1. Análise Exploratória de Dados

```
# Importando bibliotecas necessárias
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
import os

from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

from sklearn.tree import export_graphviz
import graphviz  #
https://stackoverflow.com/questions/33433274/anaconda-graphviz-cant-
import-after-installation
```

```
# Definindo caminho dos dados
dir_path = './CMAPSSData/'
train_file = 'train_FD003.txt'
test_file = 'test_FD003.txt'

# Definindo o nome das colunas para facilitar a exploração dos dados
index_names = ['unidade', 'ciclo_tempo']
setting_names = ['config_1', 'config_2', 'config_3']
sensor_names = ['s_{}'.format(i+1) for i in range(0,21)]
col_names = index_names + setting_names + sensor_names

# Lendo os dados
train = pd.read_csv((dir_path+train_file), sep='\s+', header=None,
                 names=col_names)
test = pd.read_csv((dir_path+test_file), sep='\s+', header=None,
                 names=col_names)
y_test = pd.read_csv((dir_path+'RUL_FD003.txt'), sep='\s+',
header=None,
                 names=['RemainingUsefulLife'])

# Analisar as primeiras linhas da nossa base de dados
print(train.shape)
train.head()
```

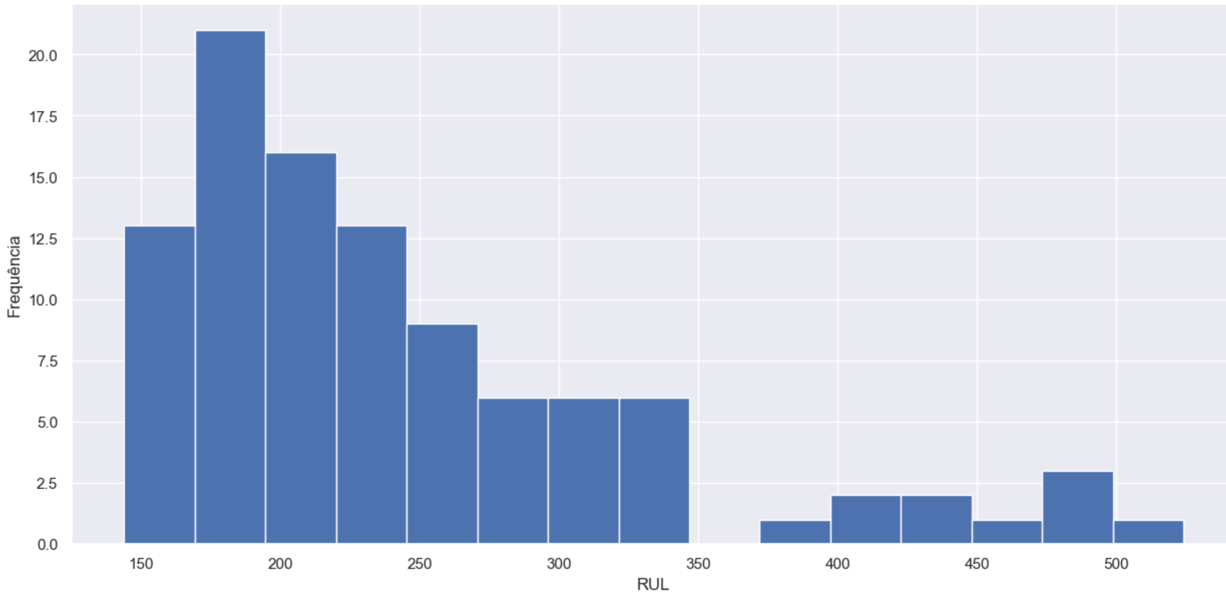
```
(24720, 26)
```

```
   unidade  ciclo_tempo  config_1  config_2  config_3     s_1     s_2  \
0        1            1   -0.0005    0.0004     100.0  518.67  642.36

1        1            2    0.0008   -0.0003     100.0  518.67  642.50
```

```
2        1            3   -0.0014   -0.0002     100.0  518.67  642.18

3        1            4   -0.0020    0.0001     100.0  518.67  642.92

4        1            5    0.0016    0.0000     100.0  518.67  641.68


       s_3      s_4    s_5  ...    s_12     s_13     s_14    s_15
s_16  s_17  \
0  1583.23  1396.84  14.62  ...  522.31  2388.01  8145.32  8.4246
0.03   391
1  1584.69  1396.89  14.62  ...  522.42  2388.03  8152.85  8.4403
0.03   392
2  1582.35  1405.61  14.62  ...  522.03  2388.00  8150.17  8.3901
0.03   391
3  1585.61  1392.27  14.62  ...  522.49  2388.08  8146.56  8.3878
