DataAnalysisNotebook

March 14, 2018

1 Power Plant Early Warning System

This is a data analysis project focused on a power-plant anomaly detection and early warning system.

This report describes the methodology that would be involved in undertaking such a project (if implemented within a realistic time frame).

1.1 Project Summary

"Imagine, you are a power-plant maintenance engineer. Your task is to keep the plant up and running and detect any deviations from normal operation as early as possible in order to avoid unplanned downtime, loss of revenue and impact on the stability of the power grid. Therefore, a typical power plant is equipped with thousands of sensors (temperatures, pressures, vibrations, ambient conditions etc.) that are continuously monitoring the condition of various components of the plant. Attached is a data set with sensor readings over a period of 20 days. Every 15 minutes the sensors measure Output power of the power plant Airflow Ambient temperature 32 temperatures at different positions in the engine How would you analyze such kind of data and which methods and algorithms would you consider? If time permits, feel free to try out your favorite method on the data set with any tool you like, to see if something suspicious or abnormal might have occurred during those 20 days of operation.

Hints: Don't spend more than 2-3 hours on this task There are a couple of instances where there is no power production (MW=0), however, this is not considered an anomaly or malfunction"

1.2 Contents

- Background (of Problem. Anomaly Detection Methods)
  - Proposed Solution

- Phase 4
  - Implementation
  - Results
  - Evaluation

- Toy early warning detection system

1.3 Data Description

The data description phase is an important step in order to make sure any analysis of the data is correctly interpreted. The data description phase includes producing a data dictionary.

1.3.1 Data Dictionary

The data dictionary provides a description of the contents, format, and structure for the input data. This will include any definitions and the data type ie boolean, categorical etc.

Column Name	Item Name	Data type	Format	Units	Description
TimeStamp	event time	Datetime	DD/MM/YYYY HH:MM:SS	date and time	Time the event data from the sensors was recorded every 15 minutes.
MW	Power Output	Float	numeric (precision up to 5 decimal places)	Mega-watts	Output power production of the power plant. Units are in mega-watts. Note: There are instances where there is no power production (MW=0), however, this is not considered an anomaly or malfunction.
Airflow	Airflow recording	Float	numeric (precision up to 6 decimal places)	volume mˆ3/h (cubic metres per hour) ??	The recorded amount of airflow.

Column Name	Item Name	Data type	Format	Units	Description
AmbientTemperature	Ambient Temperature recording	Float	numeric (precision up to 6 decimal places)	Degrees Celsius?	Measurement of the ambient temperature of the power plant.
Temperture1A	Sensor 1A	Float	numeric (precision up to 5dp)	Degrees Celsius?	Temperature output of sensor 1A which measures ??
Temperture...	...	...	...		

The full data descriptions and schema (relationship for multiple data sets) have been omitted due to brevity. The important aspects related to the work presented here have been included below.

The data description phase is important in order to make any trends or pattens from further analysis understandable and interpretable.

1.4 Descriptive Statistics

This section provides some descriptions of the data in the raw data set. The purpose is to highlight: * record counts * mins, max and mean of values * checks for missing values * check for duplicates * detect and outliers * identify any data cleaning

```
In [14]: import pandas as pd
         import numpy as np

         # read data
         df = pd.read_csv("data/PowerPlant.txt", sep='\t')
```

Check the the number of rows and columns

```
In [15]: df.shape

Out[15]: (1920, 36)
```

Take a look at the first few items of data.

```
In [16]: df.head()

Out[16]:             TimeStamp         MW  Airflow  AmbientTemperature  Temperture1A  \
         0  06/11/2017 00:00:00  149.51172      0.0           14.176818     569.57500
         1  06/11/2017 00:15:00  149.70703      0.0           15.164263     571.65710
         2  06/11/2017 00:30:00  148.53516      0.0           14.882936     570.64984
         3  06/11/2017 00:45:00  149.60938      0.0           14.620339     572.37524
```

```
4  06/11/2017 01:00:00  149.36523      0.0           14.813577     570.46515

   Temperture1B  Temperture2A  Temperture2B  Temperture3A  Temperture3B  \
0     569.57500     541.24300     540.95680     548.39700     548.39700
1     570.76404     542.95230     541.02430     550.05426     550.05426
2     569.76764     542.95230     542.14060     549.92163     549.75757
3     571.49300     542.10156     541.80756     550.91000     550.41270
4     570.67320     543.15240     541.27435     549.78100     550.06710

          ...         Temperture12A  Temperture12B  Temperture13A  Temperture13B  \
0         ...             570.72003      573.01020      560.81660      559.84370
1         ...             571.89343      574.51990      559.87195      562.21140
2         ...             571.79486      573.79880      559.46387      561.49054
3         ...             573.23410      574.65770      561.18884      562.38824
4         ...             572.35180      573.61414      561.14480      562.56790

   Temperture14A  Temperture14B  Temperture15A  Temperture15B  Temperture16A  \
0      584.17780      583.60490      549.54156      548.96924      562.70560
1      585.68830      585.09973      550.71460      550.14230      564.50885
2      584.68030      584.38610      550.90216      550.36110      563.78015
3      586.12036      585.04970      552.34076      550.69890      565.51320
4      585.27660      584.70380      551.69320      549.88257      563.59560

   Temperture16B
0      562.99180
1      563.88666
2      563.75680
3      565.04706
4      564.16800

[5 rows x 36 columns]
```

Check the timestamp variable.

```
In [17]: df['TimeStamp'].describe()
```

```
Out[17]: count                    1920
         unique                   1920
         top       06/25/2017 22:00:00
         freq                        1
         Name: TimeStamp, dtype: object
```

Check for duplicates

```
In [18]: ((df['TimeStamp'].duplicated()).any() == True)
```

```
Out[18]: False
```

After checking use timestamp as index.

```
In [66]: df['TimeStamp'] = pd.to_datetime(df['TimeStamp'])
         df.set_index(df['TimeStamp'],inplace=True)
         del df['TimeStamp']
         df.head()
```

```
Out[66]:                            MW  Airflow  AmbientTemperature  Temperture1A  \
         TimeStamp
         2017-06-11 00:00:00  149.51172      0.0           14.176818     569.57500
         2017-06-11 00:15:00  149.70703      0.0           15.164263     571.65710
         2017-06-11 00:30:00  148.53516      0.0           14.882936     570.64984
         2017-06-11 00:45:00  149.60938      0.0           14.620339     572.37524
         2017-06-11 01:00:00  149.36523      0.0           14.813577     570.46515

                              Temperture1B  Temperture2A  Temperture2B  Temperture3A  \
         TimeStamp
         2017-06-11 00:00:00     569.57500     541.24300     540.95680     548.39700
         2017-06-11 00:15:00     570.76404     542.95230     541.02430     550.05426
         2017-06-11 00:30:00     569.76764     542.95230     542.14060     549.92163
         2017-06-11 00:45:00     571.49300     542.10156     541.80756     550.91000
         2017-06-11 01:00:00     570.67320     543.15240     541.27435     549.78100

                              Temperture3B  Temperture4A      ...        Temperture12A  \
         TimeStamp                                            ...
         2017-06-11 00:00:00     548.39700      560.9884      ...            570.72003
         2017-06-11 00:15:00     550.05426      563.3641      ...            571.89343
         2017-06-11 00:30:00     549.75757      562.3492      ...            571.79486
         2017-06-11 00:45:00     550.41270      563.4940      ...            573.23410
         2017-06-11 01:00:00     550.06710      563.4265      ...            572.35180

                              Temperture12B  Temperture13A  Temperture13B  \
         TimeStamp
         2017-06-11 00:00:00      573.01020      560.81660      559.84370
         2017-06-11 00:15:00      574.51990      559.87195      562.21140
         2017-06-11 00:30:00      573.79880      559.46387      561.49054
         2017-06-11 00:45:00      574.65770      561.18884      562.38824
         2017-06-11 01:00:00      573.61414      561.14480      562.56790

                              Temperture14A  Temperture14B  Temperture15A  \
         TimeStamp
         2017-06-11 00:00:00      584.17780      583.60490      549.54156
         2017-06-11 00:15:00      585.68830      585.09973      550.71460
         2017-06-11 00:30:00      584.68030      584.38610      550.90216
         2017-06-11 00:45:00      586.12036      585.04970      552.34076
         2017-06-11 01:00:00      585.27660      584.70380      551.69320

                              Temperture15B  Temperture16A  Temperture16B
         TimeStamp
         2017-06-11 00:00:00      548.96924      562.70560      562.99180
```

```
2017-06-11 00:15:00      550.14230      564.50885      563.88666
2017-06-11 00:30:00      550.36110      563.78015      563.75680
2017-06-11 00:45:00      550.69890      565.51320      565.04706
2017-06-11 01:00:00      549.88257      563.59560      564.16800

[5 rows x 35 columns]
```

Produce data descriptions (mins, max, means etc).

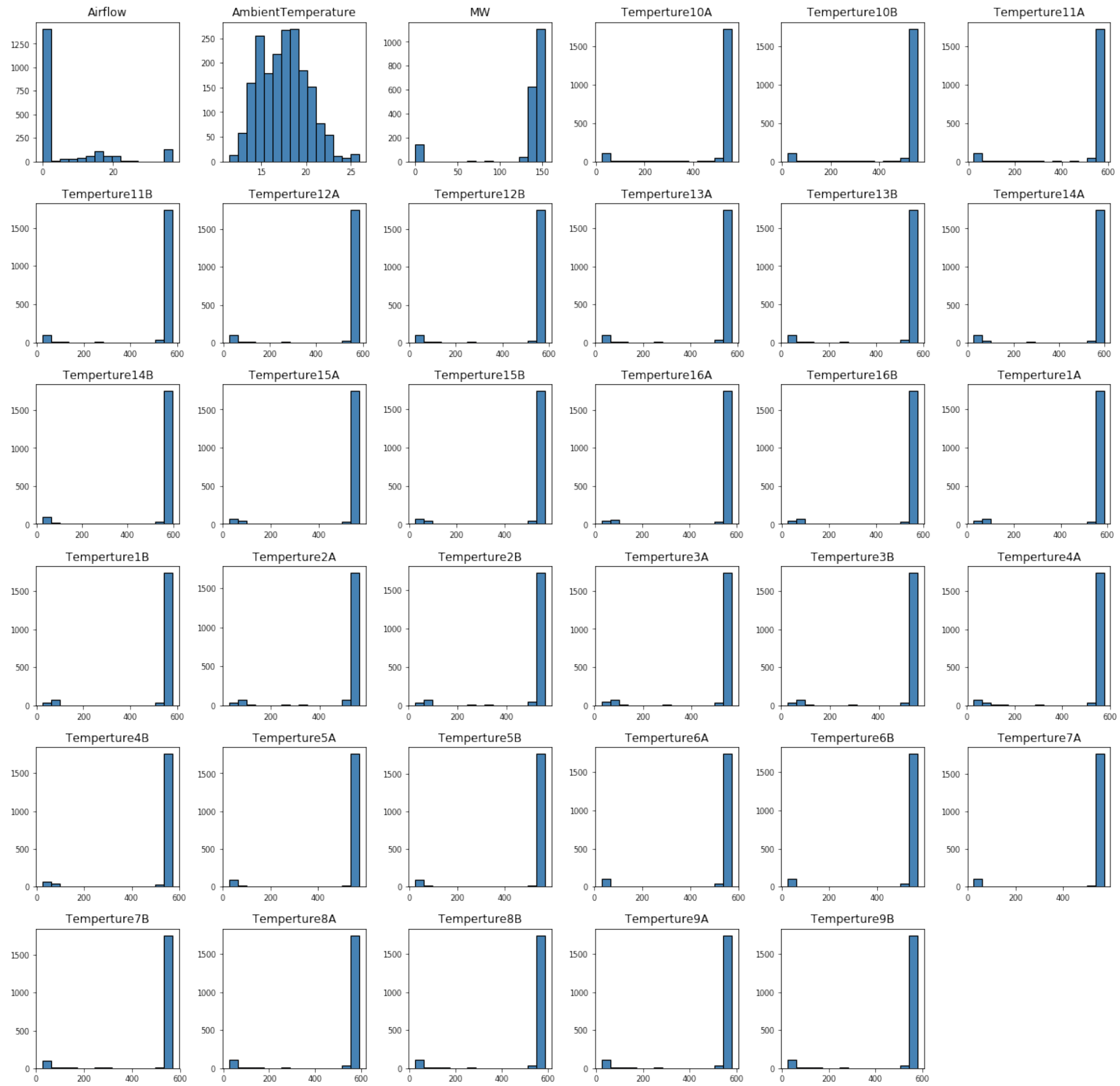
In [19]:
```
df.describe()
```

Out[19]:
```
                MW      Airflow  AmbientTemperature  Temperture1A  \
count  1920.000000  1920.000000         1920.000000   1920.000000
mean    133.879369     5.398385           17.494073    534.980150
std      38.242859    10.421131            2.609152    124.429534
min       0.000000     0.000000           11.445245     28.578466
25%     139.831543     0.000000           15.277482    566.349405
50%     145.361330     0.000000           17.511122    571.154475
75%     148.486330     7.016095           19.277029    573.270300
max     154.003900    37.000000           25.928612    585.689760

       Temperture1B  Temperture2A  Temperture2B  Temperture3A  Temperture3B  \
count   1920.000000   1920.000000   1920.000000   1920.000000   1920.000000
mean     534.693150    509.008011    507.782389    515.242243    514.798960
std      124.110622    116.417838    116.319509    119.998448    120.172039
min       25.872095     29.147110     26.106813     28.285900     26.040892
25%      564.726675    539.112000    537.762100    545.337075    543.786680
50%      570.937450    541.664000    540.833100    549.909305    549.762115
75%      573.211065    543.859440    542.679490    552.345700    552.161885
max      583.398400    563.165700    559.437300    563.930240    561.068240

       Temperture4A      ...        Temperture12A  Temperture12B  \
count   1920.000000      ...          1920.000000    1920.000000
mean     527.529844      ...           531.071926     532.820370
std      124.522066      ...           131.927662     131.971690
min       28.586680      ...            23.734856      25.628904
25%      559.176960      ...           562.113978     563.995185
50%      563.364100      ...           569.730000     571.530600
75%      565.937130      ...           572.239335     574.036295
max      576.149050      ...           584.151550     584.956050

       Temperture13A  Temperture13B  Temperture14A  Temperture14B  \
count    1920.000000    1920.000000    1920.000000    1920.000000
mean      523.069077     524.468951     548.390690     548.212686
std       128.986385     129.420565     134.245458     133.773888
min        24.989866      26.473381      25.213276      26.123314
25%       555.782940     557.613315     582.961243     582.986905
50%       560.400500     561.921920     587.545650     587.235580
```

```
75%        562.560837     564.279315     589.850575     589.429930
max        574.807800     576.525700     599.911740     599.578060

       Temperture15A  Temperture15B  Temperture16A  Temperture16B
count    1920.000000    1920.000000    1920.000000    1920.000000
mean      517.151740     516.751946     530.150782     530.352699
std       123.065793     122.974666     124.743745     124.912457
min        24.978464      26.172728      24.986704      25.571476
25%       548.029845     548.258533     559.808697     560.403675
50%       552.444200     552.161020     566.445495     566.827760
75%       555.164558     554.660478     569.490725     569.879347
max       568.643100     569.850700     578.243650     578.098600

[8 rows x 35 columns]
```

Produce histogram to show frequent of values.

In [64]:
```
df.hist(bins=15, color='steelblue', edgecolor='black', linewidth=1.0, xlabelsize=8, yla
plt.show()
```



Produce overall plot of input data. Potential anomalies can be seen.

In [62]:
```
import matplotlib.pyplot as plt
import matplotlib.font_manager

df[df.columns].plot(figsize=(12,12))
plt.title('Plot shows all sensors over time', color='black')
plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
plt.show()
```

1.5 Data Exploration

Generating descriptive statistics can be thought of from a high level. This stage goes deeper.

