Version 1.0 / 19.09.2019

Hydro power plant constraints forecast

1 4.1 Power blocks regression

2 Import libraries

Entrée [2]:

```
import math
import pandas as pd
import numpy as np
import array as arr
from pandas import ExcelWriter
from pandas import ExcelFile
import re
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import mean_squared_error, mean_absolute_error
import statistics
from functools import reduce
import random
from sklearn import metrics

%matplotlib inline
```

2.0.1 Read source file into data frame and display columns

Entrée [3]:

```
dateparse = lambda x: pd.datetime.strptime(x, '%Y-%m-%d')

df = pd.read_csv("clean_dataframe.csv", parse_dates=['Date'], date_parser=dateparse, index_
# rename date column
df.rename(columns={ df.columns[0]: "Date"}, inplace=True)
df.index = df["Date"]
```

2.0.2 Check first few lines of imported file

Entrée [338]:

```
df.head()
```

Out[338]:

Date	Date	Min prod	Inflow lake 1 [m3]	Inflow lake 2 [m3]	Inflow lake 3 [m3]	Inflow lake 4 [m3]	Vol lake 1 [%]	Max lake 1 [1000m3]	Availability plant 1 [%]	Availability plant 2 [%]	.
2014-04-01	2014-04-01	0.0	31.0	4.0	129.0	107.0	0.16467	30000.0	1.0	1.0	.
2014-04-02	2014-04-02	150.0	0.0	-14.0	148.0	116.0	0.15557	30000.0	1.0	1.0	.
2014-04-03	2014-04-03	150.0	10.0	6.0	132.0	118.0	0.14765	30000.0	1.0	1.0	.
2014-04-04	2014-04-04	150.0	19.0	6.0	150.0	118.0	0.13716	30000.0	1.0	1.0	.
2014-04-05	2014-04-05	180.0	41.0	15.0	148.0	124.0	0.13091	30000.0	1.0	1.0	.

5 rows × 62 columns

Entrée [339]:

```
df.tail()
```

Out[339]:

Date	Date	Min prod	Inflow lake 1 [m3]	Inflow lake 2 [m3]	Inflow lake 3 [m3]	Inflow lake 4 [m3]	Vol lake 1 [%]	Max lake 1 [1000m3]	Availability plant 1 [%]	Availabi plant 2
2019-06-26	2019-06-26	479.633867	1179.8	-108.0	785.1	625.8	0.63993	30000.0	1.0	
2019-06-27	2019-06-27	569.565217	1735.9	-111.0	868.0	547.2	0.66066	30000.0	1.0	
2019-06-28	2019-06-28	509.610984	1786.9	79.0	644.6	595.3	0.68188	30000.0	1.0	
2019-06-29	2019-06-29	479.633867	1614.6	83.0	609.2	479.1	0.70126	30000.0	1.0	
2019-06-30	2019-06-30	479.633867	1516.5	-105.0	834.7	357.7	0.71942	30000.0	1.0	

5 rows × 62 columns

Entrée [6]:

```
# display info about our dataframe, i.e. features types, labels, number of values including
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1917 entries, 2014-04-01 to 2019-06-30
Data columns (total 23 columns):
Date                         1917 non-null datetime64[ns]
Min prod                     1917 non-null float64
Inflow lake 1 [m3]           1917 non-null float64
Inflow lake 2 [m3]           1917 non-null float64
Inflow lake 3 [m3]           1917 non-null float64
Inflow lake 4 [m3]           1917 non-null float64
Vol lake 1 [%]               1917 non-null float64
Max lake 1 [1000m3]          1917 non-null float64
Availability plant 1 [%]     1917 non-null float64
Availability plant 2 [%]     1917 non-null float64
Availability plant 3 [%]     1917 non-null float64
Availability plant 4 [%]     1917 non-null float64
SDL [MWh]                    1917 non-null float64
Weekend                      1917 non-null bool
Variante Prio                1917 non-null float64
PrioH1                       1917 non-null float64
PrioP1                       1917 non-null float64
PrioH2                       1917 non-null float64
PrioP2                       1917 non-null float64
PrioH3                       1917 non-null float64
PrioP3                       1917 non-null float64
PrioH4                       1917 non-null float64
PrioP4                       1917 non-null float64
dtypes: bool(1), datetime64[ns](1), float64(21)
memory usage: 346.3 KB
```

Entrée [7]:

```
# Read baseline for benchmark data as well
df_benchmark = pd.read_csv("baseline_dataframe.csv", parse_dates=['Date'], date_parser=date
# Force index to be date (as provided in the first column)
df_benchmark.index = df_benchmark['Date']

df_benchmark.info()
df_benchmark.head()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1918 entries, 2014-04-01 to 2019-07-01
Data columns (total 10 columns):
Date             1918 non-null datetime64[ns]
P1 [MW]          1918 non-null float64
P2 [MW]          1918 non-null float64
P3 [MW]          1918 non-null float64
P4 [MW]          1918 non-null int64
H1 [#]           1918 non-null int64
H2 [#]           1918 non-null int64
H3 [#]           1918 non-null int64
Min Prod [MWh]   1918 non-null float64
MaxEnergy        1918 non-null float64
dtypes: datetime64[ns](1), float64(5), int64(4)
memory usage: 164.8 KB
```

Out[7]:

Date	Date	P1 [MW]	P2 [MW]	P3 [MW]	P4 [MW]	H1 [#]	H2 [#]	H3 [#]	Min Prod [MWh]	MaxEnergy
2014-04-01	2014-04-01	73.7	47.8	40.0	0	3	4	9	254.2	772.3
2014-04-02	2014-04-02	73.6	47.8	40.0	0	3	4	9	276.5	772.0
2014-04-03	2014-04-03	55.3	47.7	39.9	0	3	4	9	269.5	715.8
2014-04-04	2014-04-04	54.1	47.7	39.9	0	3	4	9	289.9	712.2
2014-04-05	2014-04-05	73.5	47.7	39.9	0	3	5	8	297.6	778.2

Entrée [8]:

```
# copy baseline values into main dataframe, using consistent labels
df["Baseline_Min prod"] = df_benchmark["Min Prod [MWh]"]
df["Baseline_Variante Prio"] = df_benchmark["MaxEnergy"]
```

2.1 Data preparation for ML

2.1.1 Test / train split and input / output features separation

Entrée [9]:

```
# define regressors, i.e. list of features to be used as input for our regression problem
regressors = ['Inflow lake 1 [m3]', \
              'Inflow lake 2 [m3]', 'Inflow lake 3 [m3]', 'Inflow lake 4 [m3]', \
              'Vol lake 1 [%]', 'Availability plant 1 [%]', \
              'Availability plant 2 [%]', 'Availability plant 3 [%]', \
              'Availability plant 4 [%]']
```

Entrée [10]:

```
# define train / test split ratio (applied to availabe data points in dataset)
splitRatio = 0.9
```

Entrée [26]:

```
# splits the input dataframe into train, test for target and input features, using the prov
def GetDataSplitMulti(df_input, regressors, target_features, ratio):
    # We split using a 90/10 ratio (parameter), but keeping the data in chronological order
    CutPoint = round(len(df.index)*ratio)
    df_model = df_input.filter(regressors, axis=1)

    xTrain = df_model.iloc[:CutPoint, :]
    xTest  = df_model.iloc[CutPoint:, :]
    yTrain = df[target_features][:CutPoint]
    yTest  = df[target_features][CutPoint:]
    return [xTrain, xTest, yTrain, yTest ]
```

Entrée [109]:

```
# Compute hourly metrics for baseline
# create an hourly dataframe over same period
# compute hourly values filling up a 24 hours vector
df_hourly = pd.DataFrame(
        {'Hours': pd.date_range(df.index.min(), df.index.max(), freq='1H', closed='left')}
     )
df_hourly.index = df_hourly['Hours']
```

Entrée [110]:

```
df_hourly.head()
```

Out[110]:

	Hours
Hours	
2014-04-01 00:00:00	2014-04-01 00:00:00
2014-04-01 01:00:00	2014-04-01 01:00:00
2014-04-01 02:00:00	2014-04-01 02:00:00
2014-04-01 03:00:00	2014-04-01 03:00:00
2014-04-01 04:00:00	2014-04-01 04:00:00

Entrée [111]:

```
len(df_hourly.index)
```

Out[111]:

