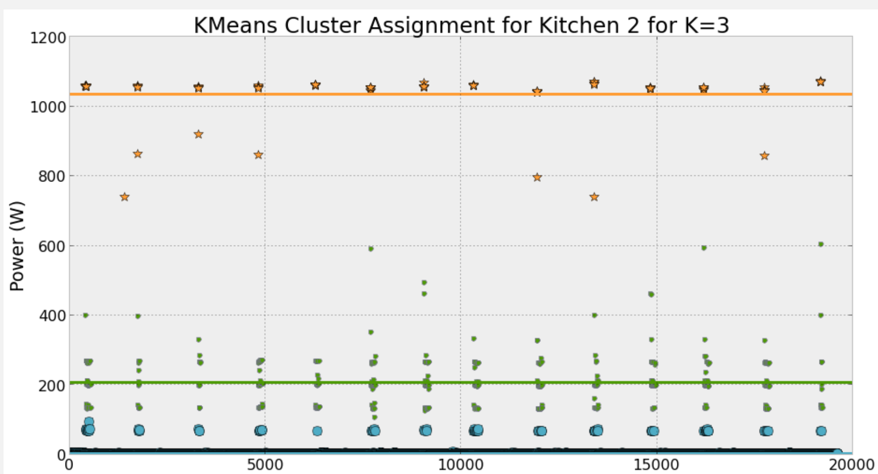

```
[t_batch_kitchen, k_means_labels_kitchen, k_means_cluster_centers_kitchen,
    k_means_labels_unique_kitchen, inertia_kitchen]=\
apply_kmeans(2,10,raw_data["kitchen"],"kmeans++")

plot_cluster_assignments(raw_data["kitchen"],k_means_labels_kitchen,
    k_means_cluster_centers_kitchen,len(k_means_labels_unique_kitchen),"Kitchen")
print "Time taken for clustering : ",t_batch_kitchen
print "Inertia of cluster assignment: ",inertia_kitchen
```

```
State 0 Centroid= 4.5853, Fraction of datapoints= 0.9976
State 1 Centroid= 671.6462, Fraction of datapoints= 0.0024
Time taken for clustering    :      0.0851709842682
Inertia of cluster assignment:      2529066.47693
```




```
[t_batch_kitchen_2, k_means_labels_kitchen_2, k_means_cluster_centers_kitchen_2,
    k_means_labels_unique_kitchen_2, inertia_kitchen_2]=\
apply_kmeans(3,10,raw_data["kitchen_2"],"kmeans++")
plot_cluster_assignments(raw_data["kitchen_2"],k_means_labels_kitchen_2,
    k_means_cluster_centers_kitchen_2,len(k_means_labels_unique_kitchen_2),"Kitchen 2")
print "Time taken for clustering : ",t_batch_kitchen_2
print "Inertia of cluster assignment: ",inertia_kitchen_2
```

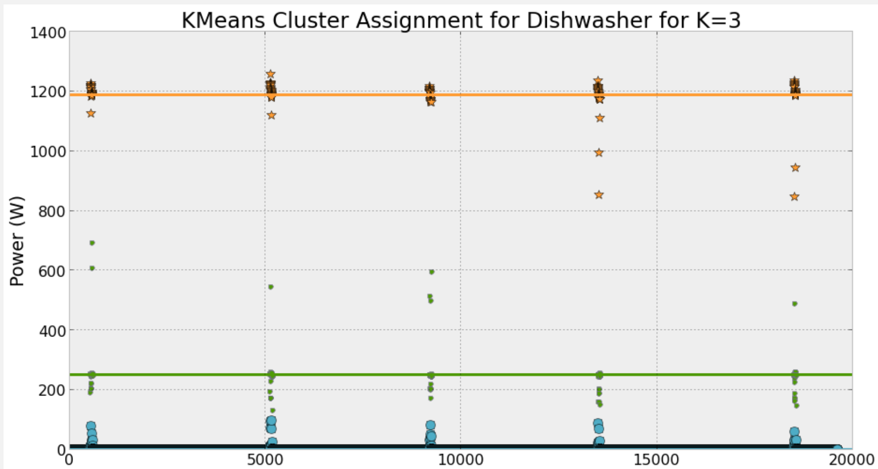
```
State 0 Centroid= 1.4546, Fraction of datapoints= 0.9729
State 1 Centroid= 1035.4956, Fraction of datapoints= 0.0042
State 2 Centroid= 205.6050, Fraction of datapoints= 0.0229
Time taken for clustering    :      0.0833849906921
Inertia of cluster assignment:      2805123.96163
```




```
[t_batch_dishwasher, k_means_labels_dishwasher, k_means_cluster_centers_dishwasher,
    k_means_labels_unique_dishwasher, inertia_dishwasher]=\
apply_kmeans(3,10,raw_data["dishwasher"],"kmeans++")
plot_cluster_assignments(raw_data["dishwasher"],k_means_labels_dishwasher,
    k_means_cluster_centers_dishwasher,len(k_means_labels_unique_dishwasher),"Dishwasher"
```

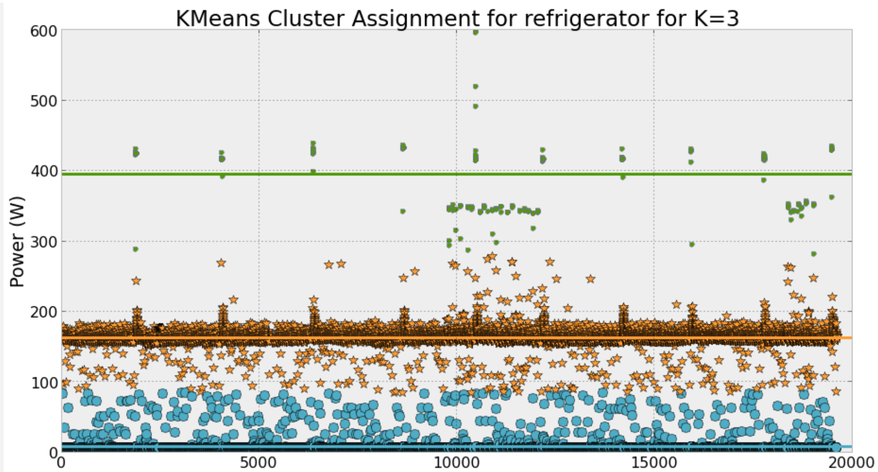
```
print "Time taken for clustering : " t_batch_dishwasher
print "Inertia of cluster assignment: " inertia_dishwasher
```

```
State 0 Centroid= 0.1364, Fraction of datapoints= 0.9874
State 1 Centroid= 1186.5108, Fraction of datapoints= 0.0063
State 2 Centroid= 249.6954, Fraction of datapoints= 0.0063
Time taken for clustering    :      0.0637760162354
Inertia of cluster assignment:      1339180.63283
```