Exploratory data analysis stage involves "Get a ′feel" for the data and note down quirks or characteristics of interest.

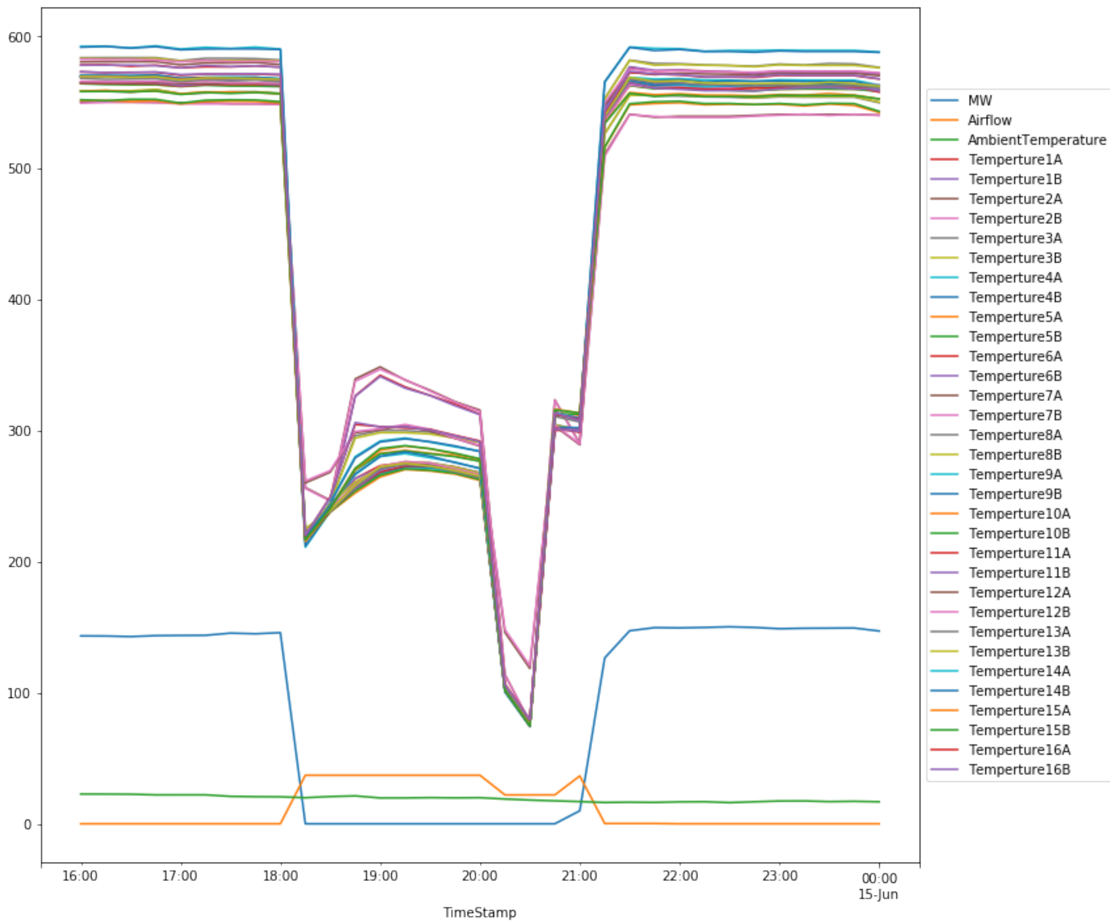
- investigate quirks
- look at variables of interest
- move the data around
- satisfy our curiosity

I am looking for inconsistencies or something weird/ interesting.
I am documenting each step and making notes.
Investigate abnormal looking regions (See plot above)
There are 4 main points to investigate.

1.5.1 1. Large fluctuation

Event start at time point 2017-06-14 18:00:00. we start to see a dip in MW and an increase in airflow and a gradual dip in temperature sensors and return to normal by time 2017-06-14 21:15:00

```
In [69]: df['2017-06-14 16:00:00':'2017-06-15 00:00:00'].plot(figsize=(12,12))
         plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
         plt.show()
```




```
In [70]: df['2017-06-14 18:00:00':'2017-06-15 00:00:00']
```

```
Out[70]:                              MW    Airflow  AmbientTemperature  Temperture1A  \
         TimeStamp
         2017-06-14 18:00:00  145.654300   0.000000           20.530846     576.77313
         2017-06-14 18:15:00    0.000000  37.000000           19.862390     220.70155
         2017-06-14 18:30:00    0.000000  37.000000           20.756523     243.25471
         2017-06-14 18:45:00    0.000000  37.000000           21.253326     326.15515
         2017-06-14 19:00:00    0.000000  37.000000           19.682156     341.83400
         2017-06-14 19:15:00    0.000000  37.000000           19.717724     332.93362
         2017-06-14 19:30:00    0.000000  37.000000           19.915941     326.50317
         2017-06-14 19:45:00    0.000000  37.000000           19.762997     320.01898
         2017-06-14 20:00:00    0.000000  37.000000           19.883732     312.11206
         2017-06-14 20:15:00    0.000000  22.000000           18.866638     104.98362
```

```
2017-06-14 20:30:00    0.000000  22.000000            18.080965     78.51992
2017-06-14 20:45:00    0.000000  22.000000            17.446442    314.35635
2017-06-14 21:00:00    9.912109  36.500000            16.921871    306.89932
2017-06-14 21:15:00  126.416016   0.205078            16.229190    545.37915
2017-06-14 21:30:00  147.119140   0.205078            16.440650    576.70880
2017-06-14 21:45:00  149.511720   0.205078            16.279482    573.59070
2017-06-14 22:00:00  149.316400   0.000000            16.710608    574.48083
2017-06-14 22:15:00  149.658200   0.000000            16.819304    573.75476
2017-06-14 22:30:00  150.146480   0.000000            16.132833    572.88030
2017-06-14 22:45:00  149.658200   0.000000            16.777464    572.04990
2017-06-14 23:00:00  148.681640   0.000000            17.337710    573.62976
2017-06-14 23:15:00  149.023440   0.000000            17.391989    573.38745
2017-06-14 23:30:00  149.121100   0.000000            16.892422    573.38745
2017-06-14 23:45:00  149.218750   0.000000            17.120367    573.45780
2017-06-15 00:00:00  146.923830   0.000000            16.772226    571.67896

                     Temperture1B  Temperture2A  Temperture2B  Temperture3A  \
TimeStamp
2017-06-14 18:00:00     576.77313     548.72410    548.151730    556.736630
2017-06-14 18:15:00     219.50287     256.25183    255.656170    217.946990
2017-06-14 18:30:00     242.06058     246.56973    245.981160    244.747040
2017-06-14 18:45:00     325.88513     339.09238    337.309500    295.799070
2017-06-14 19:00:00     340.97090     348.26510    346.419860    299.678700
2017-06-14 19:15:00     332.06116     338.22137    338.554400    299.678700
2017-06-14 19:30:00     326.40960     330.43370    329.814400    298.529240
2017-06-14 19:45:00     318.66547     321.74380    321.385530    294.149840
2017-06-14 20:00:00     311.81735     315.26685    314.286800    290.670300
2017-06-14 20:15:00     104.68076     113.76636    113.463524    101.955010
2017-06-14 20:30:00      77.88159      77.15239     77.578960     76.065895
2017-06-14 20:45:00     314.06180     323.15237    322.858340    304.300450
2017-06-14 21:00:00     306.89932     289.76358    289.171660    300.110960
2017-06-14 21:15:00     545.44165     510.38596    508.992900    525.918100
2017-06-14 21:30:00     576.96387     540.81910    540.525100    555.496340
2017-06-14 21:45:00     574.36360     538.55810    539.111600    555.186770
2017-06-14 22:00:00     574.48083     539.27893    538.420500    554.731600
2017-06-14 22:15:00     573.28100     539.27893    538.420500    554.128200
2017-06-14 22:30:00     573.36694     539.27893    538.420500    553.909300
2017-06-14 22:45:00     572.19055     539.99680    539.424500    553.160200
2017-06-14 23:00:00     573.34350     540.71760    540.145260    554.167100
2017-06-14 23:15:00     573.15594     540.71760    540.930400    553.925000
2017-06-14 23:30:00     573.15594     540.71760    539.913760    553.925000
2017-06-14 23:45:00     573.15594     540.71760    540.805240    553.913700
2017-06-15 00:00:00     571.67896     540.19830    539.912200    549.641600

                     Temperture3B  Temperture4A       ...        Temperture12A  \
TimeStamp                                             ...
2017-06-14 18:00:00    556.736630    568.184750       ...           578.777500
2017-06-14 18:15:00    216.480680    214.705930       ...           215.905490
```

```
2017-06-14 18:30:00    244.505370    245.077880      ...          239.389130
2017-06-14 18:45:00    294.009160    279.836700      ...          258.743320
2017-06-14 19:00:00    298.113370    291.740540      ...          270.991800
2017-06-14 19:15:00    298.113370    294.043950      ...          274.491640
2017-06-14 19:30:00    297.076080    290.866500      ...          273.340270
2017-06-14 19:45:00    293.959050    287.344640      ...          269.952480
2017-06-14 20:00:00    290.815730    284.038450      ...          265.194760
2017-06-14 20:15:00    101.374084    102.585526      ...          102.585526
2017-06-14 20:30:00     75.158130     75.664154      ...           75.730240
2017-06-14 20:45:00    304.005300    301.971370      ...          312.621100
2017-06-14 21:00:00    299.815580    301.292140      ...          308.963600
2017-06-14 21:15:00    526.204300    544.450200      ...          548.017000
2017-06-14 21:30:00    555.124150    568.947800      ...          573.018070
2017-06-14 21:45:00    555.759160    567.618300      ...          570.998540
2017-06-14 22:00:00    555.303960    567.896700      ...          572.190550
2017-06-14 22:15:00    554.414250    566.983400      ...          571.586800
2017-06-14 22:30:00    554.476750    566.798650      ...          571.320900
2017-06-14 22:45:00    553.446400    565.869700      ...          570.618500
2017-06-14 23:00:00    554.739440    567.045900      ...          572.198360
2017-06-14 23:15:00    554.418950    566.826970      ...          571.987370
2017-06-14 23:30:00    554.372100    566.826970      ...          571.987370
2017-06-14 23:45:00    554.379940    566.808000      ...          571.987370
2017-06-15 00:00:00    550.213900    563.091860      ...          570.247600

                     Temperture12B  Temperture13A  Temperture13B  \
TimeStamp
2017-06-14 18:00:00     581.068360      565.60870     567.326050
2017-06-14 18:15:00     217.104890      224.59564     224.895070
2017-06-14 18:30:00     240.285130      237.87917     238.791640
2017-06-14 18:45:00     258.719120      256.63504     258.147950
2017-06-14 19:00:00     272.504360      270.65310     272.207460
2017-06-14 19:15:00     276.064330      273.86566     274.804630
2017-06-14 19:30:00     274.961940      272.75455     272.643920
2017-06-14 19:45:00     270.522250      268.16990     269.325930
2017-06-14 20:00:00     266.200230      263.77292     265.051670
2017-06-14 20:15:00     102.863594      104.68076     106.236420
2017-06-14 20:30:00      75.639360       75.76330      76.401535
2017-06-14 20:45:00     312.851300      310.49387     312.621100
2017-06-14 21:00:00     309.553220      306.30940     308.373900
2017-06-14 21:15:00     549.734000      538.76600     539.757450
2017-06-14 21:30:00     574.959600      567.59480     568.947800
2017-06-14 21:45:00     573.629760      564.90950     565.885250
2017-06-14 22:00:00     573.908200      564.74817     566.465500
2017-06-14 22:15:00     573.281000      563.26250     564.693540
2017-06-14 22:30:00     573.085500      563.36410     564.547900
2017-06-14 22:45:00     572.908750      562.03174     564.207100
2017-06-14 23:00:00     573.916100      563.03880     564.469800
2017-06-14 23:15:00     573.728500      562.61206     564.050840
```

2017-06-14 23:30:00	573.728500	562.61206	565.203400
2017-06-14 23:45:00	573.775450	562.61206	564.216400
2017-06-15 00:00:00	572.537800	560.80225	562.233300

TimeStamp	Temperture14A	Temperture14B	Temperture15A
2017-06-14 18:00:00	590.52110	590.234560	556.450560
2017-06-14 18:15:00	218.57922	218.303970	215.305770
2017-06-14 18:30:00	242.41595	242.690120	240.285130
2017-06-14 18:45:00	266.18005	266.750430	270.002870
2017-06-14 19:00:00	279.92194	280.101840	284.707980
2017-06-14 19:15:00	282.17860	283.436580	287.903260
2017-06-14 19:30:00	278.97772	280.204220	285.834260
2017-06-14 19:45:00	275.68260	275.272500	281.716220
2017-06-14 20:00:00	270.69788	270.994900	278.142270
2017-06-14 20:15:00	101.95501	102.257866	101.676950
2017-06-14 20:30:00	75.33678	76.401535	75.526794
2017-06-14 20:45:00	313.21033	312.262020	316.123170
2017-06-14 21:00:00	308.96360	308.963600	313.089600
2017-06-14 21:15:00	565.18774	565.627260	534.148000
2017-06-14 21:30:00	592.11320	591.826700	557.444900
2017-06-14 21:45:00	591.05320	589.365360	555.743500
2017-06-14 22:00:00	590.80580	590.232700	556.448600
2017-06-14 22:15:00	588.87840	588.643800	555.407100
2017-06-14 22:30:00	589.42017	588.675100	555.350800
2017-06-14 22:45:00	589.40450	588.086500	554.877200
2017-06-14 23:00:00	589.66754	589.094600	555.884160
2017-06-14 23:15:00	589.47986	588.675100	555.465200
2017-06-14 23:30:00	589.47986	588.675100	556.617700
2017-06-14 23:45:00	589.47986	588.675100	555.465200
2017-06-15 00:00:00	588.28820	588.001800	552.503200

TimeStamp	Temperture15B	Temperture16A	Temperture16B
2017-06-14 18:00:00	556.450560	570.76110	571.333560
2017-06-14 18:15:00	216.480680	219.77805	220.077760
2017-06-14 18:30:00	240.268900	249.26215	248.600920
2017-06-14 18:45:00	270.910060	304.36404	305.863300
2017-06-14 19:00:00	286.068820	302.72192	302.471070
2017-06-14 19:15:00	288.199340	301.65576	302.471070
2017-06-14 19:30:00	285.906920	300.62915	300.199500
2017-06-14 19:45:00	282.519170	296.09302	295.732900
2017-06-14 20:00:00	278.134200	291.74368	291.294370
2017-06-14 20:15:00	101.676950	106.52273	105.892204
2017-06-14 20:30:00	74.453835	79.42787	79.427870
2017-06-14 20:45:00	315.502080	312.32645	313.210330
2017-06-14 21:00:00	313.089600	308.07898	307.194240
2017-06-14 21:15:00	533.861900	542.29390	543.305540

```
2017-06-14 21:30:00     556.841250      572.58325     573.473400
2017-06-14 21:45:00     554.336060      571.48510     571.610170
2017-06-14 22:00:00     555.590200      570.75920     571.045500
2017-06-14 22:15:00     554.281430      569.15600     569.434400
2017-06-14 22:30:00     554.268700      569.16670     569.445100
2017-06-14 22:45:00     554.304900      568.90100     569.473500
2017-06-14 23:00:00     555.311800      570.48080     571.053300
2017-06-14 23:15:00     555.124300      570.26184     570.579470
2017-06-14 23:30:00     555.124300      570.26184     570.579470
2017-06-14 23:45:00     555.124300      570.24290     570.579470
2017-06-15 00:00:00     552.503200      567.67145     567.957640

[25 rows x 35 columns]
```