45984

Entrée [112]:

```
firstDate = df.index.min()
powerHours = np.zeros(45984)
powerHoursBaseline =  np.zeros(45984)

# loop over all date
for myDate in df.index:
    # index is date difference times 24
    index = (myDate-firstDate).days * 24
    # compute hourly vector of original values, using the 4 pairs (power/nb of hours)
    currHour = index
    for iPair in range(1,4+1):
        pwrValue = df.loc[myDate, "PrioP"+str(iPair)]
        nbHours = int(df.loc[myDate, "PrioH"+str(iPair)])
        if pwrValue > 0:
            #print("Date %s, Pair %i, Pwr %d, Hours %f" %(myDate, iPair, pwrValue, nbHours)
            powerHours[currHour:currHour+nbHours] = pwrValue
            currHour = currHour + nbHours
    # compute hourly vector of baseline values, using the 3 pairs (power/nb of hours)
    currHour = index
    for iPair in range(1,3+1):
        pwrValue = df_benchmark.loc[myDate, "P"+str(iPair)+" [MW]"]
        nbHours = int(df_benchmark.loc[myDate, "H"+str(iPair)+" [#]"])
        if pwrValue > 0:
            #print("Date %s, Pair %i, Pwr %d, Hours %f" %(myDate, iPair, pwrValue, nbHours)
            powerHoursBaseline[currHour:currHour+nbHours] = pwrValue
            currHour = currHour + nbHours
```

Entrée [113]:

```
df_hourly["Power"] = powerHours
df_hourly["PowerBaseLine"] = powerHoursBaseline

df_hourly.head()
```

Out[113]:

	Hours	Power	PowerBaseLine
Hours			
2014-04-01 00:00:00	2014-04-01 00:00:00	73.8	73.7
2014-04-01 01:00:00	2014-04-01 01:00:00	73.8	73.7
2014-04-01 02:00:00	2014-04-01 02:00:00	73.8	73.7
2014-04-01 03:00:00	2014-04-01 03:00:00	73.8	47.8
2014-04-01 04:00:00	2014-04-01 04:00:00	66.0	47.8

Entrée [108]:

```
# compute error metrics over hourly values calculated above
print('Hourly comparison: prediction baseline vs. actual values')
print('RMSE :'+ str(round(math.sqrt(metrics.mean_squared_error(df_hourly["Power"],df_hourly
print('MAE :'+ str(round( metrics.mean_absolute_error(df_hourly["Power"],df_hourly["PowerBa
print('R^2 :'+ str(round(metrics.r2_score( df_hourly["Power"],df_hourly["PowerBaseLine"])*1
```

```
Hourly comparison: prediction baseline vs. actual values
RMSE :20.31
MAE :14.41
R^2 :42.34
```

3 Model selection

3.1 Model selection using scikit-learn library

Entrée [33]:

```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble.forest import RandomForestRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.svm import SVR
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.pipeline import Pipeline
import math

from sklearn.preprocessing import StandardScaler, MinMaxScaler
```

Entrée [34]:

```
# function to produce plots out of models predictions
# plot actual value, prediction and baseline in one plot
# plot error along time below in another plot
# Add error metrics values at the bottom and model's parameters
# Produce file in SVG format, i.e. vector format for best quality import in final report
import matplotlib.pylab as pl
import matplotlib.gridspec as gridspec
from statsmodels.graphics.gofplots import qqplot

def plotModelPrediction(model, target_label, y_train, pred, y_test, target_baseline, test_i

   # build dataframe to be plotted, plot graph and save it as a file
    if  isinstance(model, str):
        model_name = model
    else:
        model_name = type(model).__name__

    df_pred = pd.DataFrame(pred, columns=['Forecast '+model_name], index = test_index)
    df_pred["Ground truth"] = y_test
    df_pred["Mean train values"] = y_train.mean()
    df_pred["Baseline"]  = target_baseline

    fig_size = plt.rcParams["figure.figsize"]
    fig_size[0] = 15
    fig_size[1] = 15
    plt.rcParams["figure.figsize"] = fig_size

    # Create 1x3 sub plots
    gs = gridspec.GridSpec(3, 2)

    fig = pl.figure()
    ax = pl.subplot(gs[0, :]) # row 0, col 0
    df_pred.plot(title = target_label+' forecast '+model_name+'(additional regressor: '+adc

    # plot error along time
    ax = pl.subplot(gs[1, :]) # row 1, col 0
    df_error = pd.DataFrame(df_pred["Ground truth"]-df_pred['Forecast '+model_name], columr
    df_error.plot(grid=True, ax=ax)

    # plot predicted vs actual values
    ax = pl.subplot(gs[2, 0]) # row 2, col 0
    plt.scatter(df_pred["Ground truth"], df_pred['Forecast '+model_name], c='b', alpha=0.3)
    plt.plot([1,1000], [1,1000], ls="--", c="r")
    plt.title("Predicted values vs ground truth")
    plt.xlabel("Ground truth")
    plt.ylabel("Predicted value")

    # plot residuals qqplot
    ax = pl.subplot(gs[2, 1]) # row 2, col 1
    qqplot(df_error, line = "s", ax=ax)

    # add textual elements: error metrics values, model name and parameters
    txt = 'Target :'+ target_label+" / "
    txt = txt + 'RMSE :'+ str(round(math.sqrt(metrics.mean_squared_error(y_test,pred)),2))+
    txt = txt + 'MAE :'+ str(round(metrics.mean_absolute_error(y_test,pred),2))+" / "
    txt = txt + 'R^2 :'+ str(round(metrics.r2_score(y_test,pred)*100, 2))+" "
    fig.text(.5, .05, txt, ha='center')

    fig.savefig('Forecast'+target_label+model_name+'+'+addRegressor+'.svg', format='svg')
```

Entrée [35]:

```
# function to train the model and set its best parameters, then evaluate it
# return best parameters

def TrainEvalModel(X_train, X_test, y_train, y_test, target_label, target_baseline, test_ir
    pipeline = Pipeline([('preprocessor', StandardScaler()),
                         ('model', model)])
    print('Model: ', model)
    print(params)
    grid = GridSearchCV(pipeline, params, scoring='r2', n_jobs=-1, cv=3, verbose=1)
    grid.fit(X_train, y_train)
    pred = grid.best_estimator_.predict(X_test)

    print('Target :', target_label)
    print('Regressors :', X_train.columns)
    print('Parameters: ', grid.best_params_ )
    print('Root Mean Square Error: %1.4f' % (math.sqrt(metrics.mean_squared_error(y_test,pr
    print('Mean Absolute Error: %1.4f' % (metrics.mean_absolute_error(y_test,pred)))
    print('R2 score : %1.4f' %(metrics.r2_score(y_test,pred)*100))
    print('\n\n')

    plotModelPrediction(model,target_label, y_train, pred, y_test, target_baseline, test_ir

    return [math.sqrt(metrics.mean_squared_error(y_test,pred)),
                  metrics.mean_absolute_error(y_test,pred),
                  metrics.r2_score(y_test,pred)*100,
                  grid.best_params_]
```

Entrée [36]:

```
# set random seed for reproducibility
random.seed( 42 )
```

Entrée [37]:

```
df.columns
```

Out[37]:

```
Index(['Date', 'Min prod', 'Inflow lake 1 [m3]', 'Inflow lake 2 [m3]',
       'Inflow lake 3 [m3]', 'Inflow lake 4 [m3]', 'Vol lake 1 [%]',
       'Max lake 1 [1000m3]', 'Availability plant 1 [%]',
       'Availability plant 2 [%]', 'Availability plant 3 [%]',
       'Availability plant 4 [%]', 'SDL [MWh]', 'Weekend', 'Variante Prio',
       'PrioH1', 'PrioP1', 'PrioH2', 'PrioP2', 'PrioH3', 'PrioP3', 'PrioH4',
       'PrioP4', 'Baseline_Min prod', 'Baseline_Variante Prio'],
      dtype='object')
```

Entrée [39]:

```
# implement mutli-output random forest
fullRegressors = regressors
target_features = ['Min prod','Variante Prio', 'PrioH1', 'PrioP1', 'PrioH2', 'PrioP2', 'Pri

xTrain, xTest, yTrain, yTest =  GetDataSplitMulti(df, fullRegressors, target_features,0.9)
yTest.head()
```

Out[39]:

	Min prod	Variante Prio	PrioH1	PrioP1	PrioH2	PrioP2	PrioH3	PrioP3	PrioH
Date									
2018-12-21	119.908467	1241.052632	2.0	74.942792	14.0	65.949657	8.0	20.983982	0.
2018-12-22	89.931350	1241.052632	2.0	74.942792	14.0	65.949657	8.0	20.983982	0.
2018-12-23	89.931350	1241.052632	2.0	74.942792	14.0	65.949657	8.0	20.983982	0.
2018-12-24	119.908467	1241.052632	2.0	74.942792	14.0	65.949657	8.0	20.983982	0.
2018-12-25	119.908467	1241.052632	2.0	74.942792	14.0	65.949657	8.0	20.983982	0.