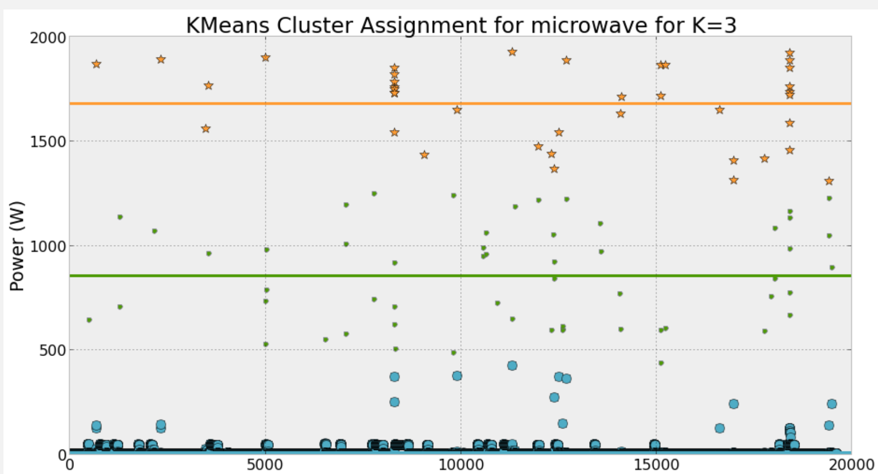

```
[t_batch_refrigerator, k_means_labels_refrigerator, k_means_cluster_centers_refrigerator
    , k_means_labels_unique_refrigerator, inertia_refrigerator]=\
apply_kmeans(3,10,raw_data["refrigerator"],"kmeans++")
plot_cluster_assignments(raw_data["refrigerator"],k_means_labels_refrigerator,
    k_means_cluster_centers_refrigerator,len(k_means_labels_unique_refrigerator),"
    refrigerator")
print "Time taken for clustering : ",t_batch_refrigerator
print "Inertia of cluster assignment: ",inertia_refrigerator
```

```
State 0 Centroid= 7.4725, Fraction of datapoints= 0.5538
State 1 Centroid= 162.1867, Fraction of datapoints= 0.4327
State 2 Centroid= 394.8063, Fraction of datapoints= 0.0136
Time taken for clustering    :      0.102931022644
Inertia of cluster assignment:      2597652.90778
```




```
[t_batch_microwave, k_means_labels_microwave, k_means_cluster_centers_microwave,
    k_means_labels_unique_microwave, inertia_microwave]=\
apply_kmeans(3,10,raw_data["microwave"],"kmeans++")
plot_cluster_assignments(raw_data["microwave"],k_means_labels_microwave,
    k_means_cluster_centers_microwave,len(k_means_labels_unique_microwave),"microwave")
print "Time taken for clustering : ",t_batch_microwave
print "Inertia of cluster assignment: ",inertia_microwave
```

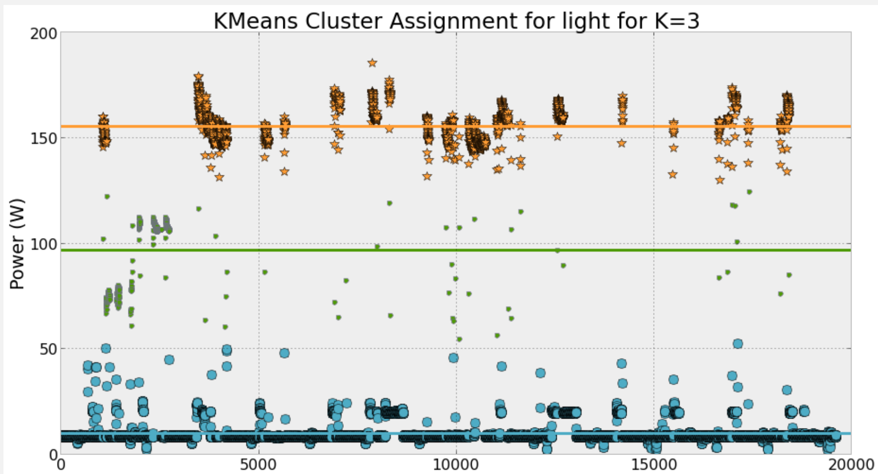
```
State 0 Centroid= 8.6130, Fraction of datapoints= 0.9952
State 1 Centroid= 1677.3997, Fraction of datapoints= 0.0020
State 2 Centroid= 852.9569, Fraction of datapoints= 0.0029
Time taken for clustering    :       0.221184015274
Inertia of cluster assignment:       8371412.23135
```




```
[t_batch_light, k_means_labels_light, k_means_cluster_centers_light,
    k_means_labels_unique_light, inertia_light]=\
apply_kmeans(3,10,raw_data["light"],"kmeans++)
plot_cluster_assignments(raw_data["light"],k_means_labels_light,
    k_means_cluster_centers_light,len(k_means_labels_unique_light),"light")
```

```
print "Time taken for clustering : ",t_batch_light
print "Inertia of cluster assignment: ",inertia_light
```

```
State 0 Centroid= 9.5566, Fraction of datapoints= 0.8668
State 1 Centroid= 155.5247, Fraction of datapoints= 0.1033
State 2 Centroid= 96.5077, Fraction of datapoints= 0.0299
Time taken for clustering    :      0.0852990150452
Inertia of cluster assignment:      508702.879442
```



Thus, we obtain the following states from cluster analysis.

```
kitchen=[5,672]
lighting=[9,96,155]
stove=[0,374]
micro=[8,852,1677]
kitchen_2=[1,206,1035]
ref=[7,162,394]
dish=[0,250,1186]
```

For mains 1, we now draw the state space, which consists of all possible combinations of appliances in their different states. We also show the correpsonding histogram which tells how close the different states are. The closer the states, the more difficult the disaggregation becomes.

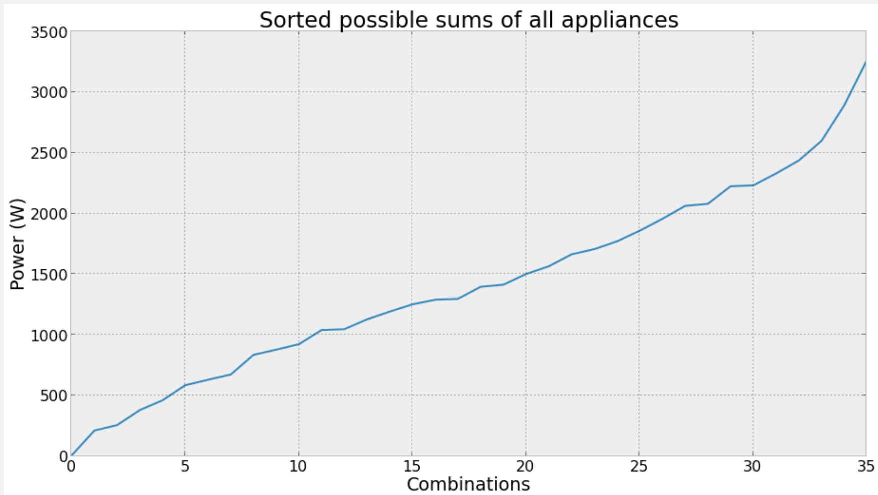
```
states_combination=list(itertools.product(kitchen,stove,kitchen_2,dish))
```

```
print "The possible different state combinations are\n Kitchen, Stove, Kitchen 2,
    Dishwasher\n",states_combination
```

