In [1]:

```
# from nilm_metadata import get_appliance_types
# appliance_types = get_appliance_types()
# print(appliance_types)

# import os
# os.getcwd()
```

Carregando bibliotecas...

In [1]:

```
!pip install seaborn

import seaborn as sns

from matplotlib import rcParams
import matplotlib.pyplot as plt
import pandas as pd
import nilmtk
from nilmtk import MeterGroup
from nilmtk.api import API
import warnings
warnings.filterwarnings("ignore")

plt.style.use('ggplot')
rcParams['figure.figsize'] = (13, 10)

# import pathlib
# pathlib.Path().resolve()
```

```
Requirement already satisfied: seaborn in ./miniconda3/envs/nilm_0.4.
3/lib/python3.7/site-packages (0.11.2)
Requirement already satisfied: scipy>=1.0 in ./miniconda3/envs/nilm_0.
4.3/lib/python3.7/site-packages (from seaborn) (1.7.1)
Requirement already satisfied: numpy>=1.15 in ./miniconda3/envs/nilm_
0.4.3/lib/python3.7/site-packages (from seaborn) (1.19.5)
Requirement already satisfied: matplotlib>=2.2 in ./miniconda3/envs/ni
lm_0.4.3/lib/python3.7/site-packages (from seaborn) (3.1.3)
Requirement already satisfied: pandas>=0.23 in ./miniconda3/envs/nilm_
0.4.3/lib/python3.7/site-packages (from seaborn) (0.25.3)
Requirement already satisfied: cycler>=0.10 in ./miniconda3/envs/nilm_
0.4.3/lib/python3.7/site-packages (from matplotlib>=2.2->seaborn) (0.1
0.0)
Requirement already satisfied: python-dateutil>=2.1 in ./miniconda3/en
vs/nilm_0.4.3/lib/python3.7/site-packages (from matplotlib>=2.2->seabo
rn) (2.8.2)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.
1 in ./miniconda3/envs/nilm_0.4.3/lib/python3.7/site-packages (from ma
tplotlib>=2.2->seaborn) (2.4.7)
Requirement already satisfied: kiwisolver>=1.0.1 in ./miniconda3/envs/
nilm_0.4.3/lib/python3.7/site-packages (from matplotlib>=2.2->seaborn)
(1.3.2)
Requirement already satisfied: six in ./miniconda3/envs/nilm_0.4.3/li
b/python3.7/site-packages (from cycler>=0.10->matplotlib>=2.2->seabor
n) (1.16.0)
Requirement already satisfied: pytz>=2017.2 in ./miniconda3/envs/nilm_
0.4.3/lib/python3.7/site-packages (from pandas>=0.23->seaborn) (2021.
1)
```

Converter

In [3]:

```
# from nilmtk.dataset_converters import convert_hb
# convert_hb('./BD/CASA/convert', './data/teste17.h5')
```

In [4]:

```
# st = pd.HDFStore("./data/teste17.h5")
# print (st.keys())

# print (st['/building1/elec/meter1'].head())
# print (st['/building1/elec/meter2'].head())
# print (st['/building1/elec/meter3'].head())

# st.close()
```

Carregando dataset

In [2]:

```
from nilmtk.api import API
import warnings
warnings.filterwarnings("ignore")

from nilmtk import DataSet
from nilmtk.utils import print_dict

hb = DataSet('teste10.h5')
#iawe = DataSet('/data/iawe.h5')

print_dict(hb.metadata)
print_dict(hb.buildings)
```

- **name**: REDD
- **long_name**: The Reference Energy Disaggregation Data set
- **creators**:
  - Kolter, Zico
  - Johnson, Matthew
- **publication_date**: 2011
- **institution**: Massachusetts Institute of Technology (MIT)
- **contact**: zkolter@cs.cmu.edu
- **description**: Several weeks of power data for 6 different homes.
- **subject**: Disaggregated power demand from domestic buildings.
- **number_of_buildings**: 1
- **timezone**: US/Eastern
- **geo_location**:
  - **locality**: Massachusetts
  - **country**: US
  - **latitude**: 42.360091
  - **longitude**: -71.09416
- **related_documents**:
  - http://redd.csail.mit.edu (http://redd.csail.mit.edu)
  - J. Zico Kolter and Matthew J. Johnson. REDD: A public data set for energy disaggregation research. In proceedings of the SustKDD workshop on Data Mining Applications in Sustainability, 2011. http://redd.csail.mit.edu/kolter-kddsust11.pdf (http://redd.csail.mit.edu/kolter-kddsust11.pdf)
- **schema**: https://github.com/nilmtk/nilm_metadata/tree/v0.2 (https://github.com/nilmtk/nilm_metadata/tree/v0.2)
- **meter_devices**:
  - **eMonitor**:
    - **model**: eMonitor
    - **manufacturer**: Powerhouse Dynamics
    - **manufacturer_url**: http://powerhousedynamics.com (http://powerhousedynamics.com)
    - **description**: Measures circuit-level power demand. Comes with 24 CTs. This FAQ page suggests the eMonitor measures real (active) power: http://www.energycircle.com/node/14103 (http://www.energycircle.com/node/14103) although the REDD readme.txt says all channels record apparent power.
    - **sample_period**: 5
    - **max_sample_period**: 30
    - **measurements**:

    - {'physical_quantity': 'power', 'type': 'active', 'upper_limit': 1142, 'lower_limit': 0}
    - {'physical_quantity': 'power', 'type': 'apparent', 'upper_limit': 1215, 'lower_limit': 0}
    - {'physical_quantity': 'power', 'type': 'reactive', 'upper_limit': 901, 'lower_limit': 0}
    - {'physical_quantity': 'power factor', 'upper_limit': 1, 'lower_limit': 0}
    - {'physical_quantity': 'voltage', 'upper_limit': 232, 'lower_limit': 0}
    - {'physical_quantity': 'current', 'upper_limit': 6, 'lower_limit': 0}
  - **wireless**: False
- **REDD_whole_house**:
  - **description**: REDD's DIY power meter used to measure whole-home AC waveforms at high frequency. To quote from their paper: "CTs from TED (http://www.theenergydetective.com (http://www.theenergydetective.com)) to measure current in the power mains, a Pico TA041 oscilloscope probe (http://www.picotechnologies.com (http://www.picotechnologies.com)) to measure voltage for one of the two phases in the home, and a National Instruments NI-9239 analog to digital converter to transform both these analog signals to digital readings. This A/D converter has 24 bit resolution with noise of approximately 70 µV, which determines the noise level of our current and voltage readings: the TED CTs are rated for 200 amp circuits and a maximum of 3 volts, so we are able to differentiate between currents of approximately ((200))(70 × 10−6)/(3) = 4.66mA, corresponding to power changes of about 0.5 watts. Similarly, since we use a 1:100 voltage stepdown in the oscilloscope probe, we can detect voltage differences of about 7mV."
  - **sample_period**: 0.5
  - **max_sample_period**: 30
  - **measurements**:
    - {'physical_quantity': 'voltage', 'upper_limit': 230, 'lower_limit': 0}
    - {'physical_quantity': 'current', 'upper_limit': 15, 'lower_limit': 0}
    - {'physical_quantity': 'power', 'type': 'active', 'upper_limit': 3016, 'lower_limit': 0}
    - {'physical_quantity': 'frequency', 'upper_limit': 61, 'lower_limit': 0}
    - {'physical_quantity': 'power factor', 'upper_limit': 1, 'lower_limit': 0}
  - **wireless**: False

- **1**: Building(instance=1, dataset='REDD')

Gráfico Geral

In [6]:

```
build = 1
elec = hb.buildings[build].elec
elec.mains().power_series_all_data().head()
```

Out[6]:

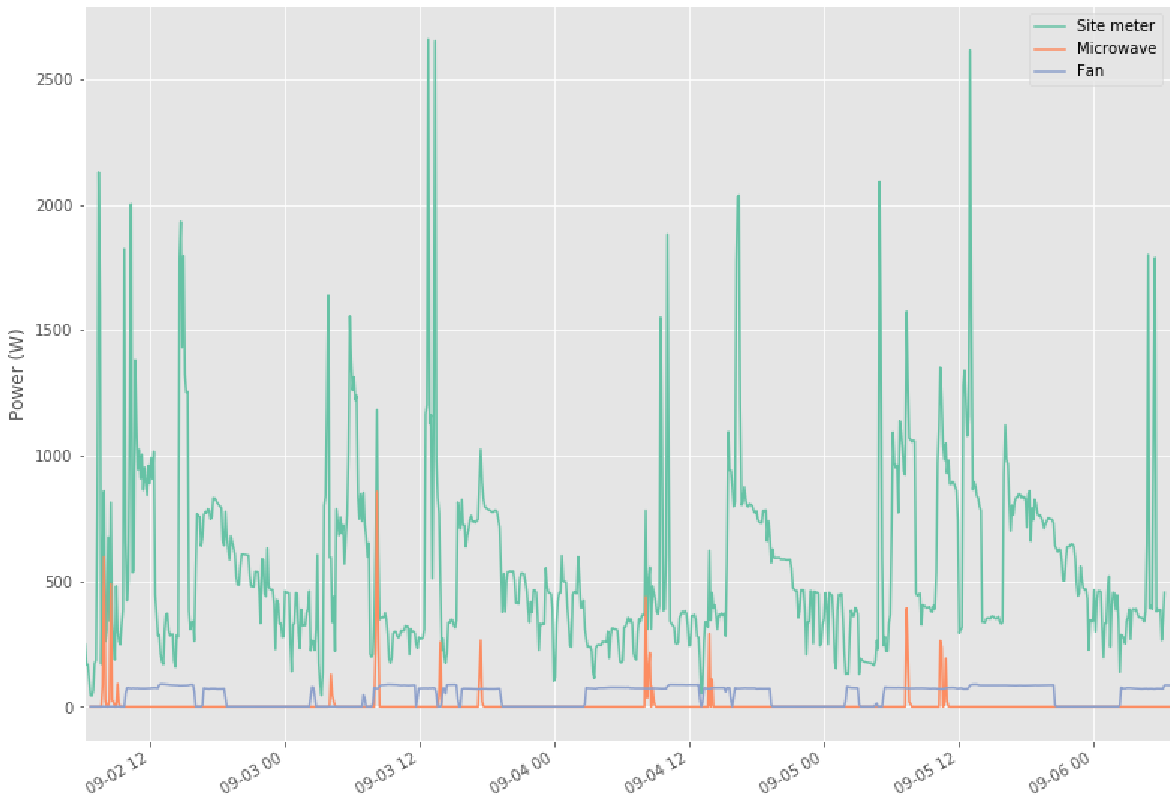
```
2021-09-02 06:14:34-04:00    167.199997
2021-09-02 06:14:35-04:00    167.199997
2021-09-02 06:14:35-04:00    167.199997
2021-09-02 06:14:36-04:00    167.199997
2021-09-02 06:14:36-04:00    166.899994
Name: (power, active), dtype: float32
```

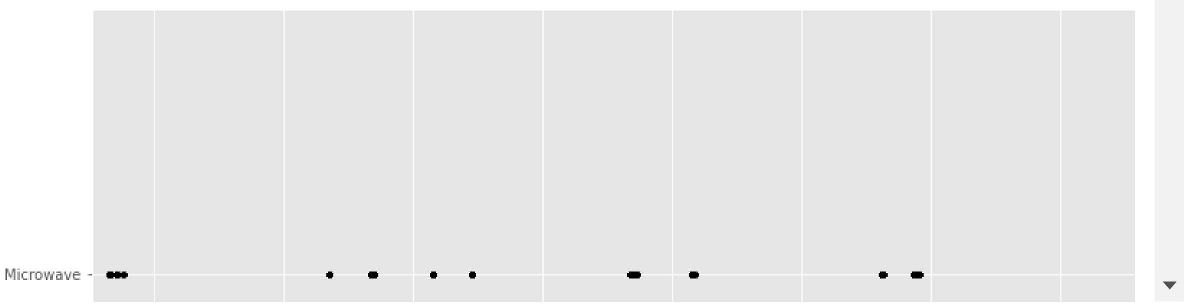
In [7]:

```
sns.set_palette("Set2", n_colors=5)
elec.mains().plot()
elec['microwave'].plot()
elec['fan'].plot()

# Set a threshold to remove residual power noise when devices are off
elec.plot_when_on(on_power_threshold = 40) # Plot appliances when they are in use¶

# elec.draw_wiring_graph()
```

Out[7]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fab4bfba510>





Dados

Proporção de energia submedida

In [8]:

```
elec.proportion_of_energy_submetered()
```

```
Running MeterGroup.proportion_of_energy_submetered...
```

Out[8]:

```
0.0928835042370596
```

Total Energy

In [9]:

```
elec.mains().total_energy()
```

Out[9]:

```
active    53.945461
dtype: float64
```

Energy per submeter

In [10]:

```
energy_per_meter = elec.submeters().energy_per_meter() # kWh, again
energy_per_meter
```

```
2/2 ElecMeter(instance=3, building=1, dataset='REDD', appliances=[Appl
iance(type='microwave', instance=1)])
```

Out[10]:

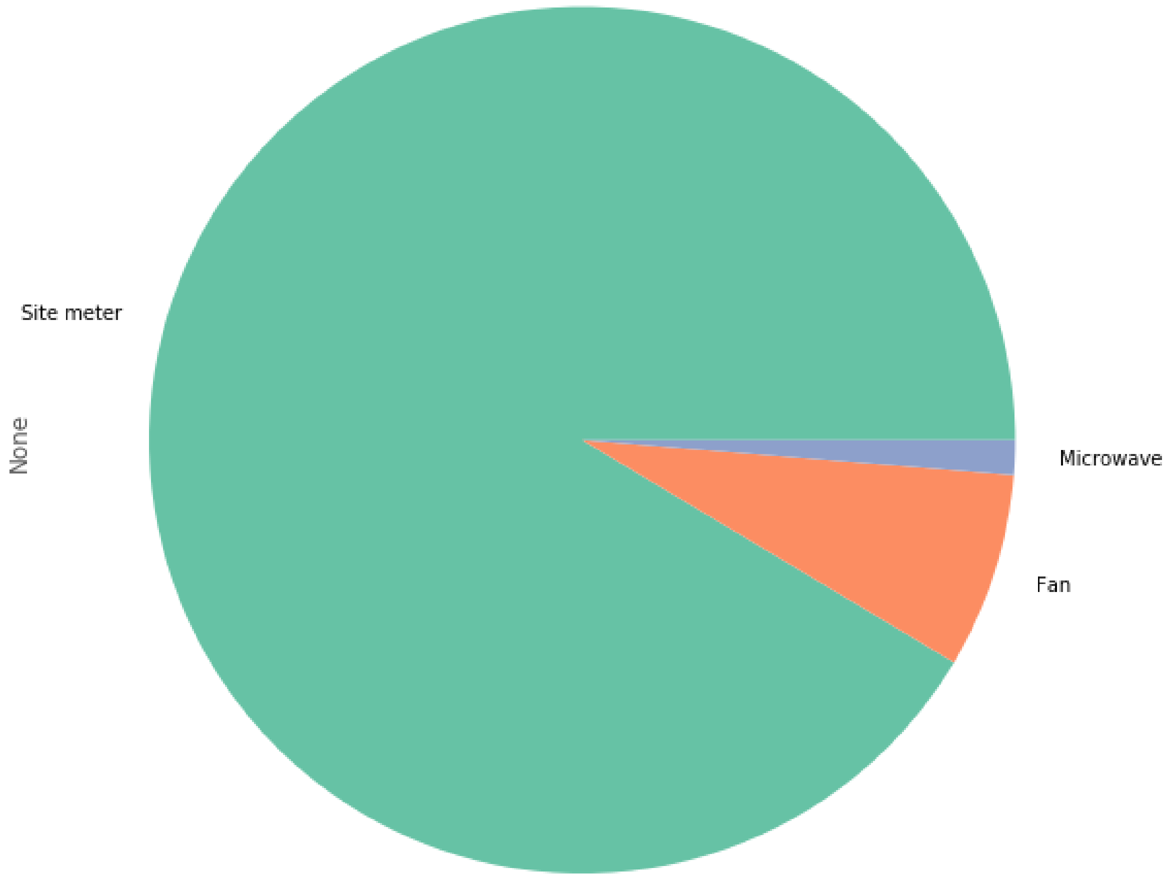
	(2, 1, REDD)	(3, 1, REDD)
active	4.298278	0.757815
apparent	NaN	NaN
reactive	NaN	NaN

Plot fraction of energy consumption of each appliance

In [11]:

```
# fraction = elec.submeters().fraction_per_meter().dropna()
fraction = elec.fraction_per_meter().dropna()
# Create convenient labels
labels = elec.get_labels(fraction.index)
plt.figure(figsize=(10,30))
fraction.plot(kind='pie', labels=labels);
```

```
3/3 ElecMeter(instance=3, building=1, dataset='REDD', appliances=[Appl
iance(type='microwave', instance=1)])
```



Quadro Geral

In [12]:

```
print(elec)
elec.mains()
```

```
MeterGroup(meters=
  ElecMeter(instance=1, building=1, dataset='REDD', site_meter, applia
nces=[])
  ElecMeter(instance=2, building=1, dataset='REDD', appliances=[Applia
nce(type='fan', instance=1)])
  ElecMeter(instance=3, building=1, dataset='REDD', appliances=[Applia
nce(type='microwave', instance=1)])
)
```

Out[12]:

```
ElecMeter(instance=1, building=1, dataset='REDD', site_meter, applianc
es=[])
```