Entrée [41]:

```
from sklearn.ensemble import RandomForestRegressor
regr_rf = RandomForestRegressor()
regr_rf.fit(xTrain, yTrain)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:245: F
utureWarning: The default value of n_estimators will change from 10 in versi
on 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

Out[41]:

```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                      max_features='auto', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=10,
                      n_jobs=None, oob_score=False, random_state=None,
                      verbose=0, warm_start=False)
```

Entrée [47]:

```
pred = regr_rf.predict(xTest)
pred.shape
```

Out[47]:

```
(192, 10)
```

Entrée [61]:

```
# build a dataframe to store results
df_pred = pd.DataFrame(data=pred, columns = target_features, index = yTest.index)
df_pred.head()
```

Out[61]:

	Min prod	Variante Prio	PrioH1	PrioP1	PrioH2	PrioP2	PrioH3	PrioP3	PrioH
Date									
2018-12-21	118.967963	1270.235858	4.3	71.911968	9.6	60.968261	8.3	36.173593	0
2018-12-22	115.963387	1245.877803	4.1	72.356293	9.7	61.203043	7.5	36.799108	1
2018-12-23	116.363387	1323.364256	5.9	71.096796	9.3	60.633318	8.4	35.389336	0
2018-12-24	122.961098	1133.995126	3.4	74.215652	10.3	63.779657	7.3	29.448261	0
2018-12-25	110.867963	1120.062998	2.9	73.861442	8.8	66.064645	7.4	38.959108	1

Entrée [62]:

```
# compute metrics on daily values, i.e minimum and maxium production
print('Daily values comparison: prediction vs. actual')
print('Minimum production')
print('RMSE :'+ str(round(math.sqrt(metrics.mean_squared_error(df_pred["Min prod"],yTest["M
print('MAE :'+ str(round( metrics.mean_absolute_error(df_pred["Min prod"],yTest["Min prod"]
print('R^2 :'+ str(round(metrics.r2_score( df_pred["Min prod"],yTest["Min prod"])*100, 2)))
print('Maximum production')
print('RMSE :'+ str(round(math.sqrt(metrics.mean_squared_error(df_pred["Variante Prio"],yTe
print('MAE :'+ str(round( metrics.mean_absolute_error(df_pred["Variante Prio"],yTest["Varia
print('R^2 :'+ str(round(metrics.r2_score( df_pred["Variante Prio"],yTest["Variante Prio"])
```

```
Daily values comparison: prediction vs. actual
Minimum production
RMSE :105.25
MAE :76.74
R^2 :35.13
Maximum production
RMSE :394.69
MAE :333.52
R^2 :-53.2
```

Entrée [63]:

```
# In order to compute the hourly metrics, build hourly values out of results
# apply first rounding algorithm
# 1) Basic rounding of hourly values
# 2) rounding keeping rounding account -> keep it as close as possible to zero
# 3) rouding hours value but correcting matching power value so the energy remains identica

# basic rounding
```

Entrée [118]:

```
df_pred.index.size
df_hourly.loc[df_pred.index.min():,].index.size
```

Out[118]:

```
4584
```

Entrée [129]:

```
# rounding function is floor
rounding_func = math.floor

# hourly dataframe to store restults, out of complete one
df_hourly_pred = df_hourly.loc[df_pred.index.min():,]

firstDate = df_pred.index.min()
powerHours = np.zeros(4584)

# loop over all date
for myDate in df_pred.index:
    # index is date difference times 24
    index = (myDate-firstDate).days * 24
    # compute hourly vector of original values, using the 4 pairs (power/nb of hours)
    currHour = index
    for iPair in range(1,4+1):
        pwrValue = df_pred.loc[myDate, "PrioP"+str(iPair)]
        nbHours = int(rounding_func(df_pred.loc[myDate, "PrioH"+str(iPair)]))
        if pwrValue > 0:
            #print("Date %s, Pair %i, Pwr %d, Hours %f" %(myDate, iPair, pwrValue, nbHours)
            powerHours[currHour:currHour+nbHours] = pwrValue
            currHour = currHour + nbHours

df_hourly_pred["PredictedPower"]= powerHours
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:24: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/s
table/indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pand
as-docs/stable/indexing.html#indexing-view-versus-copy)
```

Entrée [131]:

```
df_hourly_pred.head(24)
```

Out[131]:

	Hours	Power	PowerBaseLine	PredictedPower
Hours				
2018-12-21 00:00:00	2018-12-21 00:00:00	74.942792	85.2	71.911968
2018-12-21 01:00:00	2018-12-21 01:00:00	74.942792	85.2	71.911968
2018-12-21 02:00:00	2018-12-21 02:00:00	65.949657	76.3	71.911968
2018-12-21 03:00:00	2018-12-21 03:00:00	65.949657	46.8	71.911968
2018-12-21 04:00:00	2018-12-21 04:00:00	65.949657	46.8	60.968261
2018-12-21 05:00:00	2018-12-21 05:00:00	65.949657	46.8	60.968261
2018-12-21 06:00:00	2018-12-21 06:00:00	65.949657	46.8	60.968261
2018-12-21 07:00:00	2018-12-21 07:00:00	65.949657	46.8	60.968261
2018-12-21 08:00:00	2018-12-21 08:00:00	65.949657	46.8	60.968261
2018-12-21 09:00:00	2018-12-21 09:00:00	65.949657	46.8	60.968261
2018-12-21 10:00:00	2018-12-21 10:00:00	65.949657	46.8	60.968261
2018-12-21 11:00:00	2018-12-21 11:00:00	65.949657	46.8	60.968261
2018-12-21 12:00:00	2018-12-21 12:00:00	65.949657	46.8	60.968261
2018-12-21 13:00:00	2018-12-21 13:00:00	65.949657	46.8	36.173593
2018-12-21 14:00:00	2018-12-21 14:00:00	65.949657	46.8	36.173593
2018-12-21 15:00:00	2018-12-21 15:00:00	65.949657	46.8	36.173593
2018-12-21 16:00:00	2018-12-21 16:00:00	20.983982	0.0	36.173593
2018-12-21 17:00:00	2018-12-21 17:00:00	20.983982	0.0	36.173593
2018-12-21 18:00:00	2018-12-21 18:00:00	20.983982	0.0	36.173593
2018-12-21 19:00:00	2018-12-21 19:00:00	20.983982	0.0	36.173593
2018-12-21 20:00:00	2018-12-21 20:00:00	20.983982	0.0	36.173593
2018-12-21 21:00:00	2018-12-21 21:00:00	20.983982	0.0	0.000000
2018-12-21 22:00:00	2018-12-21 22:00:00	20.983982	0.0	0.000000
2018-12-21 23:00:00	2018-12-21 23:00:00	20.983982	0.0	0.000000

Entrée [132]:

```
# compute error metrics over hourly values calculated above
print('Hourly comparison: prediction vs. actual values')
print('RMSE :'+ str(round(math.sqrt(metrics.mean_squared_error(df_hourly_pred["Power"],df_h
print('MAE :'+ str(round( metrics.mean_absolute_error(df_hourly_pred["Power"],df_hourly_pre
print('R^2 :'+ str(round(metrics.r2_score( df_hourly_pred["Power"],df_hourly_pred["Predicte
```

```
Hourly comparison: prediction baseline vs. actual values
RMSE :22.31
MAE :14.38
R^2 :10.85
```

Entrée [138]:

```
# construct a vector of 24 hours values as target variable, to see how good it performs in

# create needed columns in the source dataset
for i in range (24):
    df["HourValue"+str(i)] = 0

# loop over all date
for myDate in df.index:
    # compute hourly vector of original values, using the 4 pairs (power/nb of hours)
    currHour = 0
    for iPair in range(1,4+1):
        pwrValue = df.loc[myDate, "PrioP"+str(iPair)]
        nbHours = int(df.loc[myDate, "PrioH"+str(iPair)])
        if pwrValue > 0 and nbHours>0:
            #print("Date %s, Pair %i, Pwr %d, Hours %f" %(myDate, iPair, pwrValue, nbHours)
            df.loc[myDate,"HourValue"+str(currHour):"HourValue"+str(currHour+nbHours-1)] =
            currHour = currHour + nbHours
    # Add the 24 vectors to 24 columns in the dataset
df.iloc[0,:]
```

```
Date 2014-04-08 00:00:00, Pair 3, Pwr 42, Hours 8.000000
Date 2014-04-09 00:00:00, Pair 1, Pwr 72, Hours 4.000000