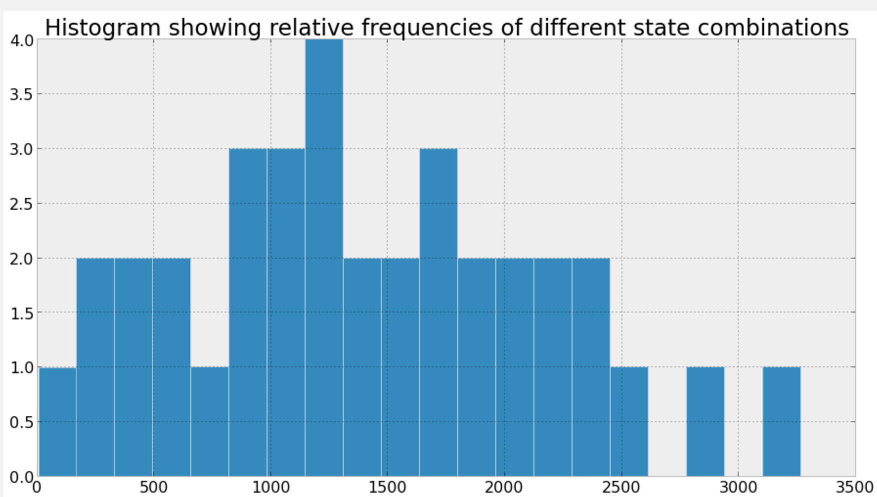
```
The possible different state combinations are
 Kitchen, Stove, Kitchen 2, Dishwasher
[(5, 0, 1, 0), (5, 0, 1, 250), (5, 0, 1, 1186), (5, 0, 206, 0), (5, 0, 206, 250), (5, 0, 206, 1186), (5,
```

```
sum_combination=np.array(np.zeros(len(states_combination)))
for i in range(0,len(states_combination)):
    sum_combination[i]=sum(states_combination[i])
```

```
from copy import deepcopy
b=deepcopy(sum_combination)
b.sort()
grid(True)
title('Sorted possible sums of all appliances');
xlabel('Combinations');
ylabel('Power (W)');
plot(b);
```




```
title('Histogram showing relative frequencies of different state combinations');
hist(b,20);
```



Now we basically need to iterate over all our sample and see which of the possible state assignment matches closest to the overall power consumption. We thus create a function to do the same.

```
def find_nearest(array,value):
    idx = (np.abs(array-value)).argmin()
    diff=array[idx]-value
    return [idx,-diff]
```

We thus apply this technique to find the residual power left from the closest state assignment.

```
residual_power_mains_1=np.zeros(len(filtered_downsampled_mains_1))
states_idx=np.zeros(len(filtered_downsampled_mains_1))
for i in range(len(filtered_downsampled_mains_1)):
    [states_idx[i],residual_power_mains_1[i]]=find_nearest(sum_combination,
        filtered_downsampled_mains_1[i])
```

```
title('Residual Power Mains 1');
xlabel('Time');
ylabel('Power (W)');
plot(residual_power_mains_1);
```

However we can also impose another conditon that the sum of powers of all the appliances is strictly less than the aggregate power observed. Thus, we can create a function for that as follows.

```
def find_nearest_positive(array,value):
    idx_temp = np.where(array-value<=0.0)[0]
    temp_arr=array[idx_temp]
    try:
        idx_in_new=np.abs(temp_arr-value).argmin()
        idx=np.where(array==temp_arr[idx_in_new])[0][0]

        diff=array[idx]-value
    except:
        idx=0
        diff=0
    return [idx,-diff]
```

```
residual_power_mains_1_positive=np.zeros(len(filtered_downsampled_mains_1))
states_idx_positive=np.zeros(len(filtered_downsampled_mains_1))
residual_power_mains_2=np.zeros(len(filtered_downsampled_mains_2))
states_idx_2=np.zeros(len(filtered_downsampled_mains_1))
for i in range(len(filtered_downsampled_mains_1)):
    [states_idx_positive[i],residual_power_mains_1_positive[i]]=find_nearest_positive(
        sum_combination,filtered_downsampled_mains_1[i])
```

```
title('Residual Power Mains 1 considering sum of appliance powers < Aggregate Power');
xlabel('Time');
ylabel('Power (W)');
grid(True);
plot(residual_power_mains_1_positive);
```

After having applied Total Load Model, we need to assign different states to different appliances.

```
length_sequence=len(filtered_downsampled_mains_1)
co_kitchen_states=np.zeros(length_sequence,dtype=np.int)
co_kitchen_power=np.zeros(length_sequence)
co_stove_states=np.zeros(length_sequence,dtype=np.int)
co_stove_power=np.zeros(length_sequence)
co_kitchen_2_states=np.zeros(length_sequence,dtype=np.int)
co_kitchen_2_power=np.zeros(length_sequence)
co_dish_states=np.zeros(length_sequence,dtype=np.int)
co_dish_power=np.zeros(length_sequence)
```

```
for i in range(length_sequence):
    if int(states_idx[i])/18==0:
        co_kitchen_states[i]=0

    else:
        co_kitchen_states[i]=1
    co_kitchen_power[i]=kitchen[co_kitchen_states[i]]

    temp=int(states_idx[i])/9
    if temp%2==0:
        co_stove_states[i]=0
    else:
        co_stove_states[i]=1
    co_stove_power[i]=stove[co_stove_states[i]]

    temp=int(states_idx[i])/3
    if temp%3==0:
        co_kitchen_2_states[i]=0
    elif temp%3==1:
        co_kitchen_2_states[i]=1
    else:
        co_kitchen_2_states[i]=2
    co_kitchen_2_power[i]=kitchen_2[co_kitchen_2_states[i]]

    temp=int(states_idx[i])%3
    if temp==0:
        co_dish_states[i]=0
    elif temp==1:
        co_dish_states[i]=1
    else:
        co_dish_states[i]=2
    co_dish_power[i]=dish[co_dish_states[i]]
```

Now we compare the produced output with Ground truth.

```
subplot(2,1,1);

plt.title('Actual Dishwasher Consumption');
plt.xlabel('Time');
plt.ylabel('Power (W)');
```

```
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_dishwasher);
subplot(2,1,2);
plt.xlabel('Time');
plt.ylabel('Power (W)');
plt.title('Observed Dishwasher Consumption');
plt.plot(downsampled_timestamp_appliance_date,co_dish_power);
```

```
plt.subplot(2,1,1)
plt.title('Actual Kitchen 1 Consumption');
plt.xlabel('Time');
plt.ylabel('Power (W)');
subplots_adjust(hspace=.5);
plt.plot(downsampled_timestamp_appliance_date,downsampled_kitchen)
plt.subplot(2,1,2)
plt.xlabel('Time');
plt.ylabel('Power (W)');
plt.title('Observed Kitchen 1 Consumption')
plt.ylim((0,800))
plt.plot(downsampled_timestamp_appliance_date,co_kitchen_power);
```

```
plt.subplot(2,1,1)
plt.title('Actual Kitchen 2 Consumption')
plt.xlabel('Time');
plt.ylabel('Power (W)');
subplots_adjust(hspace=.5);
plt.plot(downsampled_timestamp_appliance_date,downsampled_kitchen_2)
plt.subplot(2,1,2)
plt.xlabel('Time');
plt.ylabel('Power (W)');
plt.title('Observed Kitchen 2 Consumption')
plt.plot(downsampled_timestamp_appliance_date,co_kitchen_2_power);
```

```
plt.subplot(2,1,1)
plt.title('Actual Stove Consumption')
plt.xlabel('Time');
plt.ylabel('Power (W)');
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_stove)
plt.subplot(2,1,2)
plt.xlabel('Time');
plt.ylabel('Power (W)');
plt.title('Predicted Stove Consumption')
plt.plot(downsampled_timestamp_appliance_date,co_stove_power);
```