In [71]:
```
df['2017-06-14 18:00:00':'2017-06-15 00:00:00'].describe()
```

Out[71]:
```
               MW    Airflow  AmbientTemperature  Temperture1A  Temperture1B  \
count   25.000000  25.000000           25.000000     25.000000     25.000000
mean    76.814453  15.964609           18.143432    426.377258    426.089935
std     74.671335  17.517441            1.667798    166.115996    166.420773
min      0.000000   0.000000           16.132833     78.519920     77.881590
25%      0.000000   0.000000           16.777464    314.356350    314.061800
50%    126.416016   0.205078           17.391989    545.379150    545.441650
75%    149.121100  37.000000           19.762997    573.457800    573.281000
max    150.146480  37.000000           21.253326    576.773130    576.963870

       Temperture2A  Temperture2B  Temperture3A  Temperture3B  Temperture4A  \
count     25.000000     25.000000     25.000000     25.000000     25.000000
mean     411.962760    411.426180    407.938869    407.720633    412.660679
std      147.645299    147.611799    162.503104    163.080021    170.532627
min       77.152390     77.578960     76.065895     75.158130     75.664154
25%      321.743800    321.385530    295.799070    294.009160    287.344640
50%      510.385960    508.992900    525.918100    526.204300    544.450200
75%      540.198300    539.912200    553.925000    554.418950    566.826970
max      548.724100    548.151730    556.736630    556.736630    568.947800

           ...         Temperture12A  Temperture12B  Temperture13A  \
count      ...             25.000000      25.000000      25.000000
mean       ...            411.313811     412.701250     406.701442
std        ...            176.477896     177.100069     172.101335
min        ...             75.730240      75.639360      75.763300
25%        ...            269.952480     270.522250     268.169900
50%        ...            548.017000     549.734000     538.766000
75%        ...            571.987370     573.728500     563.038800
max        ...            578.777500     581.068360     567.594800

       Temperture13B  Temperture14A  Temperture14B  Temperture15A  \
count      25.000000      25.000000      25.000000      25.000000
```

```
mean      408.060222     422.315164     422.138130     406.084816
std       172.326027     183.524174     183.035983     165.942458
min        76.401535      75.336780      76.401535      75.526794
25%       269.325930     275.682600     275.272500     281.716220
50%       539.757450     565.187740     565.627260     534.148000
75%       564.547900     589.479860     588.675100     555.465200
max       568.947800     592.113200     591.826700     557.444900

       Temperture15B  Temperture16A  Temperture16B
count      25.000000      25.000000      25.000000
mean      405.853338     418.265155     418.492242
std       165.557816     168.352203     168.607451
min        74.453835      79.427870      79.427870
25%       282.519170     300.629150     300.199500
50%       533.861900     542.293900     543.305540
75%       555.124300     570.261840     570.579470
max       556.841250     572.583250     573.473400

[8 rows x 35 columns]
```

1.5.2 2. Minor fluctuation

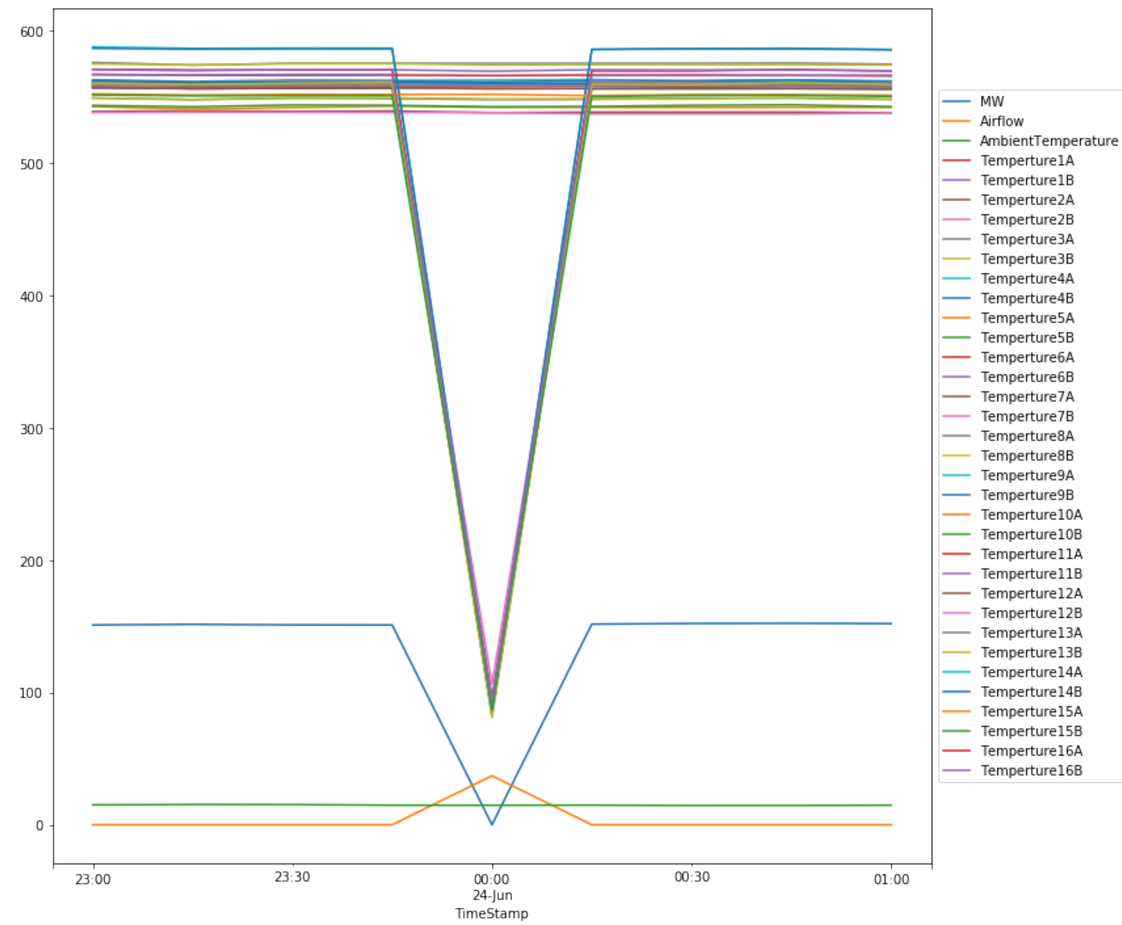
Some of the sensors remain stable, while some deviate seem to happens at point 2017-06-24 01:00:00

Exact fluctuation happens at df['2017-06-23 23:45:00':'2017-06-24 00:15:00']

We can see temperature sensors Temperture15B, Temperture16B Temperture14A, Temperture14B Temperture13B Temperture1A drop

Airflow rises and MW drops to 0.

```
In [73]: df['2017-06-23 23:00:00':'2017-06-24 01:00:00'].plot(figsize=(12,12))
         plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
         plt.show()
```




```
In [74]: df['2017-06-23 23:30:00':'2017-06-24 01:00:00']
```

```
Out[74]:                             MW  Airflow  AmbientTemperature  Temperture1A  \
         TimeStamp
         2017-06-23 23:30:00  151.02539      0.0           15.269108     570.39966
         2017-06-23 23:45:00  150.97656      0.0           14.790474     570.52480
         2017-06-24 00:00:00    0.00000     37.0           14.740068      95.41367
         2017-06-24 00:15:00  151.61133      0.0           14.840898     569.63760
         2017-06-24 00:30:00  152.09961      0.0           14.563472     569.58777
         2017-06-24 00:45:00  152.24610      0.0           14.605543     570.67804
         2017-06-24 01:00:00  152.00195      0.0           14.790501     569.54395

                              Temperture1B  Temperture2A  Temperture2B  Temperture3A  \
         TimeStamp
         2017-06-23 23:30:00     570.54820     539.08370     538.44104     549.08370
         2017-06-23 23:45:00     570.49340     539.29160     538.19390     548.78970
         2017-06-24 00:00:00     569.43445     538.06396     538.19390     547.94684
         2017-06-24 00:15:00     570.51200     538.45953     537.06476     548.14215
```

```
2017-06-24 00:30:00     570.34015     538.45953     537.06476     549.08650
2017-06-24 00:45:00     570.31946     538.45953     537.06476     549.13513
2017-06-24 01:00:00     569.83020     538.06396     537.77783     548.07970

                     Temperture3B  Temperture4A      ...       Temperture12A  \
TimeStamp                                            ...
2017-06-23 23:30:00     549.36206     562.85130      ...            556.6538
2017-06-23 23:45:00     549.29944     562.51825      ...            556.6538
2017-06-24 00:00:00     548.47220     562.75260      ...            556.7427
2017-06-24 00:15:00     548.62540     563.10126      ...            556.5190
2017-06-24 00:30:00     548.62540     561.89100      ...            556.8129
2017-06-24 00:45:00     549.49963     562.89496      ...            556.5502
2017-06-24 01:00:00     548.36590     562.10210      ...            556.0923

                     Temperture12B  Temperture13A  Temperture13B  \
TimeStamp
2017-06-23 23:30:00      558.66473      558.55850     560.322400
2017-06-23 23:45:00      558.78986      558.51935     561.016900
2017-06-24 00:00:00      557.72330      558.45970      81.183334
2017-06-24 00:15:00      557.61676      558.33940     559.620100
2017-06-24 00:30:00      558.53010      558.50660     559.416930
2017-06-24 00:45:00      557.91864      558.58470     560.621100
2017-06-24 01:00:00      558.09550      558.09550     559.526370

                     Temperture14A  Temperture14B  Temperture15A  \
TimeStamp
2017-06-23 23:30:00     586.901600      586.32870      551.97650
2017-06-23 23:45:00     586.846860      586.28950      551.88270
2017-06-24 00:00:00      86.632385       87.23792      551.89343
2017-06-24 00:15:00     585.641360      586.00590      550.97250
2017-06-24 00:30:00     586.586700      586.30020      551.76530
2017-06-24 00:45:00     586.768430      586.34890      551.74976
2017-06-24 01:00:00     585.865230      585.57880      551.22750

                     Temperture15B  Temperture16A  Temperture16B
TimeStamp
2017-06-23 23:30:00      550.93830      566.39220      566.97253
2017-06-23 23:45:00      550.93830      566.51740      567.05070
2017-06-24 00:00:00       89.35737      566.18713       94.20234
2017-06-24 00:15:00      550.17645      566.50464      566.15594
2017-06-24 00:30:00      551.08960      566.50464      566.15594
2017-06-24 00:45:00      551.17737      566.31213      566.15594
2017-06-24 01:00:00      550.36896      565.82280      566.39526

[7 rows x 35 columns]
```

```
In [75]: df['2017-06-23 23:30:00':'2017-06-24 01:00:00'].describe()
```

```
Out[75]:                MW    Airflow  AmbientTemperature  Temperture1A  Temperture1B  \
```

count	7.000000	7.000000	7.000000	7.000000	7.000000
mean	129.994420	5.285714	14.800009	502.255070	570.211123
std	57.324369	13.984686	0.230675	179.400836	0.420424
min	0.000000	0.000000	14.563472	95.413670	569.434450
25%	151.000975	0.000000	14.672805	569.565860	570.074830
50%	151.611330	0.000000	14.790474	569.637600	570.340150
75%	152.050780	0.000000	14.815700	570.462230	570.502700
max	152.246100	37.000000	15.269108	570.678040	570.548200

	Temperture2A	Temperture2B	Temperture3A	Temperture3B	Temperture4A	\
count	7.000000	7.00000	7.000000	7.000000	7.000000	
mean	538.554544	537.68585	548.609103	548.892861	562.587353	
std	0.471113	0.61268	0.532193	0.474577	0.443631	
min	538.063960	537.06476	547.946840	548.365900	561.891000	
25%	538.261745	537.06476	548.110925	548.548800	562.310175	
50%	538.459530	537.77783	548.789700	548.625400	562.752600	
75%	538.771615	538.19390	549.085100	549.330750	562.873130	
max	539.291600	538.44104	549.135130	549.499630	563.101260	

	...	Temperture12A	Temperture12B	Temperture13A	\
count	...	7.000000	7.000000	7.000000	
mean	...	556.574957	558.191270	558.437679	
std	...	0.235899	0.470786	0.170716	
min	...	556.092300	557.616760	558.095500	
25%	...	556.534600	557.820970	558.399550	
50%	...	556.653800	558.095500	558.506600	
75%	...	556.698250	558.597415	558.538925	
max	...	556.812900	558.789860	558.584700	

	Temperture13B	Temperture14A	Temperture14B	Temperture15A	\
count	7.000000	7.000000	7.000000	7.000000	
mean	491.672448	515.034652	514.869989	551.638241	
std	181.009692	188.908294	188.568221	0.382927	
min	81.183334	86.632385	87.237920	550.972500	
25%	559.471650	585.753295	585.792350	551.488630	
50%	559.620100	586.586700	586.289500	551.765300	
75%	560.471750	586.807645	586.314450	551.888065	
max	561.016900	586.901600	586.348900	551.976500	

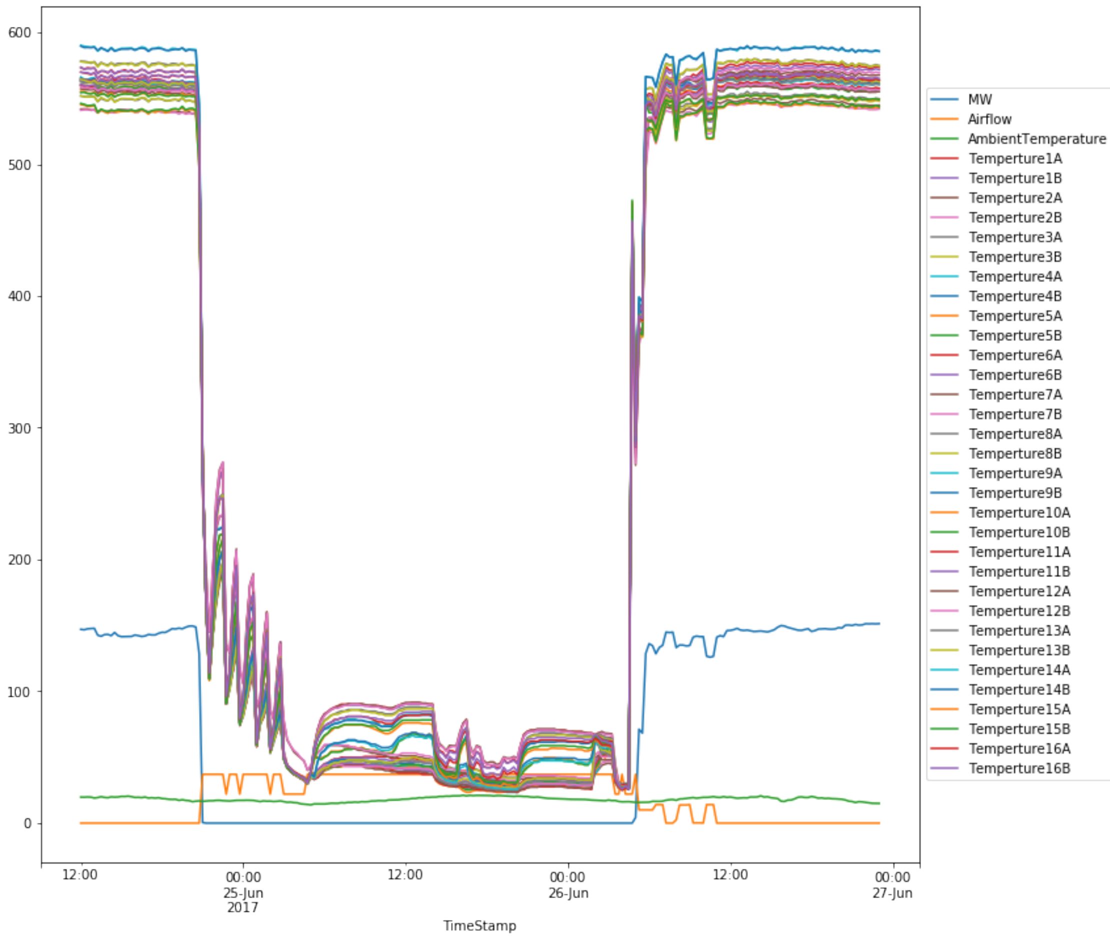
	Temperture15B	Temperture16A	Temperture16B
count	7.000000	7.000000	7.000000
mean	484.863764	566.320134	499.012664
std	174.402327	0.250761	178.504990
min	89.357370	565.822800	94.202340
25%	550.272705	566.249630	566.155940
50%	550.938300	566.392200	566.155940
75%	551.013950	566.504640	566.683895
max	551.177370	566.517400	567.050700

```
[8 rows x 35 columns]
```