Date 2014-04-09 00:00:00, Pair 2, Pwr 66, Hours 4.000000
Date 2014-04-09 00:00:00, Pair 3, Pwr 42, Hours 8.000000
Date 2014-04-10 00:00:00, Pair 1, Pwr 70, Hours 3.000000
Date 2014-04-10 00:00:00, Pair 2, Pwr 58, Hours 2.000000
Date 2014-04-10 00:00:00, Pair 3, Pwr 51, Hours 3.000000
Date 2014-04-10 00:00:00, Pair 4, Pwr 37, Hours 6.000000
Date 2014-04-11 00:00:00, Pair 1, Pwr 70, Hours 3.000000
Date 2014-04-11 00:00:00, Pair 2, Pwr 58, Hours 2.000000
Date 2014-04-11 00:00:00, Pair 3, Pwr 51, Hours 3.000000
Date 2014-04-11 00:00:00, Pair 4, Pwr 37, Hours 6.000000
Date 2014-04-12 00:00:00, Pair 1, Pwr 70, Hours 3.000000
Date 2014-04-12 00:00:00, Pair 2, Pwr 58, Hours 2.000000
Date 2014-04-12 00:00:00, Pair 3, Pwr 51, Hours 3.000000
Date 2014-04-12 00:00:00, Pair 4, Pwr 37, Hours 6.000000
Date 2014-04-13 00:00:00, Pair 1, Pwr 70, Hours 3.000000
Date 2014-04-13 00:00:00, Pair 2, Pwr 58, Hours 2.000000
Date 2014-04-13 00:00:00, Pair 3, Pwr 51, Hours 3.000000
```

Entrée [142]:

```
# implement mutli-output random forest
fullRegressors = regressors
# create list of target features
target_features = ['HourValue'+str(i) for i in range(24)]

xTrain, xTest, yTrain, yTest =  GetDataSplitMulti(df, fullRegressors, target_features,0.9)
yTest.head()
```

Out[142]:

Date	HourValue0	HourValue1	HourValue2	HourValue3	HourValue4	HourValue5	HourValue6
2018-12-21	74.942792	74.942792	65.949657	65.949657	65.949657	65.949657	65.949657
2018-12-22	74.942792	74.942792	65.949657	65.949657	65.949657	65.949657	65.949657
2018-12-23	74.942792	74.942792	65.949657	65.949657	65.949657	65.949657	65.949657
2018-12-24	74.942792	74.942792	65.949657	65.949657	65.949657	65.949657	65.949657
2018-12-25	74.942792	74.942792	65.949657	65.949657	65.949657	65.949657	65.949657

5 rows × 24 columns

Entrée [143]:

```
regr_rf = RandomForestRegressor()
regr_rf.fit(xTrain, yTrain)
pred = regr_rf.predict(xTest)
df_pred = pd.DataFrame(data=pred, columns = target_features, index = yTest.index)
df_pred.head()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:245: F
utureWarning: The default value of n_estimators will change from 10 in versi
on 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

Out[143]:

	HourValue0	HourValue1	HourValue2	HourValue3	HourValue4	HourValue5	HourValue6
Date							
2018-12-21	70.182838	70.182838	65.144897	64.244897	58.874897	58.874897	58.874897
2018-12-22	69.648558	69.648558	65.509931	64.609931	58.519931	58.519931	58.519931
2018-12-23	70.182838	70.182838	65.144897	64.244897	58.874897	58.874897	58.874897
2018-12-24	71.148696	71.148696	69.649840	67.849840	64.849840	64.849840	64.849840
2018-12-25	70.794279	70.794279	67.614966	66.714966	61.194966	60.894966	60.894966

5 rows × 24 columns

Entrée [145]:

```
yTest[target_features]
```

Out[145]:

	HourValue0	HourValue1	HourValue2	HourValue3	HourValue4	HourValue5	HourValue6	HourValue7
Date								
2018-12-21	74.942792	74.942792	65.949657	65.949657	65.949657	65.949657	65.949657	65.949657
2018-12-22	74.942792	74.942792	65.949657	65.949657	65.949657	65.949657	65.949657	65.949657
2018-12-23	74.942792	74.942792	65.949657	65.949657	65.949657	65.949657	65.949657	65.949657
2018-12-24	74.942792	74.942792	65.949657	65.949657	65.949657	65.949657	65.949657	65.949657
2018-12-25	74.942792	74.942792	65.949657	65.949657	65.949657	65.949657	65.949657	65.949657
2018-	74.942792	74.942792	65.949657	65.949657	65.949657	65.949657	65.949657	65.949657

Entrée [147]:

```
# compute metrics on daily values, i.e minimum and maxium production
print('Hourly values comparison (vector of 24 length): prediction vs. actual')
print('RMSE :'+ str(round(math.sqrt(metrics.mean_squared_error(df_pred[target_features],yTe
print('MAE :'+ str(round( metrics.mean_absolute_error(df_pred[target_features],yTest[target
print('R^2 :'+ str(round(metrics.r2_score(df_pred[target_features],yTest[target_features])*
```

```
Hourly values comparison (vector of 24 length): prediction vs. actual
RMSE :21.44
MAE :15.39
R^2 :-162.82
```

Entrée [150]:

```
# recontruct the daily maximum energy out of predicted hourly values
df_pred["PredMaxEnergy"] = 0
for i in range(24):
    df_pred["PredMaxEnergy"] = df_pred["PredMaxEnergy"] + df_pred['HourValue'+str(i)]
```

Out[150]:

	HourValue0	HourValue1	HourValue2	HourValue3	HourValue4	HourValue5	HourValue6
Date							
2018-12-21	70.182838	70.182838	65.144897	64.244897	58.874897	58.874897	58.874897
2018-12-22	69.648558	69.648558	65.509931	64.609931	58.519931	58.519931	58.519931
2018-12-23	70.182838	70.182838	65.144897	64.244897	58.874897	58.874897	58.874897
2018-12-24	71.148696	71.148696	69.649840	67.849840	64.849840	64.849840	64.849840
2018-12-25	70.794279	70.794279	67.614966	66.714966	61.194966	60.894966	60.894966

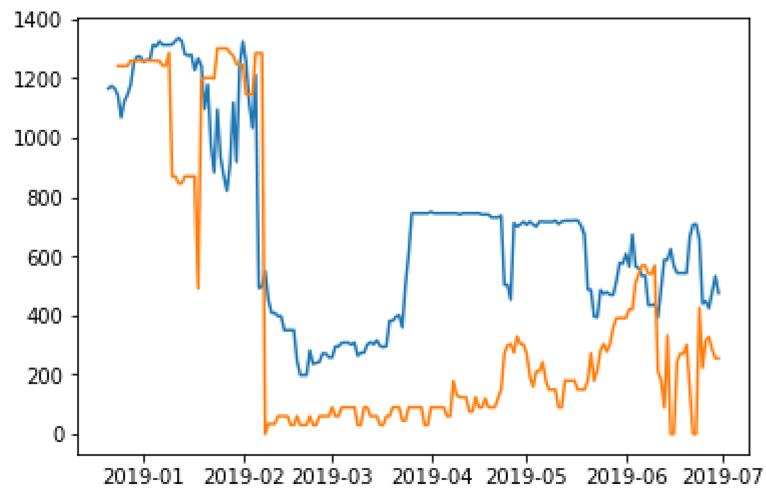
5 rows × 25 columns

Entrée [157]:

```
# plot comparison
plt.plot(df_pred["PredMaxEnergy"].index, df_pred["PredMaxEnergy"])
plt.plot(df.iloc[1920-192:,:].index, df.iloc[1920-192:,:]["Variante Prio"])
plt.legend()
```

Out[157]:

```
[<matplotlib.lines.Line2D at 0x185b7c43438>]
```



Entrée [167]:

```
# try adding additional regressors: daily values from previous models

df_MLPprediction = pd.read_csv("ForecastVariante PrioMLP (10,7,1) Act(lin, relu, relu) Drop
# rename first column
df_MLPprediction.rename(columns={ df_MLPprediction.columns[0]: "Prediction"}, inplace=True)
df_MLPprediction.head()
```

Out[167]:

Date	Prediction	Ground truth	Mean train values	Baseline
2018-12-21	849.08440	1241.052632	727.020546	855.1
2018-12-22	781.52800	1241.052632	727.020546	853.5
2018-12-23	779.63550	1241.052632	727.020546	824.0
2018-12-24	895.75410	1241.052632	727.020546	924.7
2018-12-25	817.40027	1241.052632	727.020546	868.5

Entrée [183]:

```
np.array([[['PrioH'+str(i),'PrioP'+str(i)][j] for i in range(1,4+1)] for j in range(1+1)]).
```

Out[183]:

```
array(['PrioH1', 'PrioH2', 'PrioH3', 'PrioH4', 'PrioP1', 'PrioP2',
       'PrioP3', 'PrioP4'], dtype='<U6')
```