Calculation of Residual Power and Standard Deviation

```
residual_power_total=sum(np.abs(residual_power_mains_1))
print "Residual Power is: ",residual_power_total," W"
standard_deviation=np.std(residual_power_mains_1)
```

```
print "Standard Deviation is ",standard_deviation
```

Reading original labels of different states for different appliances

```
dummy,labels_stove=np.loadtxt('clustered_stove')
dummy,labels_kitchen=np.loadtxt('clustered_kitchen')
dummy,labels_kitchen_2=np.loadtxt('clustered_kitchen_2')
dummy,labels_dish=np.loadtxt('clustered_dishwasher')
dummy,labels_ref=np.loadtxt('clustered_refrigerator')
dummy,labels_micro=np.loadtxt('clustered_microwave')
dummy,labels_lighting=np.loadtxt('clustered_lighting')
```

```
labels_stove=labels_stove.astype(np.int)
labels_kitchen=labels_kitchen.astype(np.int)
labels_kitchen_2=labels_kitchen_2.astype(np.int)
labels_dish=labels_dish.astype(np.int)
labels_ref=labels_ref.astype(np.int)
labels_micro=labels_micro.astype(np.int)
labels_lighting=labels_lighting.astype(np.int)
```

Next, we define a function to plot the confusion matrix.

```
def print_confusion_matrix(appliance,num_states,true_label,observed_label):
    correct_predicted=0
    conf_arr=[]
    for i in range(num_states):
        counts=[]
        for j in range(num_states):
            idx=np.where(true_label==i)[0]
            counts.append(len(np.where(observed_label[idx]==j)[0]))
        correct_predicted+=counts[i]
        conf_arr.append(counts)

    norm_conf = []
    for i in conf_arr:
        a = 0
        tmp_arr = []
        a = sum(i, 0)
        for j in i:
            tmp_arr.append(float(j)/float(a))
        norm_conf.append(tmp_arr)

    fig = plt.figure()
    plt.clf()
    ax = fig.add_subplot(111)
    ax.set_aspect(1)
    res = ax.imshow(np.array(norm_conf), cmap=plt.cm.jet,
              interpolation='nearest')

    width = len(conf_arr)
    height = len(conf_arr[0])
```

```
    for x in xrange(width):
        for y in xrange(height):
            ax.annotate(str(conf_arr[x][y]), xy=(y, x),
                        horizontalalignment='center',
                        verticalalignment='center')

    cb = fig.colorbar(res)
    alphabet = ['State 1','State 2','State 3']
    plt.title('Confusion Matrix for '+appliance)
    plt.xticks(range(width), alphabet[:width])
    plt.yticks(range(height), alphabet[:height])
    plt.show()
    return correct_predicted*1.0/len(true_label)
```

Plotting the confusion matices for different appliances mains 1

```
stove_accuracy=print_confusion_matrix("stove",len(stove),labels_stove,co_stove_states)
kitchen_accuracy=print_confusion_matrix("kitchen",len(kitchen),labels_kitchen,
    co_kitchen_states)
kitchen_2_accuracy=print_confusion_matrix("kitchen_2",len(kitchen_2),labels_kitchen_2,
    co_kitchen_2_states)
dishwasher_accuracy=print_confusion_matrix("dishwasher",len(dish),labels_dish,
    co_dish_states)
```

We now repeat the same procedure when we take the assumption that the sum of powers of different appliances must be less than or equal to the aggregate power.

```
co_positive_kitchen_states=np.zeros(length_sequence,dtype=np.int)
co_positive_kitchen_power=np.zeros(length_sequence)
co_positive_stove_states=np.zeros(length_sequence,dtype=np.int)
co_positive_stove_power=np.zeros(length_sequence)
co_positive_kitchen_2_states=np.zeros(length_sequence,dtype=np.int)
co_positive_kitchen_2_power=np.zeros(length_sequence)
co_positive_dish_states=np.zeros(length_sequence,dtype=np.int)
co_positive_dish_power=np.zeros(length_sequence)
```

```
for i in range(length_sequence):
    if int(states_idx_positive[i])/18==0:
        co_positive_kitchen_states[i]=0

    else:
        co_positive_kitchen_states[i]=1
    co_positive_kitchen_power[i]=kitchen[co_positive_kitchen_states[i]]

    temp=int(states_idx_positive[i])/9
    if temp%2==0:
        co_positive_stove_states[i]=0
    else:
        co_positive_stove_states[i]=1
```

```
    co_positive_stove_power[i]=stove[co_positive_stove_states[i]]

    temp=int(states_idx_positive[i])/3
    if temp%3==0:
        co_positive_kitchen_2_states[i]=0
    elif temp%3==1:
        co_positive_kitchen_2_states[i]=1
    else:
        co_positive_kitchen_2_states[i]=2
    co_positive_kitchen_2_power[i]=kitchen_2[co_positive_kitchen_2_states[i]]

    temp=int(states_idx_positive[i])%3
    if temp==0:
        co_positive_dish_states[i]=0
    elif temp==1:
        co_positive_dish_states[i]=1
    else:
        co_positive_dish_states[i]=2
    co_positive_dish_power[i]=dish[co_positive_dish_states[i]]
```

```
plt.subplot(2,1,1)
plt.title('Actual Stove Consumption')
plt.xlabel('Time');
plt.ylabel('Power (W)');
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_stove)
plt.subplot(2,1,2)
plt.xlabel('Time');
plt.ylabel('Power (W)');
plt.title('Predicted Stove Consumption (CO Positive)')
plt.plot(downsampled_timestamp_appliance_date,co_positive_stove_power);
```

```
plt.subplot(2,1,1)
plt.title('Actual Dish Washer Consumption')
plt.xlabel('Time');
plt.ylabel('Power (W)');
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_dishwasher)
plt.subplot(2,1,2)
plt.xlabel('Time');
plt.ylabel('Power (W)');
plt.title('Predicted Dish Washer Consumption (CO Positive)')
plt.plot(downsampled_timestamp_appliance_date,co_positive_dish_power);
```

```
plt.subplot(2,1,1)
plt.title('Actual Kitchen Consumption')
plt.xlabel('Time');
plt.ylabel('Power (W)');
plt.plot(downsampled_timestamp_appliance_date,downsampled_kitchen)
plt.subplot(2,1,2)
```

```
plt.title('Predicted Kitchen Consumption (CO Positive)')
plt.xlabel('Time');
plt.ylabel('Power (W)');
subplots_adjust(hspace=.5)
plt.ylim((0,800))
plt.plot(downsampled_timestamp_appliance_date,co_positive_kitchen_power);
```

```
plt.subplot(2,1,1)
plt.title('Actual Kitchen 2 Consumption')
plt.xlabel('Time');
plt.ylabel('Power (W)');
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_kitchen_2)
plt.subplot(2,1,2)
plt.title('Predicted Kitchen 2 Consumption (CO Positive)')
plt.xlabel('Time');
plt.ylabel('Power (W)');
plt.ylim((0,800))
plt.plot(downsampled_timestamp_appliance_date,co_positive_kitchen_2_power);
```

```
stove_positive_accuracy=print_confusion_matrix("stove",len(stove),labels_stove,
    co_positive_stove_states)
kitchen_positive_accuracy=print_confusion_matrix("kitchen",len(kitchen),labels_kitchen,
    co_positive_kitchen_states)
kitchen_positive_2_accuracy=print_confusion_matrix("kitchen_2",len(kitchen_2),
    labels_kitchen_2,co_positive_kitchen_2_states)
dishwasher_positive_accuracy=print_confusion_matrix("dishwasher",len(dish),labels_dish,
    co_positive_dish_states)
```

```
residual_power_positive_total=sum(np.abs(residual_power_mains_1))
```

```
residual_power_total=sum(np.abs(residual_power_positive_total))
print "Residual Power is: ",residual_power_positive_total," W"
standard_deviation=np.std(residual_power_mains_1_positive)
print "Standard Deviation is ",standard_deviation
```