1.5.3 3. Major prolonged fluctuation

Sensors showing fluctuations over a prolonged period of time. Event start time 2017-06-24 21:00:00 End time 2017-06-26 04:45:00

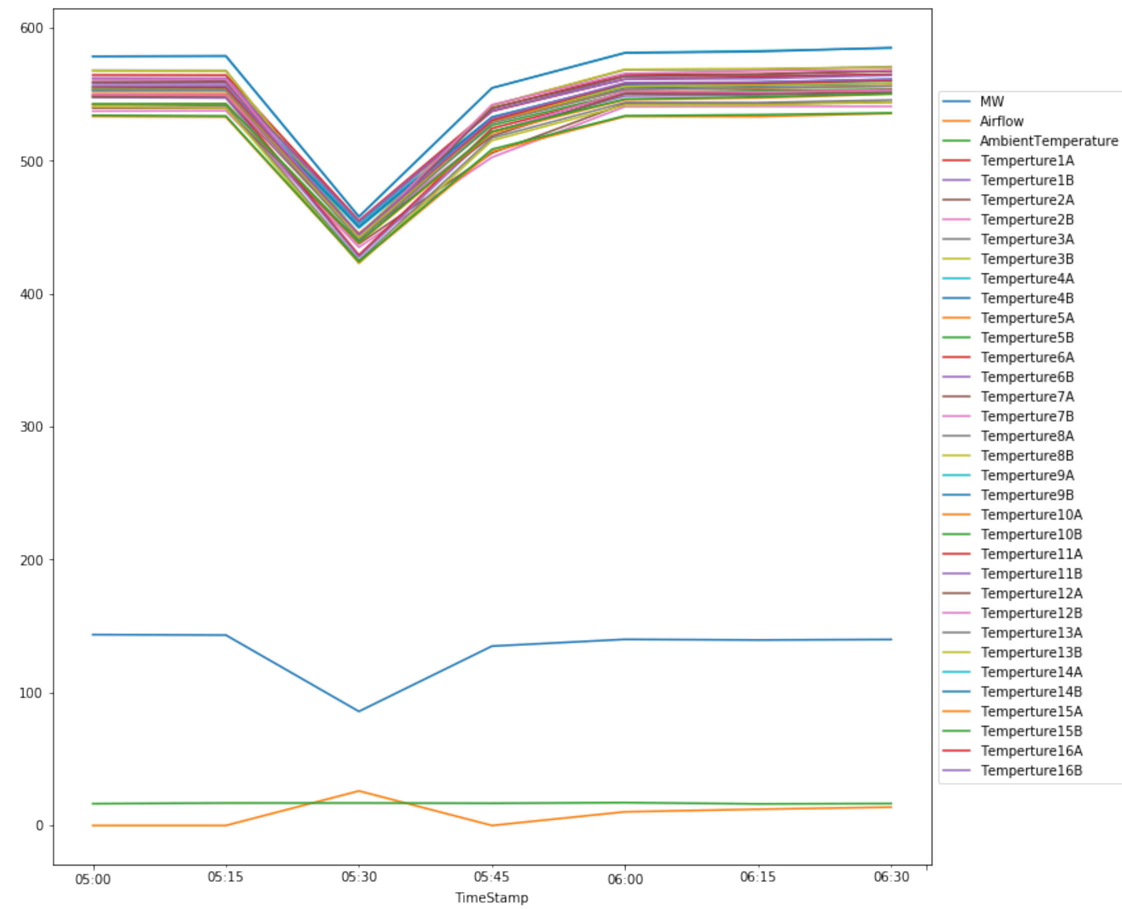
```
In [77]: df['2017-06-24 12:00:00':'2017-06-26 23:00:00'].plot(figsize=(12,12))
         plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
         plt.show()
```



1.5.4 4. Minor fluctuation

Minor dip in sensors. Event start time - minor dip at 5:30am (2017-06-30 05:30:00) until 2017-06-30 05:45:00 Event recovered by 6am

```
In [79]: df['2017-06-30 05:00:00':'2017-06-30 06:30:00'].plot(figsize=(12,12))
         plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
         plt.show()
```




```
In [81]: df['2017-06-30 05:00:00':'2017-06-30 06:30:00']

Out[81]:                              MW    Airflow  AmbientTemperature  Temperture1A  \
         TimeStamp
         2017-06-30 05:00:00  143.554690   0.000000           16.396751     564.48710
         2017-06-30 05:15:00  143.212890   0.000000           16.907219     564.33826
         2017-06-30 05:30:00   85.791016  26.000000           16.932200     455.00912
         2017-06-30 05:45:00  134.912110   0.000000           16.704288     539.51190
         2017-06-30 06:00:00  139.990230  10.290916           17.212393     564.98900
         2017-06-30 06:15:00  139.501950  12.233900           16.237576     565.15000
         2017-06-30 06:30:00  139.892580  13.795572           16.519989     567.85930

                              Temperture1B  Temperture2A  Temperture2B  Temperture3A  \
         TimeStamp
         2017-06-30 05:00:00     562.19745     539.59020     537.30084     542.16565
         2017-06-30 05:15:00     561.99380     539.59020     537.61035     541.36620
         2017-06-30 05:30:00     452.99475     437.43890     434.84323     425.02927
         2017-06-30 05:45:00     537.22253     505.72903     502.57730     517.18540
         2017-06-30 06:00:00     563.27170     542.95374     540.66437     543.81220
```

```
2017-06-30 06:15:00     563.77386     542.85990     540.83320     543.69480
2017-06-30 06:30:00     564.83234     544.05930     540.83320     545.66656

                     Temperture3B  Temperture4A      ...        Temperture12A  \
TimeStamp                                            ...
2017-06-30 05:00:00     540.44867     555.61523      ...            559.33550
2017-06-30 05:15:00     539.66486     555.71344      ...            559.75903
2017-06-30 05:30:00     422.71814     452.41913      ...            440.32190
2017-06-30 05:45:00     515.18097     532.92970      ...            539.51965
2017-06-30 06:00:00     541.80900     557.83410      ...            563.55800
2017-06-30 06:15:00     541.97003     558.90857      ...            564.91870
2017-06-30 06:30:00     544.07495     560.99010      ...            567.28687

                     Temperture12B  Temperture13A  Temperture13B  \
TimeStamp
2017-06-30 05:00:00      561.05270      552.75354      554.75670
2017-06-30 05:15:00      561.19000      553.11450      554.85490
2017-06-30 05:30:00      441.76300      440.32190      442.33936
2017-06-30 05:45:00      542.08734      528.35030      530.35380
2017-06-30 06:00:00      565.56146      553.54160      555.83093
2017-06-30 06:15:00      567.50256      554.90990      556.90533
2017-06-30 06:30:00      568.24360      555.96840      558.42224

                     Temperture14A  Temperture14B  Temperture15A  \
TimeStamp
2017-06-30 05:00:00      578.51440      578.51440      542.16565
2017-06-30 05:15:00      578.52220      578.88340      542.85547
2017-06-30 05:30:00      457.88602      457.88602      438.30392
2017-06-30 05:45:00      554.67840      554.67840      520.91530
2017-06-30 06:00:00      581.30750      581.02120      545.81530
2017-06-30 06:15:00      582.66907      582.04144      547.17580
2017-06-30 06:30:00      584.63477      585.03880      550.08435

                     Temperture15B  Temperture16A  Temperture16B
TimeStamp
2017-06-30 05:00:00      542.73800      555.61523      556.47375
2017-06-30 05:15:00      542.74570      555.11760      556.60330
2017-06-30 05:30:00      438.88052      444.64440      444.35632
2017-06-30 05:45:00      522.05270      530.36160      531.78485
2017-06-30 06:00:00      546.38760      558.12030      558.69275
2017-06-30 06:15:00      548.03424      558.28130      559.19476
2017-06-30 06:30:00      550.37040      560.41770      561.27630

[7 rows x 35 columns]
```

In [82]:
```
df['2017-06-30 05:00:00':'2017-06-30 06:30:00'].describe()
```

Out[82]:
```
                MW    Airflow  AmbientTemperature  Temperture1A  Temperture1B  \
count    7.000000   7.000000            7.000000      7.000000      7.000000
```

mean	132.407924	8.902913	16.701488	545.906383	543.755204
std	20.753479	9.721592	0.340980	41.240297	41.188155
min	85.791016	0.000000	16.237576	455.009120	452.994750
25%	137.207030	0.000000	16.458370	551.925080	549.608165
50%	139.892580	10.290916	16.704288	564.487100	562.197450
75%	141.601560	13.014736	16.919710	565.069500	563.522780
max	143.554690	26.000000	17.212393	567.859300	564.832340

	Temperture2A	Temperture2B	Temperture3A	Temperture3B	Temperture4A	\
count	7.000000	7.000000	7.000000	7.000000	7.000000	
mean	521.745896	519.237499	522.702869	520.838089	539.201467	
std	39.569580	39.698153	44.180105	44.393767	39.418387	
min	437.438900	434.843230	425.029270	422.718140	452.419130	
25%	522.659615	519.939070	529.275800	527.422915	544.272465	
50%	539.590200	537.610350	542.165650	540.448670	555.713440	
75%	542.906820	540.748785	543.753500	541.889515	558.371335	
max	544.059300	540.833200	545.666560	544.074950	560.990100	

	...	Temperture12A	Temperture12B	Temperture13A	\
count	...	7.000000	7.000000	7.000000	
mean	...	542.099950	543.914380	534.137163	
std	...	45.807315	45.911728	42.477723	
min	...	440.321900	441.763000	440.321900	
25%	...	549.427575	551.570020	540.551920	
50%	...	559.759030	561.190000	553.114500	
75%	...	564.238350	566.532010	554.225750	
max	...	567.286870	568.243600	555.968400	

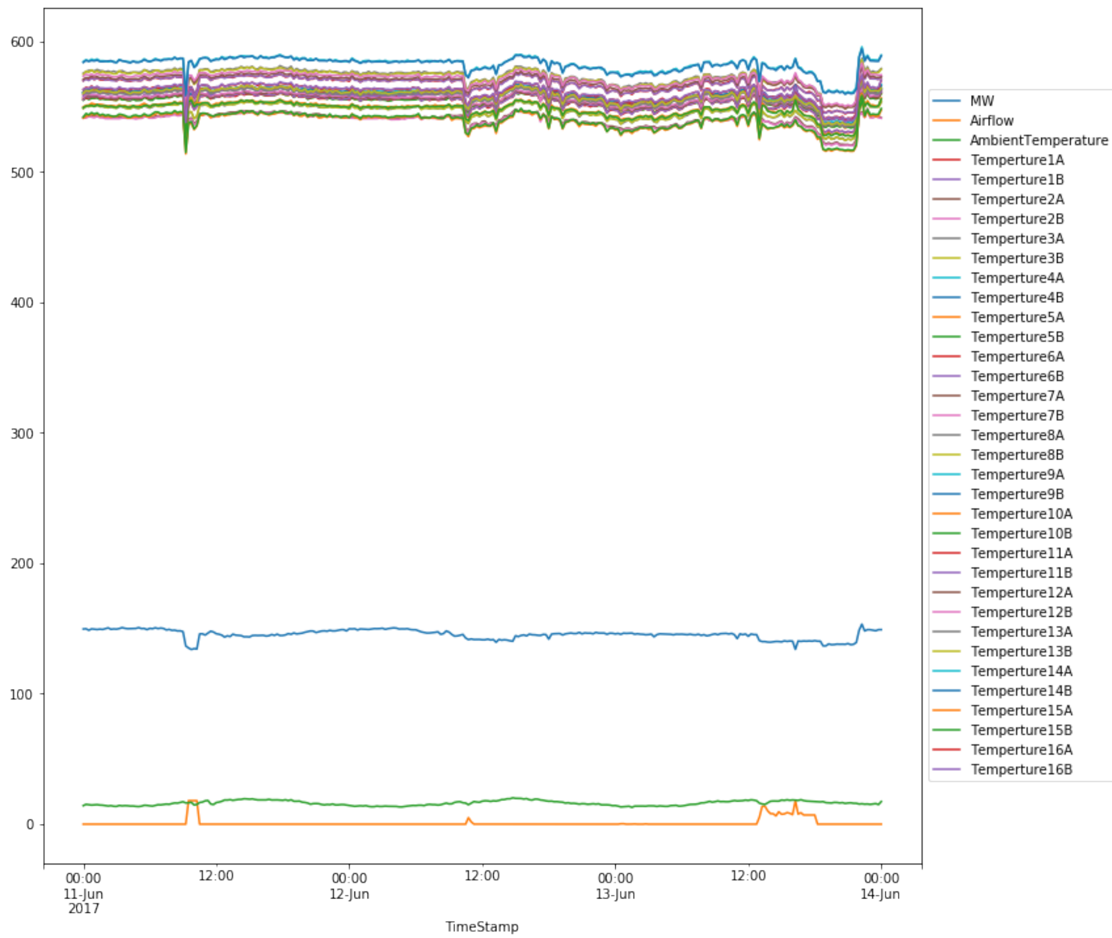
	Temperture13B	Temperture14A	Temperture14B	Temperture15A	\
count	7.000000	7.000000	7.000000	7.000000	
mean	536.209037	559.744623	559.723380	526.759399	
std	42.513264	46.035767	46.023675	40.164187	
min	442.339360	457.886020	457.886020	438.303920	
25%	542.555250	566.596400	566.596400	531.540475	
50%	554.854900	578.522200	578.883400	542.855470	
75%	556.368130	581.988285	581.531320	546.495550	
max	558.422240	584.634770	585.038800	550.084350	

	Temperture15B	Temperture16A	Temperture16B
count	7.000000	7.000000	7.000000
mean	527.315594	537.508304	538.340290
std	40.101802	42.217572	42.648784
min	438.880520	444.644400	444.356320
25%	532.395350	542.739600	544.129300
50%	542.745700	555.615230	556.603300
75%	547.210920	558.200800	558.943755
max	550.370400	560.417700	561.276300

```
[8 rows x 35 columns]
```

Normal regions Identified some normal regions (with respect to abnormal regions). Also important to describe data in normal regions.

```
In [84]: df['2017-06-11 00:00:00':'2017-06-14 00:00:00'].plot(figsize=(12,12))
         plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
         plt.show()
```




```
In [85]: df['2017-06-11 00:00:00':'2017-06-14 00:00:00']
```

```
Out[85]:                              MW   Airflow  AmbientTemperature  Temperture1A  \
         TimeStamp
         2017-06-11 00:00:00  149.51172  0.000000           14.176818     569.57500
         2017-06-11 00:15:00  149.70703  0.000000           15.164263     571.65710
         2017-06-11 00:30:00  148.53516  0.000000           14.882936     570.64984
         2017-06-11 00:45:00  149.60938  0.000000           14.620339     572.37524
         2017-06-11 01:00:00  149.36523  0.000000           14.813577     570.46515
```