In [13]:

```
from nilmtk.elecmeter import ElecMeterID##### Quadro Geral

meter1 = elec[ElecMeterID(instance=1, building=build, dataset='HB')]

next(meter1.load()).head()
```

```
-----------------------------------------------------------------------
-----
KeyError                                  Traceback (most recent call
 last)
/tmp/ipykernel_32553/1862090280.py in <module>
      1 from nilmtk.elecmeter import ElecMeterID##### Quadro Geral
      2 
----> 3 meter1 = elec[ElecMeterID(instance=1, building=build, dataset=
'HB')]
      4 
      5 next(meter1.load()).head()

~/miniconda3/envs/nilm_0.4.3/lib/python3.7/site-packages/nilmtk/meterg
roup.py in __getitem__(self, key)
    228                         if meter.identifier == key:
    229                             return meter
--> 230                 raise KeyError(key)
    231             elif isinstance(key, MeterGroupID):
    232                 key_meters = set(key.meters)

KeyError: ElecMeterID(instance=1, building=1, dataset='HB')
```

In [ ]:

```
meter1.plot()
```

A taxa de abandono é um número entre 0 e 1 que especifica a proporção de amostras ausentes. Uma taxa de abandono de 0 significa que nenhuma amostra está faltando. Um valor de 1 significaria que todas as amostras estão faltando

In [ ]:

```
meter1.dropout_rate()
```

In [ ]:

```
good_sections = meter1.good_sections(full_results=True)
good_sections.plot()
```

In [ ]:

```
good_sections.combined()
```

Microondas

In [ ]:

```
microwave= elec['microwave']
#microwave.available_columns()
next(microwave.load()).head()
```

In [ ]:

```
microwave.plot()
```

A taxa de abandono é um número entre 0 e 1 que especifica a proporção de amostras ausentes. Uma taxa de abandono de 0 significa que nenhuma amostra está faltando. Um valor de 1 significaria que todas as amostras estão faltando

In [ ]:

```
microwave.dropout_rate()
```

In [ ]:

```
good_sections = microwave.good_sections(full_results=True)
good_sections.plot()
```

In [ ]:

```
good_sections.combined()
```

Ventilador

In [ ]:

```
fan = elec['fan']
#microwave.available_columns()
next(fan.load()).head()
```

In [ ]:

```
fan.plot()
```

In [ ]:

```
good_sections = fan.good_sections(full_results=True)
good_sections.plot()
```

A taxa de abandono é um número entre 0 e 1 que especifica a proporção de amostras ausentes. Uma taxa de abandono de 0 significa que nenhuma amostra está faltando. Um valor de 1 significaria que todas as amostras estão faltando

In [ ]:

```
fan.dropout_rate()
```

In [ ]:

```
good_sections.combined()
```

Autocorrelation Plot

In [ ]:

```
# from pandas.plotting import autocorrelation_plot
# elec.mains().plot_autocorrelation();
```

Dataframe de correlação dos aparelhos

In [ ]:

```
# correlation_df = elec.pairwise_correlation()
# correlation_df
```

Traçar dados submedidos em um 1 dia

In [ ]:

```
hb.set_window(start='2021-09-05', end='2021-09-07')
elec.plot();
plt.xlabel("Time");
```

In [ ]:

```
# hb.set_window(start='2021-09-05 00:00:00', end='2021-09-06 23:59:59')
hb.set_window(start='2021-09-05', end='2021-09-07')

# elec['microwave'].plot()
elec['fan'].plot()
plt.xlabel("Time");
```

Importamos os algoritmos que desejamos executar os experimentos:

Mean: Mean Algorithm

Hart's Algorithm

CO: Combinatorial Optimization

Discriminative Sparse Coding

Additive Factorial Hidden Markov Model

Additive Factorial Hidden Markov Model with Signal Aggregate Constraints

DSC: Discriminative Sparse Coding

RNN: Long short-term memory - LSTM

DAE: Denoising Auto Encoder

Seq2Point*

Seq2Seq

WindowGRU/Online GRU: Similar a LSTM, mas usa Gated Recurrent Unit (GRU)

ELM

In [3]:

```
from nilmtk.disaggregate import Mean,CO,Hart85
# from nilmtk_contrib.disaggregate import AFHMM,AFHMM_SAC,DSC,RNN,Seq2Point,Seq2Seq
from nilmtk_contrib.disaggregate import RNN,Seq2Point,Seq2Seq,WindowGRU
```

```
Using TensorFlow backend.
```

Em seguida, inserimos os valores para os diferentes parâmetros no dicionário. Como precisamos de vários aparelhos, inserimos os nomes de todos os aparelhos necessários no parâmetro 'appliances'.