Now we see if we take actual mains as in case 1 how does it affect the results, that is if we do not filter the data, how would result be affected.

```
residual_power_mains_1_actual=np.zeros(len(downsampled_mains_1))
states_idx_actual=np.zeros(len(downsampled_mains_1))
for i in range(len(downsampled_mains_1)):
    [states_idx_actual[i],residual_power_mains_1_actual[i]]=find_nearest_positive(
        sum_combination,downsampled_mains_1[i])
```

```
co_kitchen_actual_states=np.zeros(length_sequence,dtype=np.int)
co_kitchen_actual_power=np.zeros(length_sequence)
co_stove_actual_states=np.zeros(length_sequence,dtype=np.int)
```

```
co_stove_actual_power=np.zeros(length_sequence)
co_kitchen_2_actual_states=np.zeros(length_sequence,dtype=np.int)
co_kitchen_2_actual_power=np.zeros(length_sequence)
co_dish_actual_states=np.zeros(length_sequence,dtype=np.int)
co_dish_actual_power=np.zeros(length_sequence)
```

```
for i in range(length_sequence):
    if int(states_idx_actual[i])/18==0:
        co_kitchen_actual_states[i]=0

    else:
        co_kitchen_actual_states[i]=1
    co_kitchen_actual_power[i]=kitchen[co_kitchen_actual_states[i]]

    temp=int(states_idx_actual[i])/9
    if temp%2==0:
        co_stove_actual_states[i]=0
    else:
        co_stove_actual_states[i]=1
    co_stove_actual_power[i]=stove[co_stove_actual_states[i]]

    temp=int(states_idx_actual[i])/3
    if temp%3==0:
        co_kitchen_2_actual_states[i]=0
    elif temp%3==1:
        co_kitchen_2_actual_states[i]=1
    else:
        co_kitchen_2_actual_states[i]=2
    co_kitchen_2_actual_power[i]=kitchen_2[co_kitchen_2_actual_states[i]]

    temp=int(states_idx_actual[i])%3
    if temp==0:
        co_dish_actual_states[i]=0
    elif temp==1:
        co_dish_actual_states[i]=1
    else:
        co_dish_actual_states[i]=2
    co_dish_actual_power[i]=dish[co_dish_actual_states[i]]
```

```
plt.subplot(2,1,1)
plt.title('Actual Stove Consumption')
plt.xlabel('Time');
plt.ylabel('Power (W)');
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_stove)
plt.subplot(2,1,2)
plt.xlabel('Time');
plt.ylabel('Power (W)');
plt.title('Predicted Stove Consumption')
plt.plot(downsampled_timestamp_appliance_date,co_positive_stove_power);
```

```
plt.subplot(2,1,1)
plt.title('Actual Dish Washer Consumption')
plt.xlabel('Time');
plt.ylabel('Power (W)');
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_dishwasher)
plt.subplot(2,1,2)
plt.xlabel('Time');
plt.ylabel('Power (W)');
plt.title('Predicted Dish Washer Consumption (CO Positive)')
plt.plot(downsampled_timestamp_appliance_date,co_positive_dish_power);
```

```
plt.subplot(2,1,1)
plt.title('Actual Kitchen 2 Consumption')
plt.xlabel('Time');
plt.ylabel('Power (W)');
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_kitchen_2)
plt.subplot(2,1,2)
plt.title('Predicted Kitchen 2 Consumption (CO Positive)')
plt.xlabel('Time');
plt.ylabel('Power (W)');
plt.ylim((0,800))
plt.plot(downsampled_timestamp_appliance_date,co_positive_kitchen_2_power);
```

```
stove_positive_accuracy=print_confusion_matrix("stove",len(stove),labels_stove,
    co_positive_stove_states)
kitchen_positive_accuracy=print_confusion_matrix("kitchen",len(kitchen),labels_kitchen,
    co_positive_kitchen_states)
kitchen_positive_2_accuracy=print_confusion_matrix("kitchen_2",len(kitchen_2),
    labels_kitchen_2,co_positive_kitchen_2_states)
dishwasher_positive_accuracy=print_confusion_matrix("dishwasher",len(dish),labels_dish,
    co_positive_dish_states)
```

We now do the same analysis for Mains 2 as we did for Mains 1.