2017-06-11 01:15:00	149.12110	0.000000	14.922689	571.89905
2017-06-11 01:30:00	149.41406	0.000000	14.637156	570.31165
2017-06-11 01:45:00	149.16992	0.000000	14.517420	570.19446
2017-06-11 02:00:00	149.80469	0.000000	14.262980	570.08500
2017-06-11 02:15:00	150.39062	0.000000	13.896900	570.30880
2017-06-11 02:30:00	149.26758	0.000000	14.149465	570.61847
2017-06-11 02:45:00	149.56055	0.000000	13.684243	570.41034
2017-06-11 03:00:00	149.41406	0.000000	13.589540	569.48126
2017-06-11 03:15:00	149.85352	0.000000	14.315357	570.90760
2017-06-11 03:30:00	150.58594	0.000000	13.993738	570.17377
2017-06-11 03:45:00	150.04883	0.000000	14.172539	569.90310
2017-06-11 04:00:00	149.75586	0.000000	14.080065	569.41390
2017-06-11 04:15:00	149.85352	0.000000	13.840145	569.22906
2017-06-11 04:30:00	149.90234	0.000000	13.865372	569.89264
2017-06-11 04:45:00	149.95117	0.000000	13.595994	570.01764
2017-06-11 05:00:00	150.58594	0.000000	13.471461	569.66595
2017-06-11 05:15:00	149.85352	0.000000	13.762037	569.66595
2017-06-11 05:30:00	149.95117	0.000000	14.458544	571.76355
2017-06-11 05:45:00	149.02344	0.000000	14.349164	570.48080
2017-06-11 06:00:00	150.00000	0.000000	14.027121	569.81915
2017-06-11 06:15:00	149.75586	0.000000	13.821053	571.58370
2017-06-11 06:30:00	150.43945	0.000000	14.315487	571.87780
2017-06-11 06:45:00	149.85352	0.000000	14.874554	571.33960
2017-06-11 07:00:00	150.24414	0.000000	14.782134	570.90480
2017-06-11 07:15:00	149.90234	0.000000	15.122284	571.48517
...	...	...	...	...
2017-06-13 16:45:00	140.03906	8.746099	18.693657	563.16095
2017-06-13 17:00:00	140.33203	7.000000	18.055489	561.21704
2017-06-13 17:15:00	140.18555	7.000000	17.690422	560.36150
2017-06-13 17:30:00	140.38086	7.000000	17.534039	561.30600
2017-06-13 17:45:00	140.18555	7.000000	17.483910	560.05970
2017-06-13 18:00:00	140.57617	7.000000	17.308353	557.98610
2017-06-13 18:15:00	140.18555	0.000000	17.229055	554.14075
2017-06-13 18:30:00	140.18555	0.000000	17.051395	555.04130
2017-06-13 18:45:00	136.57227	0.000000	17.245800	545.48083
2017-06-13 19:00:00	136.57227	0.000000	16.478080	545.03046
2017-06-13 19:15:00	138.08594	0.000000	16.369062	546.54730
2017-06-13 19:30:00	137.50000	0.000000	16.222750	545.79820
2017-06-13 19:45:00	137.59766	0.000000	16.635271	545.79820
2017-06-13 20:00:00	137.93945	0.000000	16.593424	546.91943
2017-06-13 20:15:00	137.84180	0.000000	16.254314	545.85290
2017-06-13 20:30:00	137.89062	0.000000	16.482513	545.76190
2017-06-13 20:45:00	137.79297	0.000000	15.900110	544.22675
2017-06-13 21:00:00	138.33008	0.000000	16.227116	545.39770
2017-06-13 21:15:00	137.50000	0.000000	16.354853	545.04910
2017-06-13 21:30:00	137.79297	0.000000	15.996697	545.04910
2017-06-13 21:45:00	139.20898	0.000000	15.971575	549.52875
2017-06-13 22:00:00	148.53516	0.000000	15.397044	574.02260

2017-06-13 22:15:00	153.22266	0.000000	15.600558	580.91797
2017-06-13 22:30:00	148.04688	0.000000	15.311116	571.07666
2017-06-13 22:45:00	149.02344	0.000000	15.430645	575.14716
2017-06-13 23:00:00	148.97461	0.000000	15.130700	571.30835
2017-06-13 23:15:00	148.58398	0.000000	15.401335	571.33170
2017-06-13 23:30:00	148.19336	0.000000	15.730461	571.18604
2017-06-13 23:45:00	149.02344	0.000000	15.004688	570.73060
2017-06-14 00:00:00	149.02344	0.000000	17.306328	572.92440

	Temperture1B	Temperture2A	Temperture2B	Temperture3A \
TimeStamp				
2017-06-11 00:00:00	569.57500	541.24300	540.95680	548.39700
2017-06-11 00:15:00	570.76404	542.95230	541.02430	550.05426
2017-06-11 00:30:00	569.76764	542.95230	542.14060	549.92163
2017-06-11 00:45:00	571.49300	542.10156	541.80756	550.91000
2017-06-11 01:00:00	570.67320	543.15240	541.27435	549.78100
2017-06-11 01:15:00	571.61290	542.14056	542.42160	550.99070
2017-06-11 01:30:00	570.95170	542.14056	541.24304	549.97626
2017-06-11 01:45:00	570.97784	542.14056	541.24304	549.92163
2017-06-11 02:00:00	570.08500	541.46670	540.60815	549.19300
2017-06-11 02:15:00	570.69666	540.89435	540.60815	549.14606
2017-06-11 02:30:00	569.83014	542.33300	540.60815	549.23206
2017-06-11 02:45:00	569.68933	541.18840	540.61597	549.45570
2017-06-11 03:00:00	569.48126	541.14930	540.57690	548.58940
2017-06-11 03:15:00	571.53485	542.35913	540.57690	549.72906
2017-06-11 03:30:00	570.80084	541.15990	541.03190	549.90070
2017-06-11 03:45:00	569.71277	541.15990	540.99590	548.82080
2017-06-11 04:00:00	569.41390	541.08180	540.79565	548.52203
2017-06-11 04:15:00	569.85360	541.08180	540.79565	548.33730
2017-06-11 04:30:00	569.77040	541.08180	540.79565	549.68220
2017-06-11 04:45:00	570.01764	541.41980	540.27510	548.69370
2017-06-11 05:00:00	569.66595	541.04767	540.76150	548.48780
2017-06-11 05:15:00	569.81450	541.04767	540.76150	549.29940
2017-06-11 05:30:00	572.04990	542.23926	542.03906	550.60820
2017-06-11 05:45:00	571.09730	542.23926	542.09370	549.47910
2017-06-11 06:00:00	570.10540	541.20080	540.91473	548.64100
2017-06-11 06:15:00	571.25830	541.25560	540.91473	549.50730
2017-06-11 06:30:00	572.28930	542.48630	541.21180	550.96160
2017-06-11 06:45:00	571.90430	542.39550	542.23430	551.01154
2017-06-11 07:00:00	570.90480	541.99994	541.71380	549.72630
2017-06-11 07:15:00	571.48517	541.99994	542.38776	550.01530
...	...	...	...	...
2017-06-13 16:45:00	562.96857	538.20960	536.64087	542.65050
2017-06-13 17:00:00	561.21704	535.74805	534.88947	540.89923
2017-06-13 17:15:00	560.06750	534.55634	533.71344	539.13520
2017-06-13 17:30:00	560.05190	534.64240	533.71344	540.32210
2017-06-13 17:45:00	560.09875	534.75970	533.90120	539.22130
2017-06-13 18:00:00	557.98610	533.08940	532.51710	537.95460

2017-06-13 18:15:00	554.68960	529.50150	528.70530	533.82294
2017-06-13 18:30:00	555.04130	528.30975	527.69824	533.68524
2017-06-13 18:45:00	544.76290	522.82404	521.97300	526.01984
2017-06-13 19:00:00	545.03046	520.98910	520.13010	524.71060
2017-06-13 19:15:00	546.22986	522.09503	521.25183	526.60800
2017-06-13 19:30:00	544.92413	520.91380	520.03930	525.16110
2017-06-13 19:45:00	546.19080	521.92615	521.05164	524.99980
2017-06-13 20:00:00	546.63324	522.59250	521.73364	526.60016
2017-06-13 20:15:00	546.17810	520.89040	519.85160	524.94510
2017-06-13 20:30:00	545.76190	520.89040	519.94836	525.88980
2017-06-13 20:45:00	544.84595	520.69006	520.11743	523.74530
2017-06-13 21:00:00	545.68384	520.78380	520.21120	525.07794
2017-06-13 21:15:00	545.22580	519.88290	519.81555	524.61975
2017-06-13 21:30:00	545.40546	520.93726	519.81555	525.51770
2017-06-13 21:45:00	549.88257	524.47120	523.18840	528.18463
2017-06-13 22:00:00	574.02260	543.97180	542.82715	551.98425
2017-06-13 22:15:00	580.91797	545.74347	544.88495	559.47940
2017-06-13 22:30:00	570.79040	542.06520	541.49290	549.47130
2017-06-13 22:45:00	575.17065	548.26700	547.40857	553.39453
2017-06-13 23:00:00	571.30835	541.83093	541.25867	549.55725
2017-06-13 23:15:00	571.06104	542.82220	541.08180	549.58070
2017-06-13 23:30:00	571.10010	542.82220	542.25770	549.58070
2017-06-13 23:45:00	570.64190	542.59070	541.23010	549.73410
2017-06-14 00:00:00	573.21070	541.15717	540.87103	553.17584

	Temperture3B	Temperture4A	...	Temperture12A	\
TimeStamp			...		
2017-06-11 00:00:00	548.39700	560.98840	...	570.72003	
2017-06-11 00:15:00	550.05426	563.36410	...	571.89343	
2017-06-11 00:30:00	549.75757	562.34920	...	571.79486	
2017-06-11 00:45:00	550.41270	563.49400	...	573.23410	
2017-06-11 01:00:00	550.06710	563.42650	...	572.35180	
2017-06-11 01:15:00	550.94390	563.31195	...	572.75793	
2017-06-11 01:30:00	549.71350	562.01890	...	571.71180	
2017-06-11 01:45:00	549.93720	563.14520	...	572.30480	
2017-06-11 02:00:00	549.19300	562.07080	...	571.51636	
2017-06-11 02:15:00	548.87555	562.04730	...	572.41430	
2017-06-11 02:30:00	550.02800	561.55310	...	571.54770	
2017-06-11 02:45:00	548.82370	561.37320	...	570.81090	
2017-06-11 03:00:00	548.58940	561.18097	...	570.62630	
2017-06-11 03:15:00	550.30920	562.89310	...	572.33890	
2017-06-11 03:30:00	549.90850	563.02576	...	572.47170	
2017-06-11 03:45:00	548.90960	561.83140	...	571.14404	
2017-06-11 04:00:00	548.23584	560.82730	...	570.55890	
2017-06-11 04:15:00	548.33730	560.35640	...	571.05330	
2017-06-11 04:30:00	549.41950	561.57650	...	571.06370	
2017-06-11 04:45:00	549.14606	562.14374	...	571.16260	
2017-06-11 05:00:00	548.48780	561.36550	...	570.81090	

2017-06-11 05:15:00	549.58550	561.58130	...	571.89340
2017-06-11 05:30:00	550.87090	563.46270	...	573.19500
2017-06-11 05:45:00	550.26733	562.35700	...	571.96387
2017-06-11 06:00:00	548.92720	561.80490	...	570.96423
2017-06-11 06:15:00	550.36580	562.16455	...	571.83090
2017-06-11 06:30:00	550.75366	563.29065	...	573.41090
2017-06-11 06:45:00	549.83570	563.32983	...	573.31226
2017-06-11 07:00:00	550.01240	562.89026	...	572.62250
2017-06-11 07:15:00	550.87880	563.18430	...	572.94790
...	...	...	...	...
2017-06-13 16:45:00	542.93665	555.52780	...	567.80300
2017-06-13 17:00:00	540.89923	553.20410	...	564.65150
2017-06-13 17:15:00	539.83575	552.49414	...	564.08215
2017-06-13 17:30:00	539.71857	552.32526	...	564.07430
2017-06-13 17:45:00	539.85614	552.39550	...	563.84280
2017-06-13 18:00:00	537.95460	550.54580	...	562.27893
2017-06-13 18:15:00	534.65015	546.66940	...	558.11590
2017-06-13 18:30:00	534.32794	546.74260	...	558.36600
2017-06-13 18:45:00	526.00420	537.60876	...	549.71850
2017-06-13 19:00:00	524.99690	537.30400	...	549.03670
2017-06-13 19:15:00	526.60800	538.09216	...	550.45483
2017-06-13 19:30:00	524.60420	536.91150	...	549.21650
2017-06-13 19:45:00	525.57720	538.10785	...	550.22833
2017-06-13 20:00:00	526.60016	538.62067	...	550.63947
2017-06-13 20:15:00	524.94510	537.85590	...	549.85913
2017-06-13 20:30:00	525.15594	537.74920	...	549.48193
2017-06-13 20:45:00	523.86255	536.83330	...	548.07180
2017-06-13 21:00:00	525.07794	537.67120	...	549.40390
2017-06-13 21:15:00	524.15670	537.21320	...	549.51825
2017-06-13 21:30:00	525.24700	537.31470	...	549.41170
2017-06-13 21:45:00	528.96810	541.23010	...	552.80360
2017-06-13 22:00:00	551.98425	564.86250	...	574.88150
2017-06-13 22:15:00	558.30340	572.04200	...	581.49070
2017-06-13 22:30:00	549.53380	561.36847	...	571.93550
2017-06-13 22:45:00	554.27650	566.31210	...	576.04510
2017-06-13 23:00:00	549.55725	562.43510	...	572.45337
2017-06-13 23:15:00	549.86690	563.02310	...	573.33563
2017-06-13 23:30:00	549.86950	561.92520	...	572.03700
2017-06-13 23:45:00	549.28937	562.76820	...	572.13855
2017-06-14 00:00:00	553.46204	566.62680	...	572.35180

	Temperture12B	Temperture13A	Temperture13B \
TimeStamp			
2017-06-11 00:00:00	573.01020	560.81660	559.84370
2017-06-11 00:15:00	574.51990	559.87195	562.21140
2017-06-11 00:30:00	573.79880	559.46387	561.49054
2017-06-11 00:45:00	574.65770	561.18884	562.38824
2017-06-11 01:00:00	573.61414	561.14480	562.56790