Entrée [244]:

```
# remove daily values from the target features
target_features = ['PrioH1', 'PrioP1', 'PrioH2', 'PrioP2', 'PrioH3', 'PrioP3', 'PrioH4', 'P
regressors = ['Inflow lake 1 [m3]', \
            'Inflow lake 2 [m3]', 'Inflow lake 3 [m3]', 'Inflow lake 4 [m3]', \
            'Vol lake 1 [%]', 'Availability plant 1 [%]', \
            'Availability plant 2 [%]', 'Availability plant 3 [%]', \
            'Availability plant 4 [%]','Variante Prio']

# implement mutli-output random forest
fullRegressors = regressors
# create list of target features
target_features = np.array([[['PrioH'+str(i),'PrioP'+str(i)][j] for i in range(1,4+1)] for

xTrain, xTest, yTrain, yTest =  GetDataSplitMulti(df, fullRegressors, target_features,0.9)
yTest.head()
```

Out[244]:

Date	PrioH1	PrioH2	PrioH3	PrioH4	PrioP1	PrioP2	PrioP3	PrioP4
2018-12-21	2.0	14.0	8.0	0.0	74.942792	65.949657	20.983982	0.0
2018-12-22	2.0	14.0	8.0	0.0	74.942792	65.949657	20.983982	0.0
2018-12-23	2.0	14.0	8.0	0.0	74.942792	65.949657	20.983982	0.0
2018-12-24	2.0	14.0	8.0	0.0	74.942792	65.949657	20.983982	0.0
2018-12-25	2.0	14.0	8.0	0.0	74.942792	65.949657	20.983982	0.0

Entrée [245]:

```
regr_rf = RandomForestRegressor()
regr_rf.fit(xTrain, yTrain)
# prediction is made with the previously predicted daily maximum energy
xTest["Variante Prio"] = df_MLPprediction["Prediction"]
pred = regr_rf.predict(xTest)
df_pred = pd.DataFrame(data=pred, columns = target_features, index = yTest.index)
df_pred.head()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:245: F
utureWarning: The default value of n_estimators will change from 10 in versi
on 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

Out[245]:

Date	PrioH1	PrioH2	PrioH3	PrioH4	PrioP1	PrioP2	PrioP3	PrioP4
2018-12-21	4.6	4.1	4.0	7.0	67.914096	51.864691	36.655149	21.646505
2018-12-22	3.2	4.1	5.1	5.2	67.500000	56.850000	41.130000	24.560000
2018-12-23	2.8	4.5	5.2	5.2	68.809153	58.880343	38.062494	20.889029
2018-12-24	5.3	4.7	5.9	0.9	70.320000	55.350000	31.200000	2.220000
2018-12-25	3.3	3.6	3.8	6.5	69.829153	59.600343	44.542494	30.749029

Entrée [246]:

```
# rounding function is floor
rounding_func = round #math.floor

# hourly dataframe to store restults, out of complete one
df_hourly_pred = df_hourly.loc[df_pred.index.min():,]

firstDate = df_pred.index.min()
powerHours = np.zeros(4584)

# loop over all date
for myDate in df_pred.index:
    # index is date difference times 24
    index = (myDate-firstDate).days * 24
    # compute hourly vector of original values, using the 4 pairs (power/nb of hours)
    currHour = index
    for iPair in range(1,4+1):
        pwrValue = df_pred.loc[myDate, "PrioP"+str(iPair)]
        nbHours = int(rounding_func(df_pred.loc[myDate, "PrioH"+str(iPair)]))
        if pwrValue > 0:
            #print("Date %s, Pair %i, Pwr %d, Hours %f" %(myDate, iPair, pwrValue, nbHours)
            powerHours[currHour:currHour+nbHours] = pwrValue
            currHour = currHour + nbHours

df_hourly_pred["PredictedPower"]= powerHours

# compute error metrics over hourly values calculated above
print('Hourly comparison: prediction vs. actual values')
print('RMSE :'+ str(round(math.sqrt(metrics.mean_squared_error(df_hourly_pred["Power"],df_h
print('MAE :'+ str(round( metrics.mean_absolute_error(df_hourly_pred["Power"],df_hourly_pre
print('R^2 :'+ str(round(metrics.r2_score( df_hourly_pred["Power"],df_hourly_pred["Predicte
```

```
Hourly comparison: prediction vs. actual values
RMSE :16.97
MAE :10.65
R^2 :48.42

C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:24: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/s
table/indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pand
as-docs/stable/indexing.html#indexing-view-versus-copy)
```

Entrée [247]:

```
# scale the target values to predict a profile, i.e. relative values and not absolute ones,
# i.e. power to be relative to daily maximum energy (taking advantage of relation linking t

maxValuesPerBlock = [df["PrioP"+str(i)].max() for i in range(1,4+1)]
maxValuesPerBlock
```

Out[247]:

```
[84.0, 75.0, 68.64759725400458, 60.29999999999999]
```

Entrée [322]:

```
# add new columns to dataframe with scaled power values
# NB: the definition of produced power "profile" is the sum of scaledPower * NoHours = 1
for i in range(1,4+1):
    scaledPower = np.zeros(len(df.index))
    for myLine in range(len(df.index)):
        #print(i, myLine, df.iloc[myLine,]["Date"], df.iloc[myLine,]["PrioP"+str(i)], df.il
        if df.iloc[myLine,]["Variante Prio"]>0:
            scaledPower[myLine] = df.iloc[myLine,]["PrioP"+str(i)] / df.iloc[myLine,]["Vari
        # scale number of hours too
    df["ScaledPowerBlock"+str(i)] =  scaledPower
    df["ScaledHours"+str(i)] = df['PrioH'+str(i)]/24

df.fillna(value = 0.0, axis='columns',inplace = True)
```

Entrée [323]:

```
df.isnull().any().any()
```

Out[323]:

```
False
```

Entrée [324]:

```
# run the aglorithm again with these new targets

regressors = ['Inflow lake 1 [m3]', \
           'Inflow lake 2 [m3]', 'Inflow lake 3 [m3]', 'Inflow lake 4 [m3]', \
           'Vol lake 1 [%]', 'Availability plant 1 [%]', \
           'Availability plant 2 [%]', 'Availability plant 3 [%]', \
           'Availability plant 4 [%]','Variante Prio']

# implement mutli-output random forest
fullRegressors = regressors
# create list of target features
target_features = np.array([[['ScaledHours'+str(i),'ScaledPowerBlock'+str(i)][j] for i in r

xTrain, xTest, yTrain, yTest =  GetDataSplitMulti(df, fullRegressors, target_features,0.9)

yTest.head()
```

Out[324]:

	ScaledHours1	ScaledHours2	ScaledHours3	ScaledHours4	ScaledPowerBlock1	ScaledP
Date						
2018-12-21	0.083333	0.583333	0.333333	0.0	0.060386	
2018-12-22	0.083333	0.583333	0.333333	0.0	0.060386	
2018-12-23	0.083333	0.583333	0.333333	0.0	0.060386	
2018-12-24	0.083333	0.583333	0.333333	0.0	0.060386	
2018-12-25	0.083333	0.583333	0.333333	0.0	0.060386	

Entrée [336]:

```
regr_rf = RandomForestRegressor()
regr_rf.fit(xTrain, yTrain)

# prediction is made with the previously predicted daily maximum energy
xTest["Variante Prio"] = df_MLPprediction["Prediction"]
pred = regr_rf.predict(xTest)
df_pred = pd.DataFrame(data=pred, columns = target_features, index = yTest.index)

# rescale to corresponding energy values
df_pred["PredictedMaxEnergy"] = df_MLPprediction["Prediction"]

df_pred["MaxEnergyFromBlocks"] = 0
df_pred["profileSum"] = 0
for i in range(1,4+1):
    df_pred["PrioH"+str(i)] = df_pred["ScaledHours"+str(i)]*24
    df_pred["PrioP"+str(i)] = df_pred["ScaledPowerBlock"+str(i)]*df_pred["PredictedMaxEnerg
    # compute "profile sum", i.e sum(scaledpower x nb hours)
    df_pred["profileSum"] += df_pred["ScaledPowerBlock"+str(i)]*df_pred["PrioH1"]
    df_pred["MaxEnergyFromBlocks"] += np.ceil(df_pred["PrioH"+str(i)])*df_pred["PrioP"+str(
df_pred.head()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:245: F
utureWarning: The default value of n_estimators will change from 10 in versi
on 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

Out[336]:

Date	ScaledHours1	ScaledHours2	ScaledHours3	ScaledHours4	ScaledPowerBlock1	ScaledP
2018-12-21	0.175000	0.212500	0.162500	0.220833	0.085299	
2018-12-22	0.129167	0.150000	0.175000	0.220833	0.091121	
2018-12-23	0.125000	0.162500	0.179167	0.204167	0.092819	
2018-12-24	0.166667	0.162500	0.329167	0.008333	0.082243	
2018-12-25	0.150000	0.154167	0.170833	0.195833	0.089755	