Distribution of states space

```
states_combination_2=list(itertools.product(ref,lighting,micro))
print "Possible state combinations for Mains2 are\nRef.,Lighting,Microwave\n",
    states_combination_2
```

```
sum_combination_2=np.array(np.zeros(len(states_combination_2)))
for i in range(0,len(states_combination_2)):
    sum_combination_2[i]=sum(states_combination_2[i])
from copy import deepcopy
b=deepcopy(sum_combination_2)
b.sort()
grid(True);
title('Sorted possible sums of all appliances');
```

```
xlabel('Combinations');
ylabel('Power (W)');
plot(b);
```

```
title('Histogram showing relative frequencies of different state combinations');
hist(b,100);
```

```
length_sequence=len(filtered_downsampled_mains_2)
co_ref_states=np.zeros(length_sequence,dtype=np.int)
co_ref_power=np.zeros(length_sequence)
co_micro_states=np.zeros(length_sequence,dtype=np.int)
co_micro_power=np.zeros(length_sequence)
co_lighting_states=np.zeros(length_sequence,dtype=np.int)
co_lighting_power=np.zeros(length_sequence)
```

```
for i in range(len(filtered_downsampled_mains_2)):
    [states_idx_2[i],residual_power_mains_2[i]]=find_nearest(sum_combination_2,
        filtered_downsampled_mains_2[i])
```

```
title('Residual Power Mains 2');
xlabel('Time');
ylabel('Power (W)');
plot(residual_power_mains_2);
```

```
for i in range(length_sequence):
    if int(states_idx_2[i])/9==0:
        co_ref_states[i]=0

    elif int(states_idx_2[i])/9==1:
        co_ref_states[i]=1
    else:
        co_ref_states[i]=2
    co_ref_power[i]=ref[co_ref_states[i]]

    temp=int(states_idx_2[i])/3
    if temp%3==0:
        co_lighting_states[i]=0
    elif temp%3==1:
        co_lighting_states[i]=1
    else:
        co_lighting_states[i]=2
    co_lighting_power[i]=lighting[co_lighting_states[i]]

    temp=int(states_idx_2[i])%3
    if temp==0:
        co_micro_states[i]=0
    elif temp==1:
        co_micro_states[i]=1
    else:
```

```
        co_micro_states[i]=2
    co_micro_power[i]=micro[co_micro_states[i]]
```

```
plt.subplot(2,1,1)
ylim((0,1000))
plt.title('Actual Ref Consumption')
plt.xlabel('Time');
plt.ylabel('Power (W)');
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_refrigerator)
plt.subplot(2,1,2)
plt.xlabel('Time');
plt.ylabel('Power (W)');
plt.title('Predicted Ref Consumption (CO)')
plt.plot(downsampled_timestamp_appliance_date,co_ref_power);
```

```
plt.subplot(2,1,1)
plt.title('Actual Lighting Consumption')
plt.xlabel('Time');
plt.ylabel('Power (W)');
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_lighting)
plt.subplot(2,1,2)
plt.title('Predicted Lighting Consumption (CO)')
plt.xlabel('Time');
plt.ylabel('Power (W)');
plt.ylim((0,200))
plt.plot(downsampled_timestamp_appliance_date,co_lighting_power);
```

```
plt.subplot(2,1,1)
plt.title('Actual Microwave Consumption')
plt.xlabel('Time');
plt.ylabel('Power (W)');
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_microwave)
plt.subplot(2,1,2)
plt.xlabel('Time');
plt.ylabel('Power (W)');
plt.title('Predicted Microwave Consumption (CO)')

plt.plot(downsampled_timestamp_appliance_date,co_micro_power);
```

```
ref_accuracy=print_confusion_matrix("Ref",len(ref),labels_ref,co_ref_states)
micro_accuracy=print_confusion_matrix("Micro",len(micro),labels_micro,co_micro_states)
lighting_accuracy=print_confusion_matrix("Lighting",len(lighting),labels_lighting,
    co_lighting_states)
```

TODO: Violation of switch continuity principle

1.7 Discrete Hidden Markov Model

```
import sys
sys.path.append('/home/nipun/git/PyHMM/src')
from dhmm_em import dhmm_em
```

Using EM algorithm, we try to learn HMM parameters for different appliances.

```
# For Stove which is two state, we try to learn the parameters using Baum
stove_prior=np.array([0.8,0.2])
stove_transmat=np.array([[0.9,0.1],[0.1,0.9]])
stove_emission=np.array([[.9,.1],[0.1,0.9]])
[LL, stove_learnt_prior, stove_learnt_transmat, stove_learnt_obsmat,nr_iter] = dhmm_em([
    labels_stove], stove_prior, stove_transmat, stove_emission, 3500,.0000001 );
```

```
title('Log Likelihood vs Iterations for Stove');
xlabel('Iterations');
ylabel('Log Likelihood');
plot(LL);
```

```
def print_hmm_parameters(obsmat,prior,transmat):
    print "Learnt HMM Parameters\nObservation Matrix ",obsmat,"\nPrior ",prior," \
        nTransition Matrix ",transmat
```

```
print_hmm_parameters(stove_learnt_obsmat,stove_learnt_prior,stove_learnt_transmat)
```

```
# For Stove which is two state, we try to learn the parameters using Baum
ref_prior=np.array([0.9,0.05,0.05])
ref_transmat=np.array([[0.95,0.05,0],[0.05,0.9,0.05],[0.05,0.05,.9]])
ref_emission=np.array([[.99,.01,0],[0.05,0.9,.05],[0.05,0.05,.9]])
[LL, ref_learnt_prior, ref_learnt_transmat, ref_learnt_obsmat,nr_iter] = dhmm_em([
    labels_ref], ref_prior, ref_transmat, ref_emission, 3500,.0000001 );
```

```
title('Log Likelihood vs Iterations for Ref.');
xlabel('Iterations');
ylabel('Log Likelihood');
plot(LL);
```

```
print_hmm_parameters(ref_learnt_obsmat,ref_learnt_prior,ref_learnt_transmat)
```

```
# For Stove which is two state, we try to learn the parameters using Baum
micro_prior=np.array([0.9,0.05,0.05])
micro_transmat=np.array([[0.95,0.05,0],[0.05,0.9,0.05],[0.05,0.05,.9]])
micro_emission=np.array([[.99,.01,0],[0.05,0.9,.05],[0.05,0.05,.9]])
[LL, micro_learnt_prior, micro_learnt_transmat, micro_learnt_obsmat,nr_iter] = dhmm_em([
    labels_micro], micro_prior, micro_transmat, micro_emission, 3500,.0000001 );
```

```
title('Log Likelihood vs Iterations for Micro');
xlabel('Iterations');
ylabel('Log Likelihood');
plot(LL);
```

```
print_hmm_parameters(micro_learnt_obsmat,micro_learnt_prior,micro_learnt_transmat)
```

```
# For Stove which is two state, we try to learn the parameters using Baum
lighting_prior=np.array([0.9,0.05,0.05])
lighting_transmat=np.array([[0.95,0.05,0],[0.05,0.9,0.05],[0.05,0.05,.9]])
lighting_emission=np.array([[.99,.01,0],[0.05,0.9,.05],[0.05,0.05,.9]])
[LL, lighting_learnt_prior, lighting_learnt_transmat, lighting_learnt_obsmat,nr_iter] =
    dhmm_em([labels_lighting], lighting_prior, lighting_transmat, lighting_emission,
    3500,.0000001 );
```

```
title('Log Likelihood vs Iterations for Lighting');
xlabel('Iterations');
ylabel('Log Likelihood');
plot(LL);
```

```
print_hmm_parameters(lighting_learnt_obsmat,lighting_learnt_prior,
    lighting_learnt_transmat)
```

```
# For Stove which is two state, we try to learn the parameters using Baum
dishwasher_prior=np.array([0.9,0.05,0.05])
dishwasher_transmat=np.array([[0.95,0.05,0],[0.05,0.9,0.05],[0.05,0.05,.9]])
dishwasher_emission=np.array([[.99,.01,0],[0.05,0.9,.05],[0.05,0.05,.9]])
[LL, dishwasher_learnt_prior, dishwasher_learnt_transmat, dishwasher_learnt_obsmat,
    nr_iter] = dhmm_em([labels_dish], dishwasher_prior, dishwasher_transmat,
    dishwasher_emission, 3500,.0000001 );
```

```
title('Log Likelihood vs Iterations for Dishwasher');
xlabel('Iterations');
ylabel('Log Likelihood');
plot(LL);
```

```
print_hmm_parameters(dishwasher_learnt_obsmat,dishwasher_learnt_prior,
    dishwasher_learnt_transmat)
```

```
# For Stove which is two state, we try to learn the parameters using Baum
kitchen_2_prior=np.array([0.9,0.05,0.05])
kitchen_2_transmat=np.array([[0.95,0.05,0],[0.05,0.9,0.05],[0.05,0.05,.9]])
kitchen_2_emission=np.array([[.99,.01,0],[0.05,0.9,.05],[0.05,0.05,.9]])
[LL, kichen_2_learnt_prior, kitchen_2_learnt_transmat, kitchen_2_learnt_obsmat,nr_iter]
    = dhmm_em([labels_kitchen_2], kitchen_2_prior, kitchen_2_transmat, kitchen_2_emission
    , 3500,.0000001 );
```

```
title('Log Likelihood vs Iterations for Kitchen 2');
xlabel('Iterations');
ylabel('Log Likelihood');
plot(LL);
```

```
print_hmm_parameters(kitchen_2_learnt_obsmat,kichen_2_learnt_prior,
    kitchen_2_learnt_transmat)
```

```
# For Stove which is two state, we try to learn the parameters using Baum
kitchen_prior=np.array([0.95,0.05])
kitchen_transmat=np.array([[0.95,0.05],[0.05,0.95]])
kitchen_emission=np.array([[.99,.01],[0.01,0.99]])
[LL, kitchen_learnt_prior, kitchen_learnt_transmat, kitchen_learnt_obsmat,nr_iter] =
    dhmm_em([labels_kitchen], kitchen_prior, kitchen_transmat, kitchen_emission,
    3500,.0000001 );
```

```
title('Log Likelihood vs Iterations for Kitchen');
xlabel('Iterations');
ylabel('Log Likelihood');
plot(LL);
```

```
print_hmm_parameters(kitchen_learnt_obsmat,kitchen_learnt_prior,kitchen_learnt_transmat)
```