2017-06-11 01:15:00	575.00140	561.02240	562.15155
2017-06-11 01:30:00	574.12427	559.69037	560.86630
2017-06-11 01:45:00	574.23364	560.49426	561.98770
2017-06-11 02:00:00	573.80664	559.78130	561.49835
2017-06-11 02:15:00	573.78314	559.19320	561.47500
2017-06-11 02:30:00	573.11970	560.33014	561.19653
2017-06-11 02:45:00	572.52070	559.38556	560.53033
2017-06-11 03:00:00	572.63025	559.17760	560.60850
2017-06-11 03:15:00	573.45280	560.38760	561.83417
2017-06-11 03:30:00	574.18940	559.58370	561.92004
2017-06-11 03:45:00	573.58280	559.84375	561.73267
2017-06-11 04:00:00	572.56274	559.11017	560.54114
2017-06-11 04:15:00	572.37800	558.63934	559.78400
2017-06-11 04:30:00	572.90370	559.27920	561.03020
2017-06-11 04:45:00	573.59330	559.85425	560.78820
2017-06-11 05:00:00	573.10110	558.78973	560.50684
2017-06-11 05:15:00	573.40310	559.74220	560.95215
2017-06-11 05:30:00	574.62646	561.74554	563.46270
2017-06-11 05:45:00	574.43396	559.60443	561.32160
2017-06-11 06:00:00	573.25440	559.51544	561.23250
2017-06-11 06:15:00	574.45435	560.66790	562.67130
2017-06-11 06:30:00	574.75635	560.48346	562.43210
2017-06-11 06:45:00	575.64170	561.31390	562.35700
2017-06-11 07:00:00	574.34015	560.02830	561.74554
2017-06-11 07:15:00	574.46520	560.63983	562.06300
...	...	...	...
2017-06-13 16:45:00	568.97925	553.23840	554.08130
2017-06-13 17:00:00	566.36884	550.91486	552.05945
2017-06-13 17:15:00	564.89856	549.78570	551.48236
2017-06-13 17:30:00	566.47340	551.30560	552.72076
2017-06-13 17:45:00	565.46630	550.05940	551.53700
2017-06-13 18:00:00	563.70990	547.97034	549.40110
2017-06-13 18:15:00	559.04480	543.83905	546.44860
2017-06-13 18:30:00	559.13860	545.20245	546.17030
2017-06-13 18:45:00	551.59170	536.13880	536.46405
2017-06-13 19:00:00	550.75366	535.01450	536.44543
2017-06-13 19:15:00	552.17180	536.72675	537.51980
2017-06-13 19:30:00	550.98517	534.62195	536.10455
2017-06-13 19:45:00	551.85920	535.81836	536.62524
2017-06-13 20:00:00	552.35645	536.61743	538.04834
2017-06-13 20:15:00	550.83470	534.78595	536.06067
2017-06-13 20:30:00	551.19885	535.42860	537.65560
2017-06-13 20:45:00	549.90594	533.76330	535.97470
2017-06-13 21:00:00	551.12080	535.38170	536.24030
2017-06-13 21:15:00	550.08276	534.93940	535.89166
2017-06-13 21:30:00	551.28986	535.10333	536.17000
2017-06-13 21:45:00	554.67970	538.94080	539.77320
2017-06-13 22:00:00	577.17200	562.57280	564.57630

```
2017-06-13 22:15:00      583.20910      570.32434      572.93210
2017-06-13 22:30:00      574.43396      559.65130      560.79600
2017-06-13 22:45:00      578.04944      563.69700      566.02580
2017-06-13 23:00:00      574.45734      560.14550      561.86270
2017-06-13 23:15:00      574.48080      560.45514      561.90180
2017-06-13 23:30:00      574.48350      559.45090      562.02673
2017-06-13 23:45:00      573.87964      559.82030      561.57150
2017-06-14 00:00:00      574.06960      562.61980      564.05084

                     Temperture14A  Temperture14B  Temperture15A  \
TimeStamp
2017-06-11 00:00:00      584.17780      583.60490      549.54156
2017-06-11 00:15:00      585.68830      585.09973      550.71460
2017-06-11 00:30:00      584.68030      584.38610      550.90216
2017-06-11 00:45:00      586.12036      585.04970      552.34076
2017-06-11 01:00:00      585.27660      584.70380      551.69320
2017-06-11 01:15:00      586.20120      585.35750      551.27686
2017-06-11 01:30:00      584.82110      584.27170      551.49010
2017-06-11 01:45:00      584.86017      584.22480      551.15710
2017-06-11 02:00:00      584.68810      584.40173      550.62380
2017-06-11 02:15:00      584.15710      584.72723      550.32196
2017-06-11 02:30:00      584.45640      584.95110      550.49390
2017-06-11 02:45:00      584.42800      583.74570      550.36383
2017-06-11 03:00:00      583.51117      583.51117      549.73410
2017-06-11 03:15:00      585.85230      585.56580      551.15980
2017-06-11 03:30:00      584.84705      584.83150      550.41064
2017-06-11 03:45:00      584.45640      584.46423      550.68630
2017-06-11 04:00:00      584.30300      583.73004      549.66660
2017-06-11 04:15:00      583.83167      583.25880      550.16080
2017-06-11 04:30:00      584.20917      584.62840      550.14520
2017-06-11 04:45:00      584.18835      583.61554      550.16090
2017-06-11 05:00:00      583.98236      583.69586      550.20470
2017-06-11 05:15:00      584.40960      584.36260      551.30250
2017-06-11 05:30:00      586.36770      585.79480      552.32520
2017-06-11 05:45:00      584.97455      584.68810      551.01935
2017-06-11 06:00:00      584.42206      584.13560      550.07180
2017-06-11 06:15:00      585.00280      585.00280      551.22424
2017-06-11 06:30:00      586.64630      585.62260      551.55740
2017-06-11 06:45:00      585.69310      585.54750      551.26650
2017-06-11 07:00:00      585.22190      584.64905      551.72940
2017-06-11 07:15:00      586.08910      585.80270      551.72940
...                            ...            ...            ...
2017-06-13 16:45:00      579.57227      578.41125      545.95940
2017-06-13 17:00:00      576.67460      576.38820      543.47470
2017-06-13 17:15:00      575.56055      575.23517      542.66310
2017-06-13 17:30:00      576.76355      575.77167      542.61926
2017-06-13 17:45:00      576.45380      575.86554      542.37994
2017-06-13 18:00:00      574.30115      573.72860      540.53015
```

2017-06-13 18:15:00	569.30930	569.02310	536.11240
2017-06-13 18:30:00	569.44226	569.15600	535.91223
2017-06-13 18:45:00	561.50620	560.78820	529.26996
2017-06-13 19:00:00	560.48346	560.19727	528.14557
2017-06-13 19:15:00	562.47424	561.90180	529.85803
2017-06-13 19:30:00	561.25134	560.72577	527.76850
2017-06-13 19:45:00	561.30300	560.50210	528.94946
2017-06-13 20:00:00	562.37260	561.80030	529.74870
2017-06-13 20:15:00	560.81950	560.43176	528.67410
2017-06-13 20:30:00	561.47000	561.14480	528.55970
2017-06-13 20:45:00	559.92975	559.23224	527.58380
2017-06-13 21:00:00	561.13690	560.56450	528.22656
2017-06-13 21:15:00	560.21590	559.64350	527.13350
2017-06-13 21:30:00	561.30600	559.96094	527.87006
2017-06-13 21:45:00	564.41003	563.24176	531.78610
2017-06-13 22:00:00	588.05520	587.48220	552.55664
2017-06-13 22:15:00	595.56010	594.09570	559.76560
2017-06-13 22:30:00	585.60223	584.55804	550.20770
2017-06-13 22:45:00	589.20400	588.32104	554.00586
2017-06-13 23:00:00	585.62570	584.76630	550.98804
2017-06-13 23:15:00	585.64920	584.70374	551.01150
2017-06-13 23:30:00	585.49554	584.51900	550.19210
2017-06-13 23:45:00	585.37050	584.47485	550.12450
2017-06-14 00:00:00	589.24810	588.67510	556.32370

	Temperture15B	Temperture16A	Temperture16B
TimeStamp			
2017-06-11 00:00:00	548.96924	562.70560	562.99180
2017-06-11 00:15:00	550.14230	564.50885	563.88666
2017-06-11 00:30:00	550.36110	563.78015	563.75680
2017-06-11 00:45:00	550.69890	565.51320	565.04706
2017-06-11 01:00:00	549.88257	563.59560	564.16800
2017-06-11 01:15:00	551.29254	564.98240	565.26860
2017-06-11 01:30:00	550.20770	563.63464	563.94430
2017-06-11 01:45:00	550.22330	563.67365	563.95990
2017-06-11 02:00:00	550.33765	563.21550	563.78796
2017-06-11 02:15:00	549.74970	563.00757	563.81146
2017-06-11 02:30:00	550.04370	563.35620	564.03516
2017-06-11 02:45:00	549.48694	562.65100	563.08560
2017-06-11 03:00:00	549.16174	562.89810	562.89810
2017-06-11 03:15:00	550.28577	563.75170	564.92000
2017-06-11 03:30:00	549.83830	563.01807	563.61380
2017-06-11 03:45:00	549.96540	563.16870	563.45483
2017-06-11 04:00:00	549.38043	562.54450	562.83070
2017-06-11 04:15:00	549.19574	562.64594	563.83484
2017-06-11 04:30:00	550.54070	563.70490	563.83484
2017-06-11 04:45:00	549.58856	563.16870	563.45483
2017-06-11 05:00:00	549.63245	562.79645	563.36890

```
2017-06-11 05:15:00      549.50540      563.63947      563.89440
2017-06-11 05:30:00      550.57690      564.91724      564.91724
2017-06-11 05:45:00      550.77710      564.22750      563.90520
2017-06-11 06:00:00      549.49950      563.23590      563.52216
2017-06-11 06:15:00      550.98510      564.42770      563.52216
2017-06-11 06:30:00      551.24774      564.73740      564.79210
2017-06-11 06:45:00      550.69415      564.14465      565.90875
2017-06-11 07:00:00      551.15710      564.03516      564.60754
2017-06-11 07:15:00      551.15710      564.70605      564.93290
...                            ...            ...            ...
2017-06-13 16:45:00      545.44965      557.80145      557.81714
2017-06-13 17:00:00      543.18854      555.49340      556.06573
2017-06-13 17:15:00      542.61926      554.30176      554.62710
2017-06-13 17:30:00      542.58020      555.50433      555.86850
2017-06-13 17:45:00      541.45890      554.38780      554.82250
2017-06-13 18:00:00      540.24396      552.83500      552.83500
2017-06-13 18:15:00      536.11240      549.25250      549.53090
2017-06-13 18:30:00      535.97480      549.20087      548.21740
2017-06-13 18:45:00      527.87787      540.60820      540.58480
2017-06-13 19:00:00      527.57306      539.59344      539.59344
2017-06-13 19:15:00      528.99160      540.38934      541.14154
2017-06-13 19:30:00      527.46670      540.29865      540.04370
2017-06-13 19:45:00      528.73364      540.41280      540.07495
2017-06-13 20:00:00      529.17620      541.19620      541.48236
2017-06-13 20:15:00      527.63070      540.12180      540.16870
2017-06-13 20:30:00      528.78345      540.00745      540.25460
2017-06-13 20:45:00      527.38840      538.74560      537.92320
2017-06-13 21:00:00      527.65410      539.67444      539.67444
2017-06-13 21:15:00      527.30540      539.50256      539.03960
2017-06-13 21:30:00      527.32100      540.40015      539.39600
2017-06-13 21:45:00      530.92750      543.84973      543.06640
2017-06-13 22:00:00      551.98425      566.86600      567.15220
2017-06-13 22:15:00      558.30340      574.07733      574.36350
2017-06-13 22:30:00      550.25946      563.65800      564.07697
2017-06-13 22:45:00      552.53600      567.99036      568.58636
2017-06-13 23:00:00      550.41570      564.15234      564.15234
2017-06-13 23:15:00      549.78094      564.74817      565.02660
2017-06-13 23:30:00      549.59630      563.64246      563.90515
2017-06-13 23:45:00      550.46260      563.59814      564.75600
2017-06-14 00:00:00      555.46520      570.06170      570.34796

[289 rows x 35 columns]
```

In [86]:
```
df['2017-06-11 00:00:00':'2017-06-14 00:00:00'].describe()
```

Out[86]:
```
                MW     Airflow  AmbientTemperature  Temperture1A  Temperture1B  \
count   289.000000  289.000000          289.000000    289.000000    289.000000
mean    145.338350    0.912587           16.079581    567.160290    567.118857
```

```
std      3.677643    3.156461            1.825785    6.563277    6.558976
min    133.837890    0.000000           12.854051  542.983500  542.697400
25%    144.238280    0.000000           14.458544  564.027470  563.704900
50%    145.703120    0.000000           15.898207  569.715700  569.744200
75%    148.095700    0.000000           17.661419  571.308400  571.269350
max    153.222660   18.000000           20.153770  580.917970  580.917970

       Temperture2A  Temperture2B  Temperture3A  Temperture3B  Temperture4A  \
count    289.000000    289.000000    289.000000    289.000000    289.000000
mean     539.716953    538.980667    546.119553    546.180662    558.678999
std        5.606760      5.589895      6.455021      6.428082      6.398190
min      519.882900    519.765750    523.204160    522.871000    535.844850
25%      537.322600    536.640870    542.756960    542.952300    555.527800
50%      541.196170    540.623900    548.522030    548.522030    561.123800
75%      542.952300    542.140600    549.976260    550.309200    562.893100
max      548.267000    547.512150    559.479400    558.303400    572.042000

           ...        Temperture12A  Temperture12B  Temperture13A  \
count      ...           289.000000     289.000000     289.000000
mean       ...           569.179953     570.985760     556.621301
std        ...             5.920231       5.974548       6.495164
min        ...           547.577640     549.279000     533.555300
25%        ...           566.579960     568.552200     553.423000
50%        ...           571.053300     573.119700     559.110170
75%        ...           572.757930     574.548340     560.796000
max        ...           581.490700     583.209100     570.324340

       Temperture13B  Temperture14A  Temperture14B  Temperture15A  \
count     289.000000     289.000000     289.000000     289.000000
mean      558.151239     582.052750     581.594256     548.046497
std         6.568227       6.298544       6.367138       5.978793
min       535.167970     559.310500     558.118900     526.800500
25%       554.978760     579.449950     578.814760     545.374270
50%       560.572300     584.334200     584.003400     550.116700
75%       562.151550     585.750730     585.357500     551.729400
max       572.932100     595.560100     594.095700     559.765600

       Temperture15B  Temperture16A  Temperture16B
count     289.000000     289.000000     289.000000
mean      547.552154     560.703063     560.952867
std         5.956134       6.324559       6.434496
min       526.110700     538.134300     537.676300
25%       544.931950     557.704500     558.006500
50%       549.596300     562.898100     563.218300
75%       551.055600     564.540160     564.849730
max       558.303400     574.077330     574.363500

[8 rows x 35 columns]
```

1.5.5 Summary

At this point we have done some * data descriptions, * descriptive statistics and * some data exploration

1.6 Domain Experts

At this stage the Data Description, Descriptive Statistics and Data Exploration would be presented to the domain experts.

The aim is to find out:

- Does the data look correct?
- ie, do the values for the temperature make sense etc. If not, why not? Does this highlight a problem?
- is there any corruption in the raw data
- sensor malfunction
- scenario that was previously unknown, ie we did not know about that. ie cleaning or maintenance.
- quick that was not known. ie a sensor acted different to expected under certain conditions.
- Check data cleaning logic rules with domain exports
- Indicate failures in the data descriptions (or with labels if we had any)
- Ask questions about any interesting characteristics in the data found during data exploration.
- Why do we get a drop in MW? It does seem to correlate with fluctuations.

1.7 Data Cleaning and Validation

Domain experts will inform out cleaning and validation strategy (In practice can be iterated of many data sets).

Using domain exports advice to devise: * Any logic rules (conversion of units or calculations) - Convert units of a reading. Maybe different sensors used at certain time periods.

- Clinical calculation. ie BMI from height and weight
- Complex calculation. ie level of disease based on readings.
- Credibility checks (correctness, accuracy reliable)
- Incorrectly entered data
- Missing information
- Validation rules (format, length, range checks)
- Encode MW=0 as missing data?

We can be sure (to a certain degree) that we are working with a clean data set.

1.8 Problem statement

Using the project summary, descriptive statistics and data exploration along with feedback from the domain experts a problem statement can be formulated and defined.

"[] keep the plant up and running and detect any deviations from normal operation as early as possible in order to avoid unplanned downtime, loss of revenue and impact on the stability of the power grid."

1.9 Background: Anomaly Detection Methods

This section provides background into the problem. Relevant literature or interesting approaches or previous work.

Important. If this is a new area for me, I will sometimes take a look at previous work, and perform a few experiments. Which I could present to domain experts.

1.9.1 What is an Anomaly?

- A single event in data is anomalous if it's too far off from the rest. Fraud detection based on spending.
- Context specific abnormality. This could be seasonal, but otherwise is normal. Spending at holiday times.
- Collective anomalies are a set of events which correspond to an abnormal event. New location and high spending.

1.9.2 Categories of Data

- Supervised - These approaches requires a data set that has been labelled with some indication of normal and abnormal. The solution would involve training and testing a model, then prediction on new data.
- Semi-supervised - These approach have a small amount of labelled data. This could be a sample of labels indicating normal or abnormal. This can be used for training and evaluation.
- Unsupervised - These approaches use unlabelled data. The assumption is that the majority indicates normal activity.

1.9.3 Possible Approaches for Anomaly Detection

- Statistical Methods
- Moving average (low pass filter) Assume mean is normal behaviour, deviation from the mean is an abnormal event.
- Density-Based Anomaly Detection
- K-nearest neighbour algorithm Assume nearest (euclidean distance) set of data points are normal, otherwise abnormal
- Clustering-Based Anomaly Detection

- K-means clustering algorithm Data that falls outside of these clusters could be considered abnormal
- Support Vector Machine-Based Anomaly Detection
- Typically used in supervised learning. But one class SVM is very well suited to anomaly detection.