Métricas: [https://github.com/nilmtk/nilmtk/blob/master/nilmtk/losses.py (https://github.com/nilmtk/nilmtk/blob/master/nilmtk/losses.py)](https://github.com/nilmtk/nilmtk/blob/master/nilmtk/losses.py)

Error: [https://github.com/nilmtk/nilmtk-contrib/issues/56 (https://github.com/nilmtk/nilmtk-contrib/issues/56)](https://github.com/nilmtk/nilmtk-contrib/issues/56)

In [4]:

```
d = {
  'power': {
    'mains': ['active'],
    'appliance': ['active']
#     'mains': ['active', 'frequency', 'power factor', 'current', 'voltage'],
#     'appliance': ['active', 'apparent', 'reactive', 'power factor', 'current', 'v
  },
  'sample_rate': 5,
  'display_predictions': True,
  'appliances': ['microwave', 'fan'],
  'methods': {
      'Mean':Mean({}),
      "CO":CO({}),
      'Hart85':Hart85({}),
      'RNN':RNN({'n_epochs':50,'batch_size':1024}),
      'Seq2Point':Seq2Point({'n_epochs':50,'batch_size':1024}),
      'Seq2Seq':Seq2Seq({'n_epochs':50,'batch_size':1024}),
      'WindowGRU':WindowGRU({'n_epochs':30,'batch_size':1024})
  },
 'train': {
    'datasets': {
      'Redd': {
        'path': 'teste10.h5',
        'buildings': {
              1: {
                'start_time': '2021-09-02',
                'end_time': '2021-09-04'
              },

        }
      },

    }
  },

  'test': {
    'datasets': {
      'Redd': {
        'path': 'teste10.h5',
        'buildings': {
              1: {
                    'start_time': '2021-09-05',
                    'end_time': '2021-09-07'
         }
        }
      }
    },
    'metrics':['rmse', 'mae', 'relative_error', 'r2score', 'nde', 'nep', 'f1score']
  }
}
```

raiz do erro quadrático médio (RMSE) e o erro médio absoluto (MAE)

Quanto menor o seu valor, melhor é o modelo, já que a previsão se mostra mais próxima ao valor real. Comparando as duas métricas têm se que o RMSE penaliza desvios grandes, enquanto o MAE tem pesos iguais para todos os desvios.

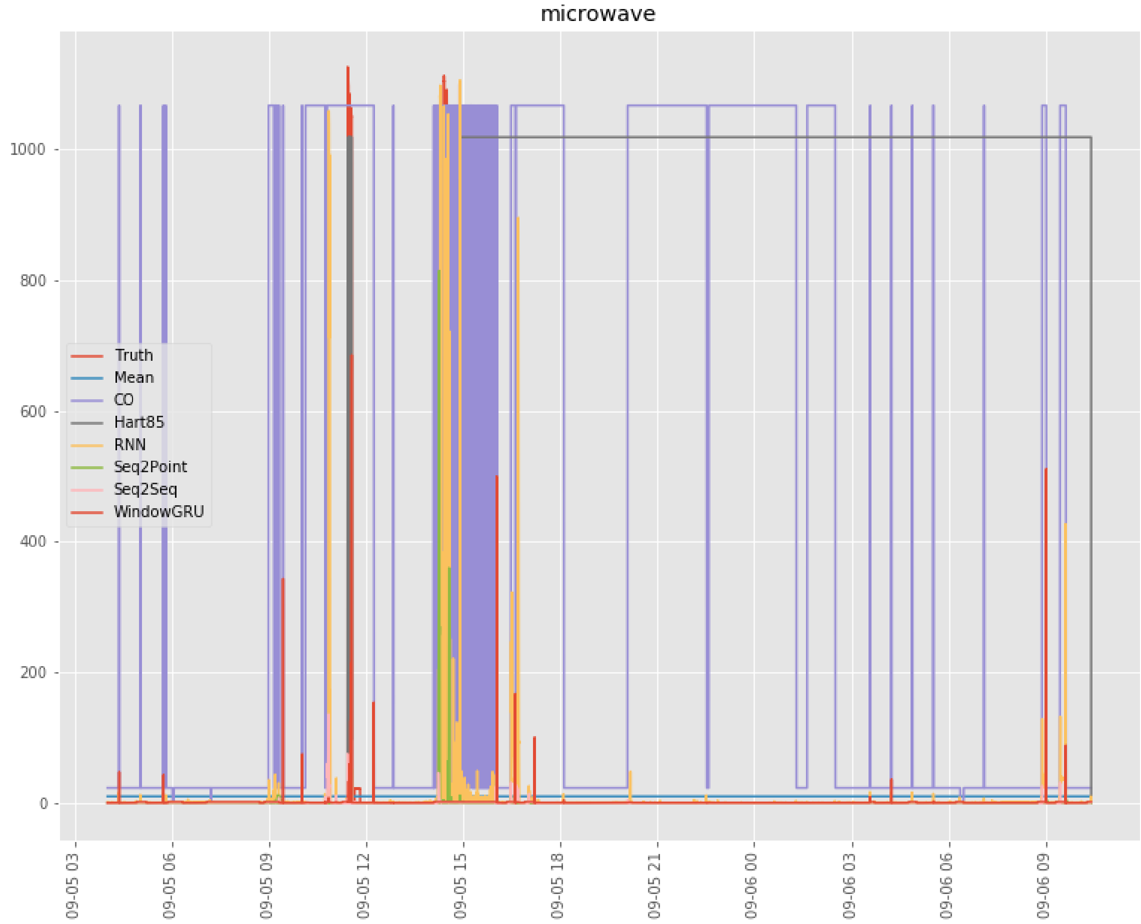
We can observe the prediction vs. truth graphs in the above cell. The accuracy metrics can be accessed using the following commands:

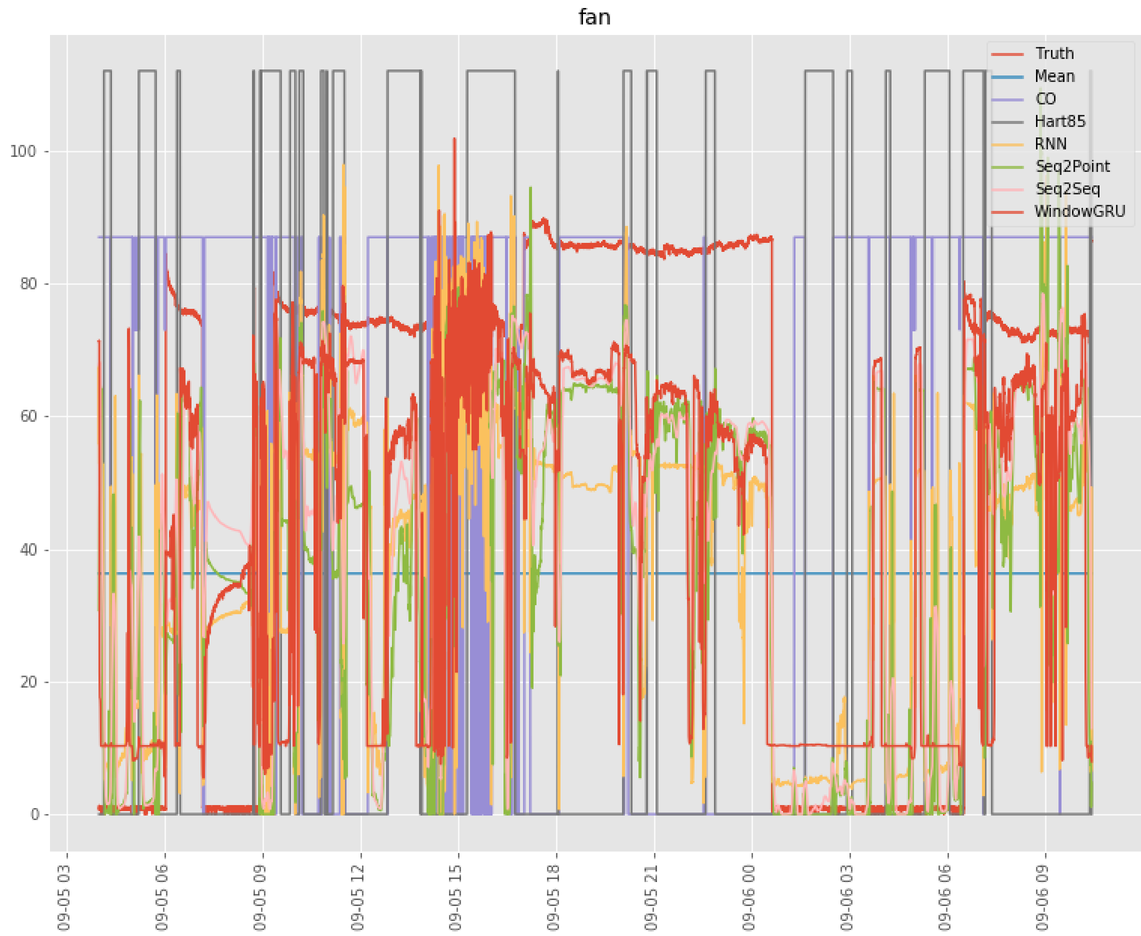
In [5]:

```
api_res = API(d)
```

```
Joint Testing for all algorithms
Loading data for  Redd  dataset
Dropping missing values
Generating predictions for : Mean
Generating predictions for : CO
...............CO disaggregate_chunk running.............
Generating predictions for : Hart85ave'
Finding Edges, please wait ...
Edge detection complete.
Creating transition frame ...
Transition frame created.
Creating states frame ...
States frame created.
Finished.
Generating predictions for : RNN
Generating predictions for : Seq2Point
Generating predictions for : Seq2Seq
Generating predictions for : WindowGRU
............  rmse  ..............
                Mean          CO      Hart85        RNN  Seq2Point  
Seq2Seq  \
microwave  72.196198  641.571289  814.688399  81.805744  73.505182  
71.240436   
fan        40.406717   61.360020   67.758518  30.848777  31.693466  
28.850022   

           WindowGRU  
microwave  68.787493  
fan        28.741579  
............  mae  ..............
                Mean          CO      Hart85        RNN  Seq2Point  
Seq2Seq  \
microwave  15.895829  400.856476  652.531494   9.868121   6.047862  
5.783867   
fan        39.986385   48.507507   56.794392  25.926266  24.624743  
22.582453   

           WindowGRU  
microwave   6.235532  
fan        21.768835  
............  relative_error  ..............
               Mean        CO     Hart85       RNN  Seq2Point   Seq2
Seq  \
microwave  1.314395   0.96001   2.894340  1.991973   1.778302  2.655
047   
fan        1.071395  20.42346  39.817631  1.246896   1.968228  0.969
891   

           WindowGRU  
microwave   1.607041  
fan         0.993014  
............  r2score  ..............
               Mean         CO      Hart85       RNN  Seq2Point   Se
q2Seq  \
microwave -0.006476 -78.481200 -127.161510 -0.292237  -0.043303  0.0
19996   