Entrée [327]:

```
print("Max profile sum: ",df_pred["profileSum"].max())
print("Min profile sum: ",df_pred["profileSum"].min())
```

```
Max profile sum:  2.5038670502672185
Min profile sum:  0.5138748444129306
```

Entrée [337]:

```
# rounding function is ceiling function
rounding_func = math.ceil

# hourly dataframe to store restults, out of complete one
df_hourly_pred = df_hourly.loc[df_pred.index.min():,]

firstDate = df_pred.index.min()
powerHours = np.zeros(4584)

# loop over all date
for myDate in df_pred.index:
    # index is date difference times 24
    index = (myDate-firstDate).days * 24
    # compute hourly vector of original values, using the 4 pairs (power/nb of hours)
    currHour = index
    for iPair in range(1,4+1):
        pwrValue = df_pred.loc[myDate, "PrioP"+str(iPair)]
        nbHours = int(rounding_func(df_pred.loc[myDate, "PrioH"+str(iPair)]))
        if pwrValue > 0:
            #print("Date %s, Pair %i, Pwr %d, Hours %f" %(myDate, iPair, pwrValue, nbHours)
            powerHours[currHour:currHour+nbHours] = pwrValue
            currHour = currHour + nbHours

df_hourly_pred["PredictedPower"]= powerHours

# compute error metrics over hourly values calculated above
print('Hourly comparison: prediction vs. actual values')
print('RMSE :'+ str(round(math.sqrt(metrics.mean_squared_error(df_hourly_pred["Power"],df_h
print('MAE :'+ str(round( metrics.mean_absolute_error(df_hourly_pred["Power"],df_hourly_pre
print('R^2 :'+ str(round(metrics.r2_score( df_hourly_pred["Power"],df_hourly_pred["Predicte
print('Mean power value :'+ str(round(df_hourly_pred["Power"].mean(), 2)))

# compare to baseline over this period
df_hourly_period = df_hourly.iloc[int(len(df_hourly.index)*0.9):,]
print('Hourly comparison: prediction baseline vs. actual values')
print('RMSE :'+ str(round(math.sqrt(metrics.mean_squared_error(df_hourly_period["Power"],df
print('MAE :'+ str(round( metrics.mean_absolute_error(df_hourly_period["Power"],df_hourly_p
print('R^2 :'+ str(round(metrics.r2_score( df_hourly_period["Power"],df_hourly_period["Powe

#compare daily values: input (predicted by previous algo) and output (computed from predice
print('Daily values comparison: prediction (from blocks) vs. input values (predicted previc
print('RMSE :'+ str(round(math.sqrt(metrics.mean_squared_error(df_pred["MaxEnergyFromBlocks
print('MAE :'+ str(round( metrics.mean_absolute_error(df_pred["MaxEnergyFromBlocks"],df_pre
print('R^2 :'+ str(round(metrics.r2_score( df_pred["MaxEnergyFromBlocks"],df_pred["Predicte
```

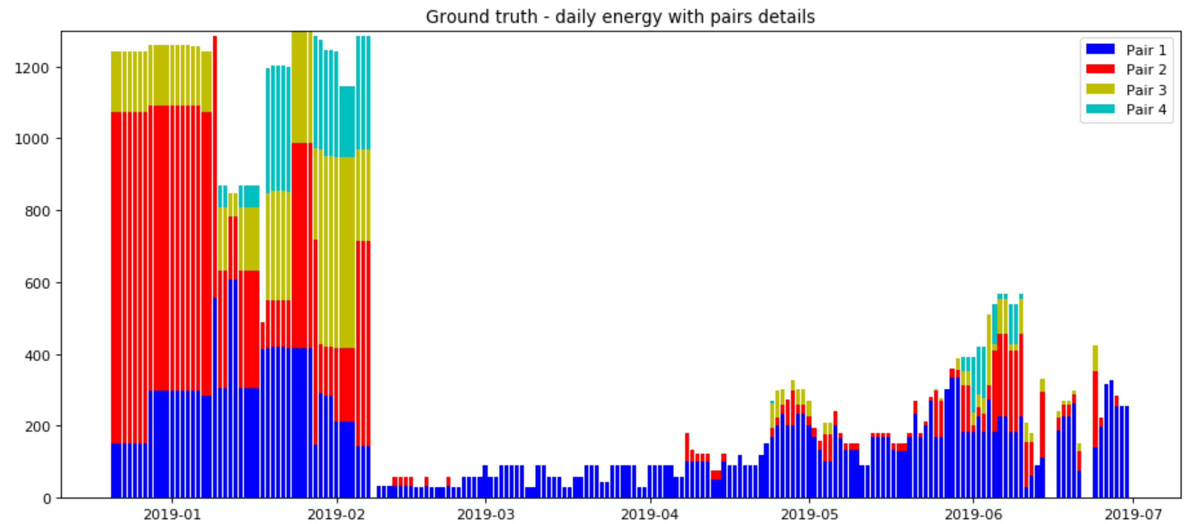
```
Hourly comparison: prediction vs. actual values
RMSE :14.06
MAE :8.78
R^2 :64.56
Mean power value :17.55
Hourly comparison: prediction baseline vs. actual values
RMSE :24.18
MAE :19.05
R^2 :-4.39
Daily values comparison: prediction (from blocks) vs. input values (predic
ted previously)
RMSE :87.28
```

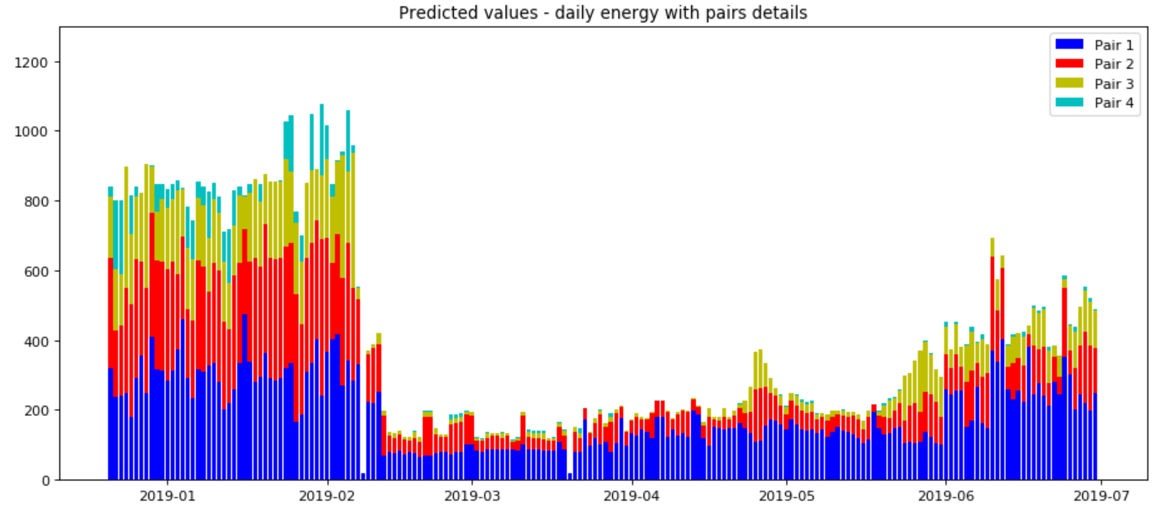
```
MAE :78.03
R^2 :92.08

C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:24: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/s
table/indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pand
as-docs/stable/indexing.html#indexing-view-versus-copy)
```

Entrée [333]:

```
# plot ground truth on test period

# loop over lines in the dataframe, check only test occurences
toPlotDataFrames = [df.iloc[int(len(df.index)*0.9):,], df_pred]
labelPlots = ['Ground truth - daily energy with pairs details',
              'Predicted values - daily energy with pairs details']

for (df_plot,labelPlot) in zip(toPlotDataFrames, labelPlots):
    # loop over the 4 pairs : power, nb of hours
    for i in range(1, 4+1):
        df_plot["EnergyPair"+str(i)] = df_plot["PrioH"+str(i)]*df_plot["PrioP"+str(i)]

    # plot stacked graph for total period

    fig=plt.figure(figsize=(14, 6), dpi= 80, edgecolor='k')
    plt.bar(df_plot.index, df_plot.EnergyPair1, color = 'b', label="Pair 1")
    plt.bar(df_plot.index, df_plot.EnergyPair2, color = 'r', bottom = df_plot.EnergyPair1,
    plt.bar(df_plot.index, df_plot.EnergyPair3, color = 'y', bottom = df_plot.EnergyPair1+d
    plt.bar(df_plot.index, df_plot.EnergyPair4, color = 'c', bottom = df_plot.EnergyPair1+d
    plt.ylim(0, 1400)
    plt.title(labelPlot)
    plt.legend(loc='upper right')
    plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:11: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/s
table/indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pand
as-docs/stable/indexing.html#indexing-view-versus-copy)
  # This is added back by InteractiveShellApp.init_path()
```