1.9.4 Support Vector Machine (SVM)

Support vectors are the individual instances (of n-dimension) in the feature space. The support vector machine is the frontier (line) which best segments the instances in this feature space.

There are many possible frontiers which can segment instances. The objective function - will first find all the frontiers that segment the classes which have the minimum distance to a certain class. - Then it will select the single frontiers that has the maximum distance from each of the classes.

Kernels * Linear SVM * Non-linear

Robust to Outliers SVM are said to be robust to outliers.

If we use the example of dots on one side, and stars on the other. We can use SVM to draw a decision boundary between the dots and stars segmenting into two classes.

If we swap a star and a dot. A SVM can still work out the correct decision boundary to segment these two classes correctly. It will assume that the swapped star and dots are outliers. And they will not adversely effect the decision boundary.

1.9.5 One Class SVM

One Class SVM is an unsupervised algorithm that learns a decision function (boundary) by classifying training data as either part of a single class, or an outlier.

The algorithm will try to create a decision boundary to classify the majority of the training data, while at the same time determining which data (if any), are outliers.

This makes the OneClassSVM a good algorithm in practice for novelty detection.

1.10 Proposed Solution

Given the nature of problem and the data set, I proposed an unsupervised anomaly detection solution using One class SVM.

- Suitability to the anomaly detection problem
- Nature of the unsupervised power plant data set
- Past experience of using this algorithm in this setting

1.11 Implementation

One class SVM using the sklearn library in python.

```
In [89]: import pandas as pd
         import numpy as np
```

```
from sklearn import svm
from sklearn import preprocessing

# Read PowerPlant Data
df = pd.read_csv("data/PowerPlant.txt", sep='\t')
df['TimeStamp'] = pd.to_datetime(df['TimeStamp'])
df.set_index(df['TimeStamp'],inplace=True)
del df['TimeStamp']
```

1.11.1 Data Preprocessing

Pre-Process data into representation suitable for machine learning algorithm. Transformations applied: * Centre Data - use zero mean to centre features * Scale Data - dividing features by their standard deviation

Objective is to create data that is somewhat normally distributed.

If a feature has a variance that is orders of magnitude larger than others, then it could dominate the objective function in the learning algorithm. This could make it unable to learn from other features correctly as expected.

Further data preprocessing techniques Feature selection to discover important of features

- Principal Component Analysis (PCA) to reduce dimensionality.
- Information gain

The descriptive statistics and data exploration did reveal to me that there is most likely a reduction in dimensionality of this feature space.

What this means in real terms. A group of sensors seem to have the same readings and range. Adding multiple of these sensors does not add any new information. Only potentially extra complexity in the modelling stage.

```
In [91]: # Data PreProcessing
         npArray = df.values
         ss_ = preprocessing.StandardScaler(with_mean=True,with_std=True)
         X_train = ss_.fit_transform(npArray)
```

1.11.2 Training Model

The OneClassSVM model is fit to the preprocessed data using params: * Radial Basis Function (rbf) kernel - Non-linear kernel - gamma - defines how much influence a single data instance has. The larger gamma value the closer other examples must be to be affected. - nu - regularization parameter. At most n% of training misclassified. At least n% of training examples being support vectors.

```
In [92]: # fit the model
         clf = svm.OneClassSVM(nu=0.1, kernel="rbf", gamma=0.1)
         clf.fit(X_train)

Out[92]: OneClassSVM(cache_size=200, coef0=0.0, degree=3, gamma=0.1, kernel='rbf',
               max_iter=-1, nu=0.1, random_state=None, shrinking=True, tol=0.001,
               verbose=False)
```

1.11.3 Results

OneClassSVM predictions The resulting model and how it fits the input data is investigated by first looking at its predictions.

We can think of these values as the 'contamination' ratio of abnormal events.

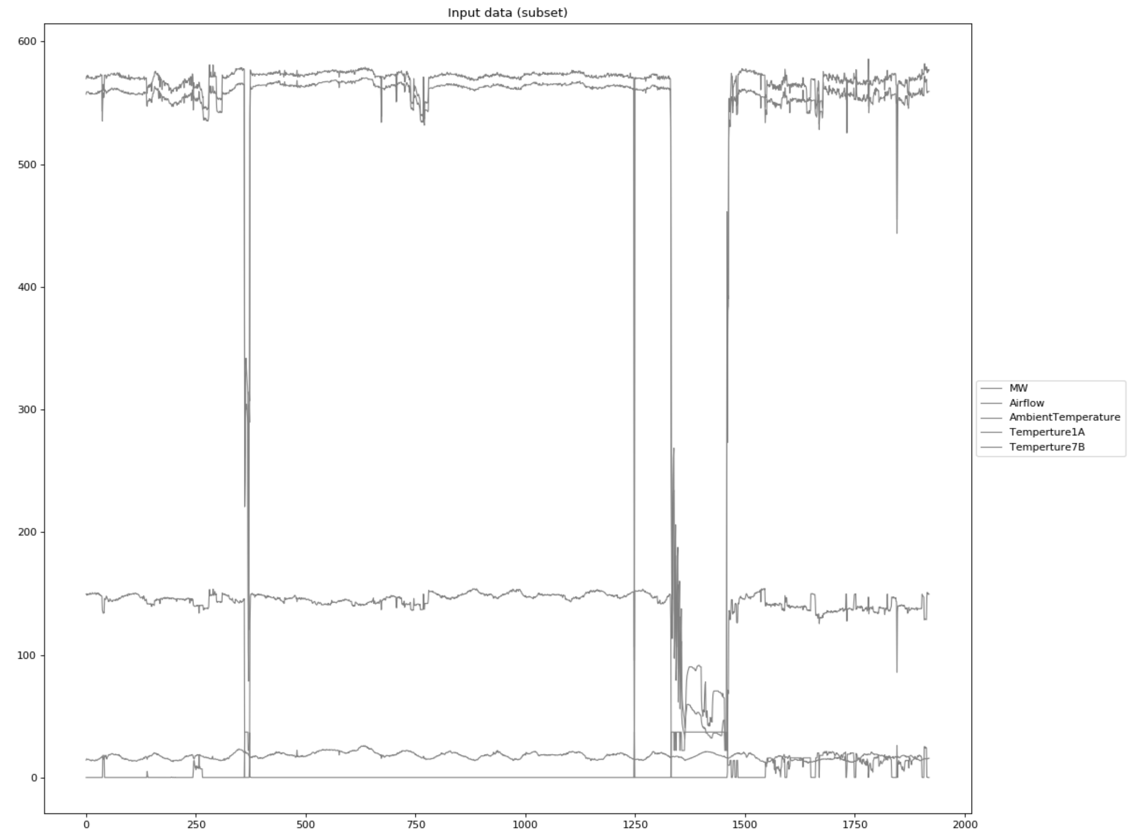
```
In [93]: # Predict classifcation on input data
         y_pred_train = clf.predict(X_train)

         # get number of classified as normal=1 or abnormal=-1
         n_normal_train   = y_pred_train[y_pred_train == 1].size
         n_abnormal_train = y_pred_train[y_pred_train == -1].size

         # get the distance of each instance from the decision boundary (as determined by the ke
         decisionFunctionAll = clf.decision_function(X_train)

         print(" Total instances = "+str(df.shape[0]) )
         print("  Normal          = "+str(n_normal_train) )
         print("  Abnormal        = "+str(n_abnormal_train) )
```

```
 Total instances = 1920
  Normal          = 1729
  Abnormal        = 191
```

OneClassSVM predictions vs input data The model predictions are then compared to input data visually for interpretation.

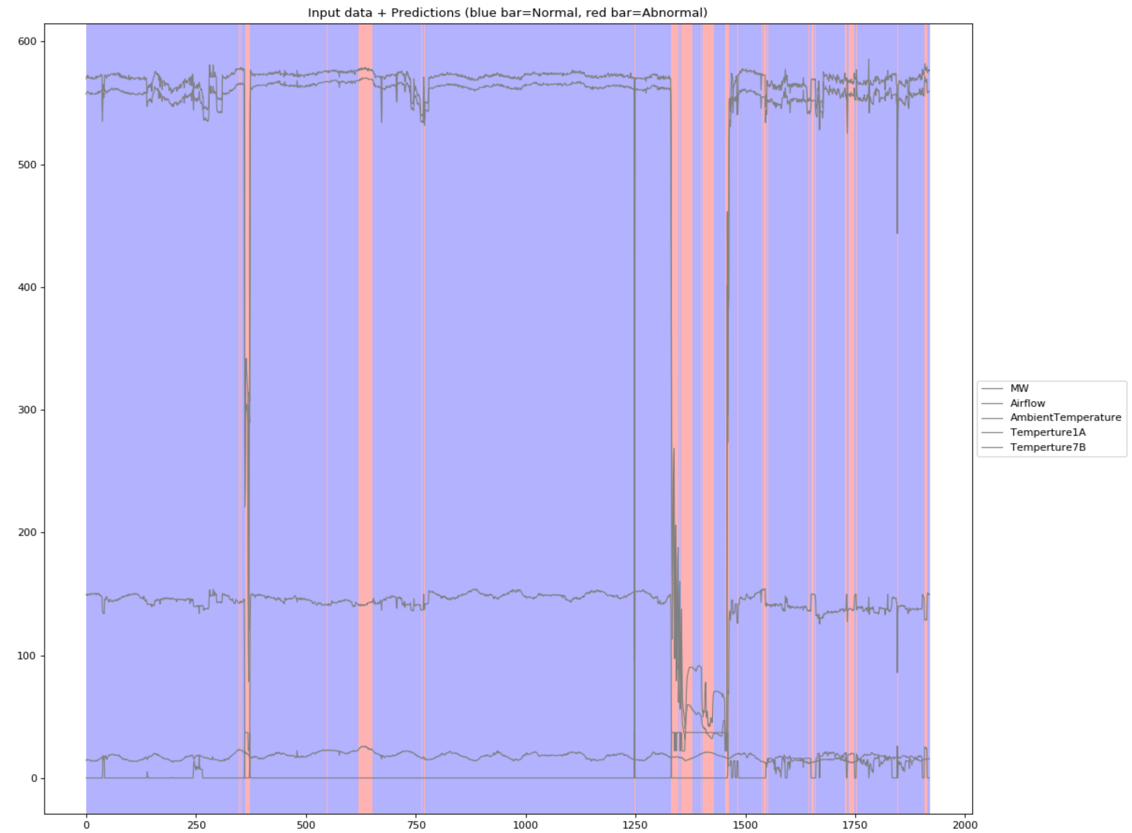
Input data (subset)

```
In [30]: import matplotlib.pyplot as plt
         import matplotlib.font_manager

         fig=plt.figure(figsize=(16, 14), dpi= 80, facecolor='w', edgecolor='k')
         plt.title("Input data (subset)")
         s = 10
         colorData="gray"
         df2 = plt.plot(range(0,df.shape[0]), df['MW'], color=colorData, linewidth=1)
         df3 = plt.plot(range(0,df.shape[0]), df['Airflow'], color=colorData, linewidth=1)
         df4 = plt.plot(range(0,df.shape[0]), df['AmbientTemperature'], color=colorData, linewid
         df5 = plt.plot(range(0,df.shape[0]), df['Temperture1A'], color=colorData, linewidth=1)
         df6 = plt.plot(range(0,df.shape[0]), df['Temperture7B'], color=colorData, linewidth=1)

         plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
         plt.show()
```



Input data + Predictions (blue bar=Normal, red bar=Abnormal)

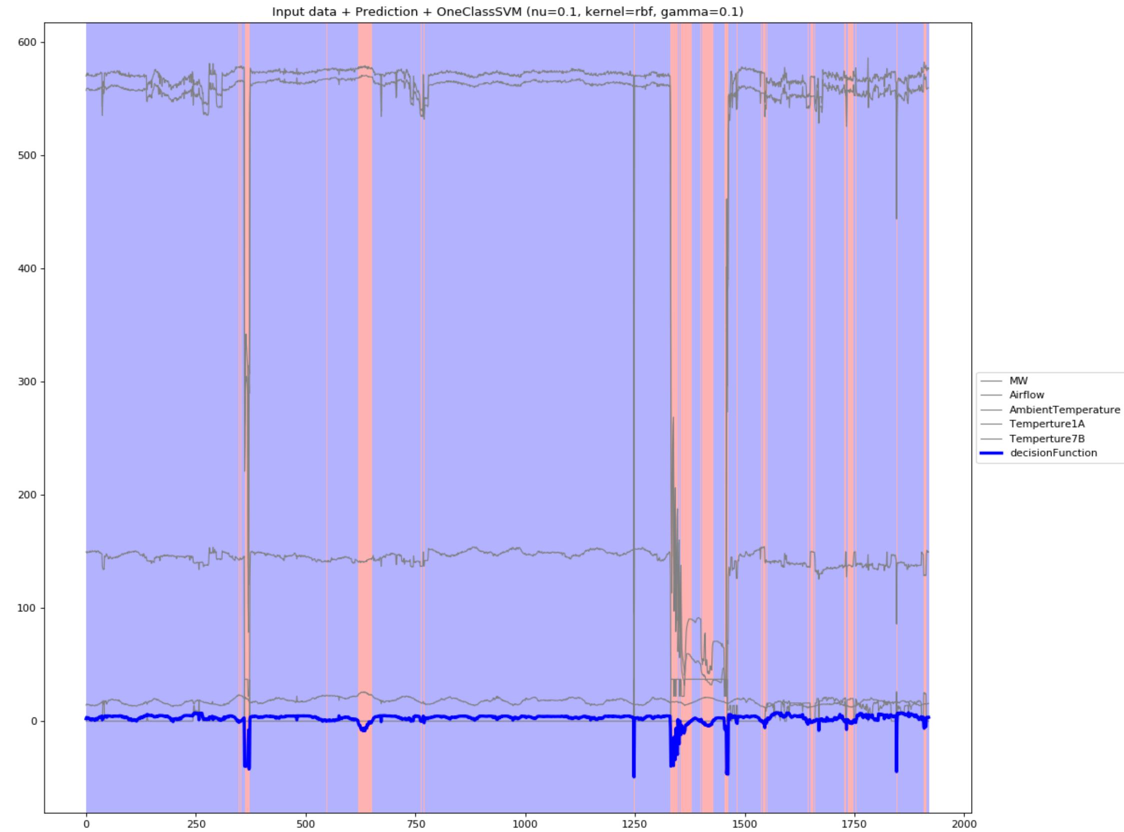
```
In [32]: fig=plt.figure(figsize=(16, 14), dpi= 80, facecolor='w', edgecolor='k')
         plt.title("Input data + Predictions (blue bar=Normal, red bar=Abnormal)")
         s = 10
         colorData="gray"
         df2 = plt.plot(range(0,df.shape[0]), df['MW'], color=colorData, linewidth=1)
         df3 = plt.plot(range(0,df.shape[0]), df['Airflow'], color=colorData, linewidth=1)
         df4 = plt.plot(range(0,df.shape[0]), df['AmbientTemperature'], color=colorData, linewid
         df5 = plt.plot(range(0,df.shape[0]), df['Temperture1A'], color=colorData, linewidth=1)
         df6 = plt.plot(range(0,df.shape[0]), df['Temperture7B'], color=colorData, linewidth=1)

         for i in range(0,len(y_pred_train)):
                 if y_pred_train[i]==1:
                         plt.axvspan(i, i+1, facecolor='b', alpha=0.3)
                 else:
                         plt.axvspan(i, i+1, facecolor='r', alpha=0.3)


         plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
         plt.show()
```



Input data + Predictions + OneClassSVM (nu=0.1, kernel=rbf, gamma=0.1)

In [33]:
```
fig=plt.figure(figsize=(16, 14), dpi= 80, facecolor='w', edgecolor='k')
plt.title("Input data + Prediction + OneClassSVM (nu=0.1, kernel=rbf, gamma=0.1)")
s = 10
colorData="gray"
df2 = plt.plot(range(0,df.shape[0]), df['MW'], color=colorData, linewidth=1)
df3 = plt.plot(range(0,df.shape[0]), df['Airflow'], color=colorData, linewidth=1)
df4 = plt.plot(range(0,df.shape[0]), df['AmbientTemperature'], color=colorData, linewid
df5 = plt.plot(range(0,df.shape[0]), df['Temperture1A'], color=colorData, linewidth=1)
df6 = plt.plot(range(0,df.shape[0]), df['Temperture7B'], color=colorData, linewidth=1)
dfAll = plt.plot(range(0,df.shape[0]), decisionFunctionAll, label='decisionFunction', c

for i in range(0,len(y_pred_train)):
        if y_pred_train[i]==1:
                plt.axvspan(i, i+1, facecolor='b', alpha=0.3)
        else:
                plt.axvspan(i, i+1, facecolor='r', alpha=0.3)
```

```
plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
plt.show()
```



Disclaimer: This model is not the worlds best model, nor have the parameters been optimised as such.