1.8 Creating FHMM

Combining different states according to technique used for FHMM. We define functions for combining constituent priors into prior for FHMM and similarly for Transition and Emission matrices.

For mains 2

```
def calculate_combined_pie(ordered_list_appliance_pies):
    total_series=len(ordered_list_appliance_pies)
    result=np.array(ordered_list_appliance_pies[0])
    for i in range(total_series-1):
        m=np.vstack(result.flatten())
        size_n=len(ordered_list_appliance_pies[i+1])
        n=np.reshape(ordered_list_appliance_pies[i+1],(1,size_n))
        result=np.dot(m,n)
    return result.flatten()
```

```
pie_combined=calculate_combined_pie([ref_learnt_prior,lighting_learnt_prior,
    micro_learnt_prior])
```

Combining the transition matrices and the emission matrices. It should be seen that it can be done by Kronecker multiplication.

```
def calculate_combined_A(ordered_transmat_list):
    total_series=len(ordered_transmat_list)
```

```
    result=ordered_transmat_list[0]
    for i in range(total_series-1):
        result=np.kron(result,ordered_transmat_list[i+1])
    return result
```

```
A_combined=calculate_combined_A([ref_learnt_transmat,lighting_learnt_transmat,
    micro_learnt_transmat])
A_combined.shape
B_combined=calculate_combined_A([ref_learnt_obsmat,lighting_learnt_obsmat,
    micro_learnt_obsmat])
B_combined.shape
```

Now Viterbi algorithm is used to decode the most likely sequence.

```
from viterbi_path import path;
```

We plot the predicted state sequence and compare against observed state sequence.

```
title('Observed State Sequence');
plot(states_idx_2);
```

We now see the observations and map them from 0 to 26 based on closeness to the total power in those cases.

```
viterbi_produced_path=path(pie_combined,A_combined,B_combined,states_idx_2)
path_produced=viterbi_produced_path[0]
```

```
title('Predicted State Sequence according to Viterbi');
plot(path_produced);
```

```
length_sequence=len(filtered_downsampled_mains_2)
hmm_ref_states=np.zeros(length_sequence,dtype=np.int)
hmm_ref_power=np.zeros(length_sequence)
hmm_micro_states=np.zeros(length_sequence,dtype=np.int)
hmm_micro_power=np.zeros(length_sequence)
hmm_lighting_states=np.zeros(length_sequence,dtype=np.int)
hmm_lighting_power=np.zeros(length_sequence)
```

```
for i in range(length_sequence):
    if int(path_produced[i])/9==0:
        hmm_ref_states[i]=0

    elif int(path_produced[i])/9==1:
        hmm_ref_states[i]=1
    else:
        hmm_ref_states[i]=2
    hmm_ref_power[i]=ref[hmm_ref_states[i]]
```

```
    temp=int(path_produced[i])/3
    if temp%3==0:
        hmm_lighting_states[i]=0
    elif temp%3==1:
        hmm_lighting_states[i]=1
    else:
        hmm_lighting_states[i]=2
    hmm_lighting_power[i]=lighting[hmm_lighting_states[i]]

    temp=int(path_produced[i])%3
    if temp==0:
        hmm_micro_states[i]=0
    elif temp==1:
        hmm_micro_states[i]=1
    else:
        hmm_micro_states[i]=2
    hmm_micro_power[i]=micro[hmm_micro_states[i]]
```

```
plt.subplot(3,1,1)
ylim((0,1000))
plt.title('Actual Ref Consumption')
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_refrigerator)
plt.subplot(3,1,2)
plt.title('Predicted Ref Consumption (FHMM)')
plt.plot(downsampled_timestamp_appliance_date,hmm_ref_power);
plt.subplot(3,1,3)
plt.title('Predicted Ref Consumption (CO)')
plt.plot(downsampled_timestamp_appliance_date,co_ref_power);
```

```
plt.subplot(3,1,1)
plt.title('Actual Lighting Consumption')
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_lighting)
plt.subplot(3,1,2)
plt.ylim((0,200))
plt.title('Predicted Lighting Consumption (FHMM)')
plt.plot(downsampled_timestamp_appliance_date,hmm_lighting_power);
plt.subplot(3,1,3)
plt.ylim((0,200))
plt.title('Predicted Lighting Consumption (CO)')
plt.plot(downsampled_timestamp_appliance_date,co_lighting_power);
```

```
plt.subplot(3,1,1)
plt.title('Actual Micro Consumption')
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_microwave)
plt.subplot(3,1,2)
plt.title('Predicted Micro Consumption (FHMM)')
plt.plot(downsampled_timestamp_appliance_date,hmm_micro_power);
```

```
plt.subplot(3,1,3)
plt.title('Predicted Micro Consumption (CO)')
plt.plot(downsampled_timestamp_appliance_date,co_micro_power);
```

```
ref_accuracy=print_confusion_matrix("Ref",len(ref),labels_ref,hmm_ref_states)
micro_accuracy=print_confusion_matrix("Micro",len(micro),labels_micro,hmm_micro_states)
lighting_accuracy=print_confusion_matrix("Lighting",len(lighting),labels_lighting,
    hmm_lighting_states)
```