Entrée [ ]:

```
# recompute
```

Entrée [ ]:

```
# try with hourly values instead of power blocks
# (no need to reconstruct blocks)

# add 24 columns to dataset
# fill up the columns by filling up a 24 values np.array
# then assign it to dataframe
```

Entrée [ ]:

```
# build neural network to do multi-regression
# -> on power blocks (4 + 4 targets)
# -> same but including previous
```

3.2 Multi-regression with Multi Layer Perceptron

Here we build a MLP to perform a mutli-output regression, still using previous maximum energy as input (on top of other inputs)

Entrée [350]:

```
# defined are xTrain, xTest, yTrain, yTest

#Scale the input data
stScaler = StandardScaler()
stScaler.fit(xTrain)
xTrainScaled = stScaler.transform(xTrain)
xTestScaled = stScaler.transform(xTest)

OutputTrainH1 = yTrain["ScaledHours1"]
OutputTrainP1 = yTrain["ScaledPowerBlock1"]
OutputTrainH2 = yTrain["ScaledHours2"]
OutputTrainP2 = yTrain["ScaledPowerBlock2"]
OutputTrainH3 = yTrain["ScaledHours3"]
OutputTrainP3 = yTrain["ScaledPowerBlock3"]
OutputTrainH4 = yTrain["ScaledHours4"]
OutputTrainP4 = yTrain["ScaledPowerBlock4"]

OutputTestH1 = yTest["ScaledHours1"]
OutputTestP1 = yTest["ScaledPowerBlock1"]
OutputTestH2 = yTest["ScaledHours2"]
OutputTestP2 = yTest["ScaledPowerBlock2"]
OutputTestH3 = yTest["ScaledHours3"]
OutputTestP3 = yTest["ScaledPowerBlock3"]
OutputTestH4 = yTest["ScaledHours4"]
OutputTestP4 = yTest["ScaledPowerBlock4"]
```

Entrée [349]:

```
yTrain.head()
```

Out[349]:

	ScaledHours1	ScaledHours2	ScaledHours3	ScaledHours4	ScaledPowerBlock1	ScaledP
Date						
2014-04-01	0.166667	0.166667	0.333333	0.0	0.081782	
2014-04-02	0.166667	0.166667	0.333333	0.0	0.081782	
2014-04-03	0.166667	0.166667	0.333333	0.0	0.081782	
2014-04-04	0.166667	0.166667	0.333333	0.0	0.081782	
2014-04-05	0.166667	0.166667	0.333333	0.0	0.080882	

Entrée [426]:

```
# building MLP model with 4x2 outputs
import keras
from keras.utils import plot_model
from keras.models import Model
from keras.layers import Input
from keras.layers import Dense
visible = Input(shape=(10,))
hidden1 = Dense(10, activation='relu', name='Hidden1')(visible)
hidden2 = Dense(7, activation='relu', name='Hidden2')(hidden1)
hiddenH3 = Dense(5, activation='relu', name='Hidden13')(hidden2)
hiddenP3 = Dense(5, activation='relu', name='Hidden23')(hidden2)

# output layers use a linear activation function
NbHours1_ouput = Dense(1, activation='linear', name='NbHours1')(hiddenH3)
NbHours2_ouput = Dense(1, activation='linear', name='NbHours2')(hiddenH3)
NbHours4_ouput = Dense(1, activation='linear', name='NbHours3')(hiddenH3)
NbHours3_ouput = Dense(1, activation='linear', name='NbHours4')(hiddenH3)
power1_output = Dense(1, activation='linear', name='Power1')(hiddenP3)
power2_output = Dense(1, activation='linear', name='Power2')(hiddenP3)
power3_output = Dense(1, activation='linear', name='Power3')(hiddenP3)
power4_output = Dense(1, activation='linear', name='Power4')(hiddenP3)


model = Model(inputs=visible, outputs=[ NbHours1_ouput, NbHours2_ouput, NbHours3_ouput, NbH
                                        power1_output, power2_output, power3_output, power4
                                      ])
# summarize layers
print(model.summary())
```

```
________________________________________________________________________________
________________________
Layer (type)                    Output Shape         Param #     Connected
to
================================================================================
========================
input_6 (InputLayer)            (None, 10)           0

________________________________________________________________________________
________________________
Hidden1 (Dense)                 (None, 10)           110         input_6
[0][0]

________________________________________________________________________________
________________________
Hidden2 (Dense)                 (None, 7)            77          Hidden1
[0][0]

________________________________________________________________________________
________________________
Hidden13 (Dense)                (None, 5)            40          Hidden2
[0][0]

________________________________________________________________________________
________________________
Hidden23 (Dense)                (None, 5)            40          Hidden2
[0][0]

________________________________________________________________________________
________________________
NbHours1 (Dense)                (None, 1)            6           Hidden13
[0][0]

________________________________________________________________________________
________________________
```

```
NbHours2 (Dense)                (None, 1)            6           Hidden13
[0][0]
__________________________________________________________________________
________________________
NbHours4 (Dense)                (None, 1)            6           Hidden13
[0][0]
__________________________________________________________________________
________________________
NbHours3 (Dense)                (None, 1)            6           Hidden13
[0][0]
__________________________________________________________________________
________________________
Power1 (Dense)                  (None, 1)            6           Hidden23
[0][0]
__________________________________________________________________________
________________________
Power2 (Dense)                  (None, 1)            6           Hidden23
[0][0]
__________________________________________________________________________
________________________
Power3 (Dense)                  (None, 1)            6           Hidden23
[0][0]
__________________________________________________________________________
________________________
Power4 (Dense)                  (None, 1)            6           Hidden23
[0][0]
==========================================================================
========================
Total params: 315
Trainable params: 315
Non-trainable params: 0
__________________________________________________________________________
________________________
None
```

Entrée [427]:

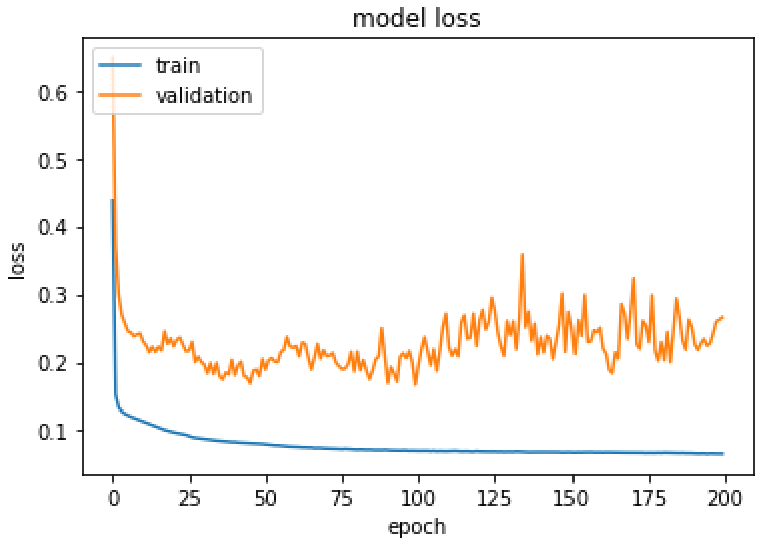
```
model.compile(optimizer='adam',
              loss={'NbHours1': 'mean_squared_error', 'NbHours2': 'mean_squared_error',
                    'NbHours3': 'mean_squared_error', 'NbHours4': 'mean_squared_error',
                    'Power1': 'mean_squared_error', 'Power2': 'mean_squared_error',
                    'Power3': 'mean_squared_error', 'Power4': 'mean_squared_error'
                   },
              loss_weights={ 'NbHours1': 1.0, 'NbHours2': 1.0, 'NbHours3': 1.0, 'NbHours4':
                            'Power1': 1.0,'Power2': 1.0,'Power3': 1.0,  'Power4': 1.0 })

history = model.fit(x=xTrainScaled, y=[ OutputTrainH1, OutputTrainH2, OutputTrainH3, Output
                                        OutputTrainP1, OutputTrainP2, OutputTrainP3,  Outpu
                    validation_data=(xTestScaled,[OutputTestH1, OutputTestH2, OutputTestH3,
                                                  OutputTestP1, OutputTestP2, OutputTestP3,
                                     epochs=200, batch_size=8)
```

```
Train on 1725 samples, validate on 192 samples
Epoch 1/200
1725/1725 [==============================] - 2s 1ms/step - loss: 0.4380 -
NbHours1_loss: 0.0541 - NbHours2_loss: 0.1246 - NbHours4_loss: 0.1162 - Nb
Hours3_loss: 0.0710 - Power1_loss: 0.0231 - Power2_loss: 0.0051 - Power3_l
oss: 0.0278 - Power4_loss: 0.0160 - val_loss: 0.6486 - val_NbHours1_loss:
0.0412 - val_NbHours2_loss: 0.0938 - val_NbHours4_loss: 0.0511 - val_NbHou
rs3_loss: 0.0471 - val_Power1_loss: 0.0798 - val_Power2_loss: 0.0137 - val
_Power3_loss: 0.1957 - val_Power4_loss: 0.1262
Epoch 2/200
1725/1725 [==============================] - 0s 209us/step - loss: 0.1522
- NbHours1_loss: 0.0241 - NbHours2_loss: 0.0273 - NbHours4_loss: 0.0370 -
NbHours3_loss: 0.0340 - Power1_loss: 0.0172 - Power2_loss: 0.0033 - Power3
_loss: 0.0059 - Power4_loss: 0.0032 - val_loss: 0.3715 - val_NbHours1_los
s: 0.0262 - val_NbHours2_loss: 0.0542 - val_NbHours4_loss: 0.0337 - val_Nb
Hours3_loss: 0.0292 - val_Power1_loss: 0.0676 - val_Power2_loss: 0.0106 -
val_Power3_loss: 0.0930 - val_Power4_loss: 0.0569
Epoch 3/200
1725/1725 [==============================] - 0s 234us/step - loss: 0.1337
```