The plots above are an illustration of how: * we can translate the complexities of a machine learning model back to the real input data * the the predictions (blue bar=Normal, red bar=Abnormal) correspond to events in the input data * the decision function (determined by the OneClassSVM) related to predictions and its variance (<0=Abnormal).

1.11.4 Evaluation

What has been shown above is a way to look at how the model has performed.

I now look at formal methods to evaluate the performance of the proposed model.

Problem with performance metrics in this domain: * anomaly events maybe rare * anomaly events maybe of unknown type * anomaly detection is an unbalanced class problem * little or no data labels

There are two possible solutions to the evaluation problem: * Create synthetic data with labelling * Make your own labels and test against them

In this work I propose to make my own labelling (you will notice I already did this in the data description stage). I then use metrics (typically used for classification) to measure the performance of the model.

Model evaluation using data labels The first step is to label the data as normal and abnormal. I do this using the results of my data description investigation.

In [94]:
```
# Create labels for powerplant data (normal=1 abnormal=-1)
df['Labels'] = pd.Series([1 for x in range(len(df.index))], index=df.index)

# Event 1
df.loc['2017-06-14 18:00:00':'2017-06-14 21:15:00','Labels'] = -1

# Event 2
df.loc['2017-06-23 23:45:00':'2017-06-24 00:15:00','Labels'] = -1

# Event 3
df.loc['2017-06-24 21:00:00':'2017-06-26 04:45:00','Labels'] = -1

# Event 4
df.loc['2017-06-30 05:30:00':'2017-06-30 05:45:00','Labels'] = -1


# predicted labels
y_pred = y_pred_train

# true labels (as per my interpretation!)
y_true = df['Labels'].values

#
normalNumber = y_true[y_true == 1].size
abnormalNumber = y_true[y_true == -1].size
```

In [ ]:
```
We can then use a variety of standard metrics to evaluation the performance of the model
```

In [95]:
```
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import roc_auc_score

accuracyScore = accuracy_score(y_true, y_pred)
precisionScore = precision_score(y_true, y_pred)
recallScore = recall_score(y_true, y_pred)
f1Score = f1_score(y_true, y_pred)
rocScore = roc_auc_score(y_true, y_pred)

print(" Total instances   = "+str(df.shape[0]) )
print("  Normal (true)    = "+str(normalNumber) )
print("  Abnormal (true) = "+str(abnormalNumber) )
print
print("  Normal (predict)   = "+str(n_normal_train) )
```

```
        print("  Abnormal (predict) = "+str(n_abnormal_train) )
        print
        print("  AccuracyScore  = "+str(accuracyScore) )
        print("  PrecisionScore = "+str(precisionScore) )
        print("  RecallScore    = "+str(recallScore) )
        print("  F1Score        = "+str(f1Score) )
        print("  RocScore       = "+str(rocScore) )
```

```
 Total instances  = 1920
  Normal (true)   = 1773
  Abnormal (true) = 147

  Normal (predict)   = 1729
  Abnormal (predict) = 191

  AccuracyScore  = 0.9197916666666667
  PrecisionScore = 0.9681897050318103
  RecallScore    = 0.9441624365482234
  F1Score        = 0.9560251284980013
  RocScore       = 0.7850063883421389
```

What each of these metrics are telling us.

- Accuracy: Overall, how often is the classifier correct?
- Precision: When it predicts yes, how often is it correct?
- F Score: This is a weighted average of the true positive rate (recall) and precision.
- ROC Curve: Summarizes the performance of a classifier over all possible thresholds.

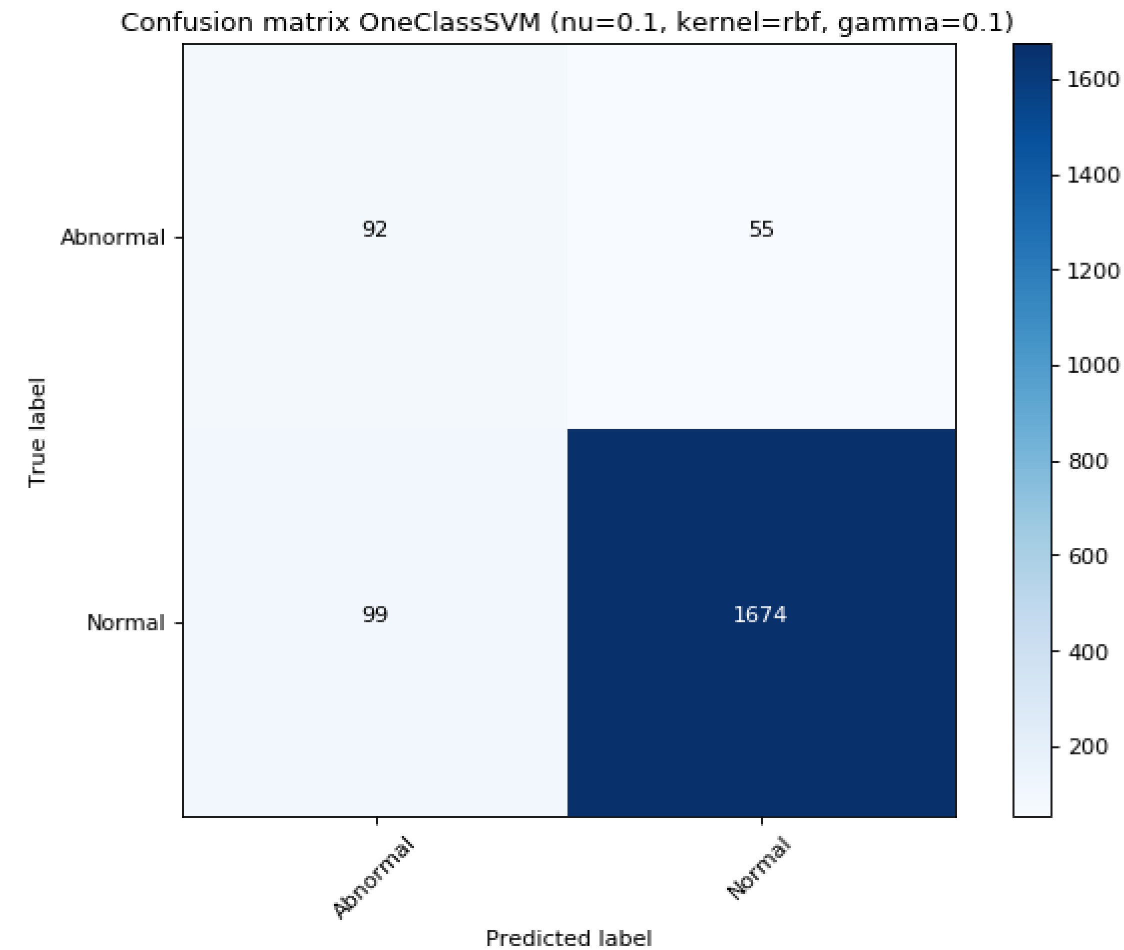
Imbalance of labels to consider when interpreting the metrics.

I want to focus on an important aspect in this particular domain which can be interpreted by using the confusion matrix from this models classification of input data.

```
In [48]: import itertools
        def plot_confusion_matrix(cm, classes, normalize=False, title='Confusion matrix', cmap=
            if normalize:
                cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
                print("Normalized confusion matrix")
            else:
                print('Confusion matrix, without normalization')

            plt.imshow(cm, interpolation='nearest', cmap=cmap)
            plt.title(title)
            plt.colorbar()
            tick_marks = np.arange(len(classes))
            plt.xticks(tick_marks, classes, rotation=45)
            plt.yticks(tick_marks, classes)

            fmt = '.2f' if normalize else 'd'
```

```python
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')


# Calculate confusion matrix
cnf_matrix = confusion_matrix(y_true, y_pred)

# Plot confusion matrix
plt.figure()
fig=plt.figure(figsize=(8, 6), dpi= 80, facecolor='w', edgecolor='k')
class_names=['Abnormal','Normal']
plot_confusion_matrix(cnf_matrix, classes=class_names, title='Confusion matrix OneClass
plt.show()
```

```
Confusion matrix, without normalization


<matplotlib.figure.Figure at 0x7fa161f90450>
```




```
In [39]: from sklearn.metrics import confusion_matrix
         tn, fp, fn, tp = confusion_matrix(y_true, y_pred).ravel()
         print("   tn= "+str(tn) )
         print("   fp= "+str(fp) )
         print("   fn= "+str(fn) )
         print("   tp= "+str(tp) )
```

```
tn= 92
fp= 55
fn= 99
tp= 1674
```

Confusion Matrix

- True positives (tp): Model predicted abnormal but was normal
- True negatives (tn): Model predicted normal correctly

- false positives (fp): Model predicted normal, but was abnormal (Type II error)
- false negatives (fn): Model predicted abnormal, but was normal (Type I error)

Importance of Type II Errors It is acknowledged that no computational model or algorithm can be 100% accurate all of the time.

An important aspect for the proposed model is the trade off between Type I and Type II errors.

In this particular scenario we do not want to miss-classify a (critical) abnormal event as normal. Therefore we would want to 'tune' the algorithm accordingly.

This should provide us with a model in which Type II errors are tolerated in order to catch all potentially dangerous abnormal events.

1.12 Toy Early Warning Detection System

The code below is a toy example of how an early warning detection system could be implemented. This system uses the OneClassSVM model to fit the input data and detect anomalies. It then use this model and a user defined threshold to determine if a new data instance is abnormal or not and to what degree.

```
In [ ]: import pandas as pd
        import numpy as np
        from sklearn import svm
        from sklearn import preprocessing

        # Read PowerPlant data
        df = pd.read_csv("data/PowerPlant.txt", sep='\t')
        df['TimeStamp'] = pd.to_datetime(df['TimeStamp'])
        df.set_index(df['TimeStamp'],inplace=True)
        del df['TimeStamp']

        # Normalise data
        npArray = df.values
        ss_ = preprocessing.StandardScaler(with_mean=True,with_std=True)
        X_scaled = ss_.fit_transform(npArray)

        # Fit the model
        clf = svm.OneClassSVM(nu=0.1, kernel="rbf", gamma=0.1)
        clf.fit(X_scaled)

        # Set thershold levels
        lowWarning=-4.0
        mediumWarning=-8.0
        highWarning=-10.0

        for i in range(0,len(X_scaled)):
                # read new instance
                rowDF = df.iloc[i]
                out=""+str(rowDF.name)+" "
```

```
# get prediction for new instance
if clf.predict(X_scaled[i].reshape(1, -1))[0] == 1:
        out=out+"Normal "
else:
        # get distance of current reading to model decision boundary
        testDecisionFunction = clf.decision_function( X_scaled[i].reshape(1, -1)
        out=out+"Abnormal ("+str(testDecisionFunction[0][0])+") "

        # determine warning level
        if testDecisionFunction[0][0] > lowWarning: out=out+"Low Warning!"
        elif testDecisionFunction[0][0] > mediumWarning: out=out+"Medium Warning
        elif testDecisionFunction[0][0] > highWarning: out=out+"High Warning!!!"
        else: out=out+"Critical!!!"
print(out)
```

2 Selected Output

Example: Small spike 2017-06-13 01:00:00 Normal 2017-06-13 01:15:00 Normal 2017-06-13 01:30:00 Abnormal (-0.4883898324369156) Low Warning! 2017-06-13 01:45:00 Normal 2017-06-13 02:00:00 Normal

Example: Escalating warning levels 2017-06-17 10:30:00 Normal 2017-06-17 10:45:00 Normal 2017-06-17 11:00:00 Abnormal (-1.713211014203921) Low Warning! 2017-06-17 11:15:00 Abnormal (-2.6012780830166307) Low Warning! 2017-06-17 11:30:00 Abnormal (-3.7745073279804444) Low Warning! 2017-06-17 11:45:00 Abnormal (-3.4689648957383312) Low Warning! 2017-06-17 12:00:00 Abnormal (-3.816489565535697) Low Warning! 2017-06-17 12:15:00 Abnormal (-5.946031858579197) Medium Warning!! 2017-06-17 12:30:00 Abnormal (-6.575669107907494) Medium Warning!! 2017-06-17 12:45:00 Abnormal (-7.774132768041703) Medium Warning!! 2017-06-17 13:00:00 Abnormal (-6.712997173845061) Medium Warning!! 2017-06-17 13:15:00 Abnormal (-6.606271771662811) Medium Warning!! 2017-06-17 13:30:00 Abnormal (-6.433806274950982) Medium Warning!! 2017-06-17 13:45:00 Abnormal (-8.577912822244265) High Warning!!! 2017-06-17 14:00:00 Abnormal (-6.403362770820955) Medium Warning!! 2017-06-17 14:15:00 Abnormal (-6.351860361820528) Medium Warning!! 2017-06-17 14:30:00 Abnormal (-7.953127325688186) Medium Warning!! 2017-06-17 14:45:00 Abnormal (-8.53646009433698) High Warning!!! 2017-06-17 15:00:00 Abnormal (-5.7401220288735) Medium Warning!! 2017-06-17 15:15:00 Abnormal (-5.520689558120111) Medium Warning!! 2017-06-17 15:30:00 Abnormal (-6.200828795440607) Medium Warning!! 2017-06-17 15:45:00 Abnormal (-6.265127126213244) Medium Warning!! 2017-06-17 16:00:00 Abnormal (-2.908596802214575) Low Warning! 2017-06-17 16:15:00 Abnormal (-3.9769445779516275) Low Warning! 2017-06-17 16:30:00 Abnormal (-2.5595056361885824) Low Warning! 2017-06-17 16:45:00 Abnormal (-2.868124294077248) Low Warning! 2017-06-17 17:00:00 Abnormal (-0.6137912139521049) Low Warning! 2017-06-17 17:15:00 Abnormal (-1.67508089020383) Low Warning! 2017-06-17 17:30:00 Abnormal (-1.0236988075665607) Low Warning! 2017-06-17 17:45:00 Abnormal (-1.1565361122721) Low Warning! 2017-06-17 18:00:00 Abnormal (-0.6426051202003435) Low Warning! 2017-06-17 18:15:00 Abnormal (-1.67236571939074) Low Warning! 2017-06-17 18:30:00 Abnormal (-1.1537559391425347) Low Warning! 2017-06-17 18:45:00 Abnormal (-0.0704779854887505) Low Warning! 2017-06-17 19:00:00 Normal 2017-06-17

19:15:00 Normal

2.1 Conclusion

This work evaluates the OneClassSVM model for the unsupervised anomaly detection in the context of a power plant early warning detection system.

2.2 Further Reading / References

Chandola et al's (2009) Anomaly Detection: A Survey https://www-users.cs.umn.edu/~baner029/papers/09/anomaly.pdf

Ted Dunning and Ellen Friedman (2014) Practical machine learning: a new look at anomaly detection pdf http://info.mapr.com/rs/mapr/images/Practical_Machine_Learning_Anomaly_Detection.pdf