0.03   392
4  1588.63  1397.65  14.62  ...  522.58  2388.03  8147.80  8.3869
0.03   392

   s_18   s_19   s_20     s_21
0  2388  100.0  39.11  23.3537
1  2388  100.0  38.99  23.4491
2  2388  100.0  38.85  23.3669
3  2388  100.0  38.96  23.2951
4  2388  100.0  39.14  23.4583

[5 rows x 26 columns]

# Analisando os ciclos de tempo
train[index_names].groupby('unidade').max().describe()

       ciclo_tempo
count    100.00000
mean     247.20000
std       86.48384
min      145.00000
25%      189.75000
50%      220.50000
75%      279.75000
max      525.00000

# Inspecionando alguns dados estatisticos do conjunto
# Sensores com desvio padrao proximos de 0 nao agregam informacao ao
modelo
train[sensor_names].describe().transpose()

        count        mean          std        min        25%
50%  \
s_1   24720.0   518.670000  6.684921e-11   518.6700   518.6700
```

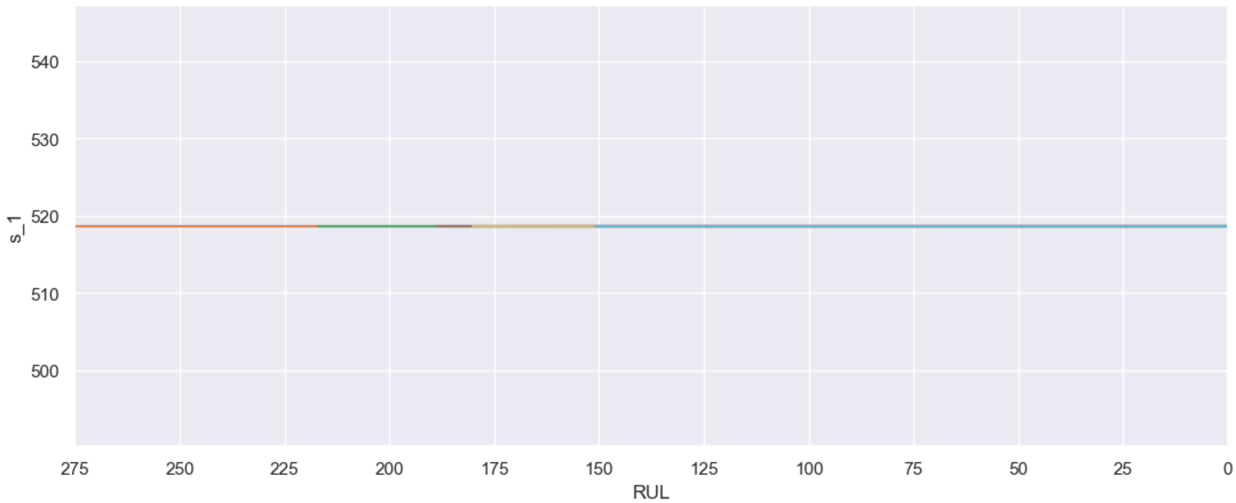
```
518.6700
s_2   24720.0   642.457858  5.230311e-01   640.8400   642.0800
642.4000
s_3   24720.0  1588.079175  6.810418e+00  1564.3000  1583.2800
1587.5200
s_4   24720.0  1404.471212  9.773178e+00  1377.0600  1397.1875
1402.9100
s_5   24720.0    14.620000  3.602525e-12    14.6200    14.6200
14.6200
s_6   24720.0    21.595841  1.811600e-02    21.4500    21.5800
21.6000
s_7   24720.0   555.143808  3.437343e+00   549.6100   553.1100
554.0500
s_8   24720.0  2388.071555  1.582849e-01  2386.9000  2388.0000
2388.0700
s_9   24720.0  9064.110809  1.998029e+01  9017.9800  9051.9200
9060.0100
s_10  24720.0     1.301232  3.484849e-03     1.2900     1.3000
1.3000
s_11  24720.0    47.415707  3.000742e-01    46.6900    47.1900
47.3600
s_12  24720.0   523.050873  3.255314e+00   517.7700   521.1500
521.9800
s_13  24720.0  2388.071643  1.581207e-01  2386.9300  2388.0100
2388.0700
s_14  24720.0  8144.202916  1.650412e+01  8099.6800  8134.5100
8141.2000
s_15  24720.0     8.396176  6.051161e-02     8.1563     8.3606
8.3983
s_16  24720.0     0.030000  1.750371e-14     0.0300     0.0300
0.0300
s_17  24720.0   392.566545  1.761459e+00   388.0000   391.0000