Entrée [428]:

```
print(history.history.keys())
# "Loss"
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```

```
dict_keys(['val_loss', 'val_NbHours1_loss', 'val_NbHours2_loss', 'val_NbHour
s4_loss', 'val_NbHours3_loss', 'val_Power1_loss', 'val_Power2_loss', 'val_Po
wer3_loss', 'val_Power4_loss', 'loss', 'NbHours1_loss', 'NbHours2_loss', 'Nb
Hours4_loss', 'NbHours3_loss', 'Power1_loss', 'Power2_loss', 'Power3_loss',
'Power4_loss'])
```



Entrée [429]:

```
yPred= model.predict(xTestScaled)
len(yPred[0])
```

Out[429]:

```
192
```

Entrée [430]:

```
yPreNp = np.array(yPred)
yPreNp.transpose()[0].shape
```

Out[430]:

```
(192, 8)
```

Entrée [431]:

```
yTest.columns
```

Out[431]:

```
Index(['ScaledHours1', 'ScaledHours2', 'ScaledHours3', 'ScaledHours4',
       'ScaledPowerBlock1', 'ScaledPowerBlock2', 'ScaledPowerBlock3',
       'ScaledPowerBlock4'],
      dtype='object')
```

Entrée [434]:

```
df_pred = pd.DataFrame(data = yPreNp.transpose()[0], columns = yTest.columns, index = yTest
df_pred.head(5)
```

Out[434]:

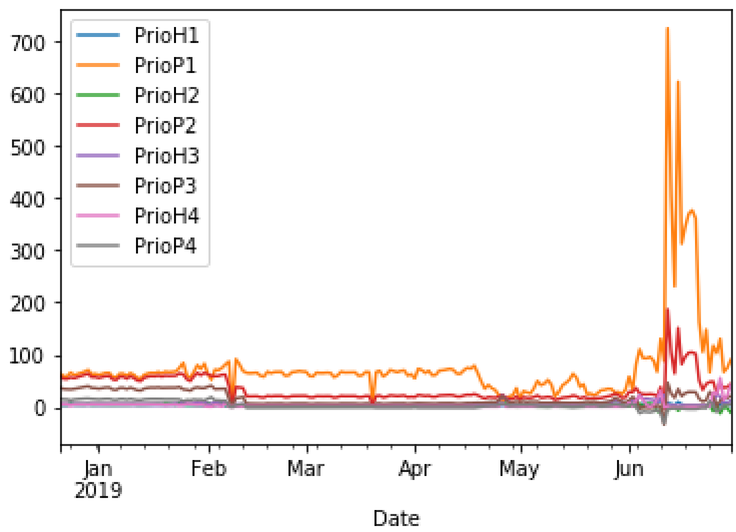
Date	ScaledHours1	ScaledHours2	ScaledHours3	ScaledHours4	ScaledPowerBlock1	ScaledP
2018-12-21	0.169246	0.182461	0.183397	0.207927	0.074634	
2018-12-22	0.169753	0.181891	0.174261	0.214651	0.074809	
2018-12-23	0.169615	0.182046	0.176752	0.212818	0.074761	
2018-12-24	0.204813	0.247420	0.204125	0.101257	0.073105	
2018-12-25	0.174739	0.201008	0.190202	0.187762	0.074094	

Entrée [433]:

```
# rescale to corresponding energy values
df_pred["PredictedMaxEnergy"] = df_MLPprediction["Prediction"]

df_pred["MaxEnergyFromBlocks"] = 0
df_pred["profileSum"] = 0
for i in range(1,4+1):
    df_pred["PrioH"+str(i)] = df_pred["ScaledHours"+str(i)]*24
    df_pred["PrioP"+str(i)] = df_pred["ScaledPowerBlock"+str(i)]*df_pred["PredictedMaxEnerg
    # compute "profile sum", i.e sum(scaledpower x nb hours)
    df_pred["profileSum"] += df_pred["ScaledPowerBlock"+str(i)]*df_pred["PrioH1"]
    df_pred["MaxEnergyFromBlocks"] += np.ceil(df_pred["PrioH"+str(i)])*df_pred["PrioP"+str(

df_pred[['PrioH1', 'PrioP1', 'PrioH2', 'PrioP2', 'PrioH3',
       'PrioP3', 'PrioH4', 'PrioP4']].plot()

#df_pred.plot(title = 'Power Blocks forecast with MLP')
```

Out[433]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x185d2da1cf8>
```



Entrée [ ]:

```
# rounding function is ceiling function
rounding_func = math.ceil

# hourly dataframe to store restults, out of complete one
df_hourly_pred = df_hourly.loc[df_pred.index.min():,]

firstDate = df_pred.index.min()
powerHours = np.zeros(4584)

# loop over all date
for myDate in df_pred.index:
    # index is date difference times 24
    index = (myDate-firstDate).days * 24
    # compute hourly vector of original values, using the 4 pairs (power/nb of hours)
    currHour = index
    for iPair in range(1,4+1):
        pwrValue = df_pred.loc[myDate, "PrioP"+str(iPair)]
        nbHours = int(rounding_func(df_pred.loc[myDate, "PrioH"+str(iPair)]))
        if pwrValue > 0:
            #print("Date %s, Pair %i, Pwr %d, Hours %f" %(myDate, iPair, pwrValue, nbHours)
            powerHours[currHour:currHour+nbHours] = pwrValue
            currHour = currHour + nbHours

df_hourly_pred["PredictedPower"]= powerHours

# compute error metrics over hourly values calculated above
print('Hourly comparison: prediction vs. actual values')
print('RMSE :'+ str(round(math.sqrt(metrics.mean_squared_error(df_hourly_pred["Power"],df_h
print('MAE :'+ str(round( metrics.mean_absolute_error(df_hourly_pred["Power"],df_hourly_pre
print('R^2 :'+ str(round(metrics.r2_score( df_hourly_pred["Power"],df_hourly_pred["Predicte
print('Mean power value :'+ str(round(df_hourly_pred["Power"].mean(), 2)))

# compare to baseline over this period
df_hourly_period = df_hourly.iloc[int(len(df_hourly.index)*0.9):,]
print('Hourly comparison: prediction baseline vs. actual values')
print('RMSE :'+ str(round(math.sqrt(metrics.mean_squared_error(df_hourly_period["Power"],df
print('MAE :'+ str(round( metrics.mean_absolute_error(df_hourly_period["Power"],df_hourly_p
print('R^2 :'+ str(round(metrics.r2_score( df_hourly_period["Power"],df_hourly_period["Powe

#compare daily values: input (predicted by previous algo) and output (computed from predice
print('Daily values comparison: prediction (from blocks) vs. input values (predicted previc
print('RMSE :'+ str(round(math.sqrt(metrics.mean_squared_error(df_pred["MaxEnergyFromBlocks
print('MAE :'+ str(round( metrics.mean_absolute_error(df_pred["MaxEnergyFromBlocks"],df_pre
print('R^2 :'+ str(round(metrics.r2_score( df_pred["MaxEnergyFromBlocks"],df_pred["Predicte
```

Entrée [ ]:

```
```