We do a similar analysis for Mains 1.

```
pie_combined_1=calculate_combined_pie([kitchen_learnt_prior,stove_learnt_prior,
    kitchen_2_prior,dishwasher_learnt_prior])
A_combined_1=calculate_combined_A([kitchen_learnt_transmat,stove_learnt_transmat,
    kitchen_2_transmat,dishwasher_learnt_transmat])
B_combined_1=calculate_combined_A([kitchen_learnt_obsmat,stove_learnt_obsmat,
    kitchen_2_learnt_obsmat,dishwasher_learnt_obsmat])
```

```
viterbi_produced_path_1=path(pie_combined_1,A_combined_1,B_combined_1,states_idx)
path_produced_1=viterbi_produced_path_1[0]
```

```
hmm_kitchen_actual_states=np.zeros(length_sequence,dtype=np.int)
hmm_kitchen_actual_power=np.zeros(length_sequence)
hmm_stove_actual_states=np.zeros(length_sequence,dtype=np.int)
hmm_stove_actual_power=np.zeros(length_sequence)
hmm_kitchen_2_actual_states=np.zeros(length_sequence,dtype=np.int)
hmm_kitchen_2_actual_power=np.zeros(length_sequence)
hmm_dish_actual_states=np.zeros(length_sequence,dtype=np.int)
hmm_dish_actual_power=np.zeros(length_sequence)
```

```
for i in range(length_sequence):
    if int(path_produced_1[i])/18==0:
        hmm_kitchen_actual_states[i]=0

    else:
        hmm_kitchen_actual_states[i]=1
    hmm_kitchen_actual_power[i]=kitchen[hmm_kitchen_actual_states[i]]

    temp=int(path_produced_1[i])/9
    if temp%2==0:
        hmm_stove_actual_states[i]=0
    else:
        hmm_stove_actual_states[i]=1
    hmm_stove_actual_power[i]=stove[hmm_stove_actual_states[i]]

    temp=int(path_produced_1[i])/3
    if temp%3==0:
        hmm_kitchen_2_actual_states[i]=0
    elif temp%3==1:
```

```
        hmm_kitchen_2_actual_states[i]=1
    else:
        hmm_kitchen_2_actual_states[i]=2
    hmm_kitchen_2_actual_power[i]=kitchen_2[hmm_kitchen_2_actual_states[i]]

    temp=int(path_produced_1[i])%3
    if temp==0:
        hmm_dish_actual_states[i]=0
    elif temp==1:
        hmm_dish_actual_states[i]=1
    else:
        hmm_dish_actual_states[i]=2
    hmm_dish_actual_power[i]=dish[hmm_dish_actual_states[i]]
```

```
plt.subplot(3,1,1)
ylim((0,1000))
plt.title('Actual Kitchen Consumption')
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_kitchen)
plt.subplot(3,1,2)
ylim((0,1000))
plt.title('Predicted Kitchen Consumption (FHMM)')
plt.plot(downsampled_timestamp_appliance_date,hmm_kitchen_actual_power);
plt.subplot(3,1,3)
ylim((0,1000))
plt.title('Predicted Kitchen Consumption (CO)')
plt.plot(downsampled_timestamp_appliance_date,co_kitchen_power);
```

```
plt.subplot(3,1,1)
ylim((0,1000))
plt.title('Actual Kitchen 2 Consumption')
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_kitchen_2)
plt.subplot(3,1,2)
ylim((0,1000))
plt.title('Predicted Kitchen 2 Consumption (FHMM)')
plt.plot(downsampled_timestamp_appliance_date,hmm_kitchen_2_actual_power);
plt.subplot(3,1,3)
ylim((0,1000))
plt.title('Predicted Kitchen 2 Consumption (CO)')
plt.plot(downsampled_timestamp_appliance_date,co_kitchen_2_power);
```

```
plt.subplot(3,1,1)
plt.title('Actual Stove Consumption')
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_stove)
plt.subplot(3,1,2)
plt.title('Predicted Stove Consumption (FHMM)')
plt.plot(downsampled_timestamp_appliance_date,hmm_stove_actual_power);
plt.subplot(3,1,3)
```

```
plt.title('Predicted Stove Consumption (CO)')
plt.plot(downsampled_timestamp_appliance_date,co_stove_power);
```

```
plt.subplot(3,1,1)
plt.title('Actual Dishwasher Consumption')
subplots_adjust(hspace=.5)
plt.plot(downsampled_timestamp_appliance_date,downsampled_dishwasher)
plt.subplot(3,1,2)
plt.title('Predicted Dishwasher Consumption (FHMM)')
plt.plot(downsampled_timestamp_appliance_date,hmm_dish_actual_power);
plt.subplot(3,1,3)
plt.title('Predicted Dishwasher Consumption (CO)')
plt.plot(downsampled_timestamp_appliance_date,co_dish_power);
```

```
kitchen_accuracy=print_confusion_matrix("Kitchen",len(kitchen),labels_kitchen,
    hmm_kitchen_actual_states)
kitchen_2_accuracy=print_confusion_matrix("Kitchen 2",len(kitchen_2),labels_kitchen_2,
    hmm_kitchen_2_actual_states)
stove_accuracy=print_confusion_matrix("Stove",len(stove),labels_stove,
    hmm_stove_actual_states)
dish_accuracy=print_confusion_matrix("Dish Washer",len(dish),labels_dish,
    hmm_dish_actual_states)
```

We now compare the accuracies of the two approaches across different mains circuits.

```
plt.title('Disaggregation Accuracy for Mains 1');
plt.ylabel('Accuracy')
plt.ylim((50,100))
plt.bar( numpy.arange(4) * 2, [98.0501392758,92.9649543305,98.5489408564,97.324609704],
    color = 'red' );
plt.bar( numpy.arange(4) * 2 +0.8, [97.58,96.25,99.31,98.7], color = 'green' );
locs, labels = xticks();
xticks(locs+1, ('Kitchen',' ', 'Kitchen 2',' ', 'Stove',' ', 'Dishwasher'));
plt.legend(('FHMM','CO'),);
#set_xticklabels( ('G1', 'G2', 'G3', 'G4') )
```

```
plt.title('Disaggregation Accuracy for Mains 2');
plt.ylabel('Accuracy')
plt.ylim((50,100))
plt.bar( numpy.arange(3) * 2, [91.03,93.03,82.8], color = 'red' );
plt.bar( numpy.arange(3) * 2 +0.8, [93.29,93.54,82.2], color = 'green' );
locs, labels = xticks();
xticks(locs+1, ('Refrigerator',' ', 'Microwave',' ', 'Lighting'));
plt.legend(('FHMM','CO'),);
```