fan       -0.203323  -1.774893   -2.383787  0.298624   0.259688  0.3
```

```
86566

           WindowGRU
microwave   0.086321
fan         0.391169
............  nde  ..............
               Mean        CO     Hart85       RNN  Seq2Point   Seq2
Seq  \
microwave  1.000520  8.891119  11.290236  1.133693   1.018660  0.987
275
fan        0.626589  0.951513   1.050734  0.478373   0.491472  0.447
379

           WindowGRU
microwave   0.953281
fan         0.445697
............  nep  ..............
               Mean         CO      Hart85       RNN  Seq2Point   Se
q2Seq  \
microwave  2.997714  75.595497  123.057617  1.860979   1.140536  1.0
90750
fan        0.755440   0.916424    1.072983  0.489810   0.465221  0.4
26637

           WindowGRU
microwave   1.175927
fan         0.411266
............  f1score  ..............
               Mean        CO    Hart85       RNN  Seq2Point   Seq2S
eq  \
microwave  0.042654  0.042864  0.023410  0.186901   0.155477  0.0802
29
fan        0.802654  0.621322  0.366968  0.868128   0.880807  0.8867
29

           WindowGRU
microwave   0.149813
fan         0.808703
```


microwave
Truth
Mean
CO
Hart85
RNN
Seq2Point
Seq2Seq
WindowGRU
0
200
400
600
800
1000
09-05 03
09-05 06
09-05 09
09-05 12
09-05 15
09-05 18
09-05 21
09-06 00
09-06 03
09-06 06
09-06 09


fan
Truth
Mean
CO
Hart85
RNN
Seq2Point
Seq2Seq
WindowGRU
0
20
40
60
80
100
09-05 03
09-05 06
09-05 09
09-05 12
09-05 15
09-05 18
09-05 21
09-06 00
09-06 03
09-06 06
09-06 09

In [ ]:

```
import numpy as np
import pandas as pd

vals = np.concatenate([np.expand_dims(df.values,axis=2) for df in api_res.errors],a


cols = api_res.errors[0].columns
indexes = api_res.errors[0].index


mean = np.mean(vals,axis=2)
std = np.std(vals,axis=2)
print ('\n\n')
print ("Mean")
print (pd.DataFrame(mean,index=indexes,columns=cols))
print ('\n\n')
print ("Standard Deviation")
print (pd.DataFrame(std,index=indexes,columns=cols))
```

In [ ]:

```
```