392.0000
s_18  24720.0  2388.000000  0.000000e+00  2388.0000  2388.0000
2388.0000
s_19  24720.0   100.000000  0.000000e+00   100.0000   100.0000
100.0000
s_20  24720.0    38.988552  2.488647e-01    38.1700    38.8300
38.9900
s_21  24720.0    23.393024  1.492338e-01    22.8726    23.2962
23.3916

            75%        max
s_1    518.6700   518.6700
s_2    642.7900   645.1100
s_3   1592.4125  1615.3900
s_4   1410.6000  1441.1600
s_5     14.6200    14.6200
s_6     21.6100    21.6100
```

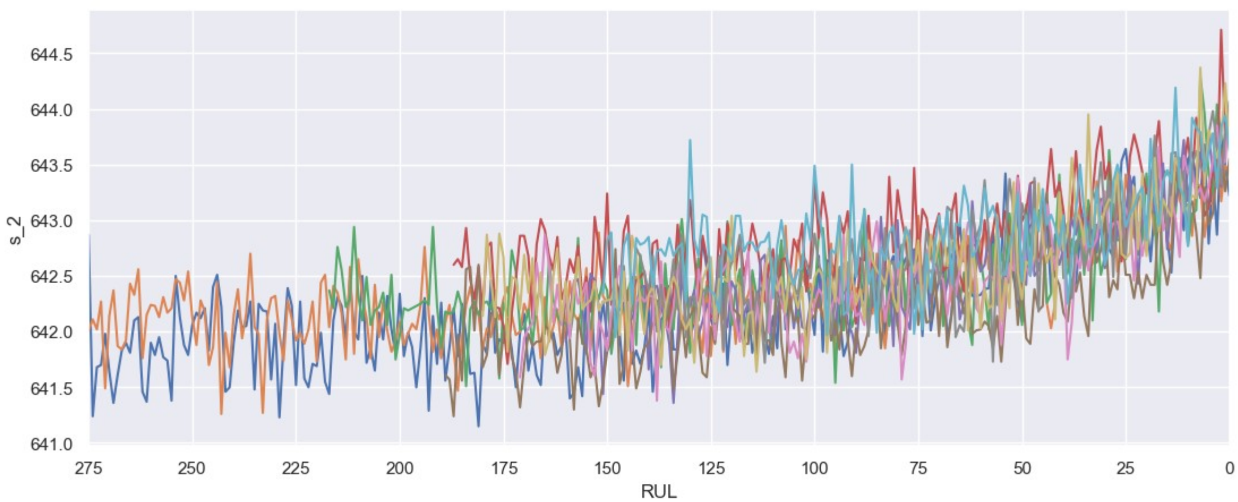
```
s_7     556.0400   570.4900
s_8    2388.1400  2388.6000
s_9    9070.0925  9234.3500
s_10      1.3000     1.3200
s_11     47.6000    48.4400
s_12    523.8400   537.4000
s_13   2388.1400  2388.6100
s_14   8149.2300  8290.5500
s_15      8.4370     8.5705
s_16      0.0300     0.0300
s_17    394.0000   399.0000
s_18   2388.0000  2388.0000
s_19    100.0000   100.0000
s_20     39.1400    39.8500
s_21     23.4833    23.9505

def add_RUL(df):
    # Obter o numero total de ciclos para cada unidade
    grouped_by_unit = df.groupby(by="unidade")
    max_cycle = grouped_by_unit["ciclo_tempo"].max()

    # Mesclar o valor do ciclo maximo no dataframe de origem
    result_frame = df.merge(max_cycle.to_frame(name='ciclo_max'),
left_on='unidade', right_index=True)

    # Calcular o RUL para cada linha
    remaining_useful_life = result_frame["ciclo_max"] -
result_frame["ciclo_tempo"]
    result_frame["RUL"] = remaining_useful_life

    # Remover o valor do ciclo maximo, que nao e mais necessario
    result_frame = result_frame.drop("ciclo_max", axis=1)
    return result_frame

train = add_RUL(train)
train[index_names+['RUL']].head()

   unidade  ciclo_tempo  RUL
0        1            1  258
1        1            2  257
2        1            3  256
3        1            4  255
4        1            5  254

df_max_rul = train[['unidade',
'RUL']].groupby('unidade').max().reset_index()
df_max_rul['RUL'].hist(bins=15, figsize=(15,7))
plt.xlabel('RUL')
plt.ylabel('Frequência')
plt.show()
```

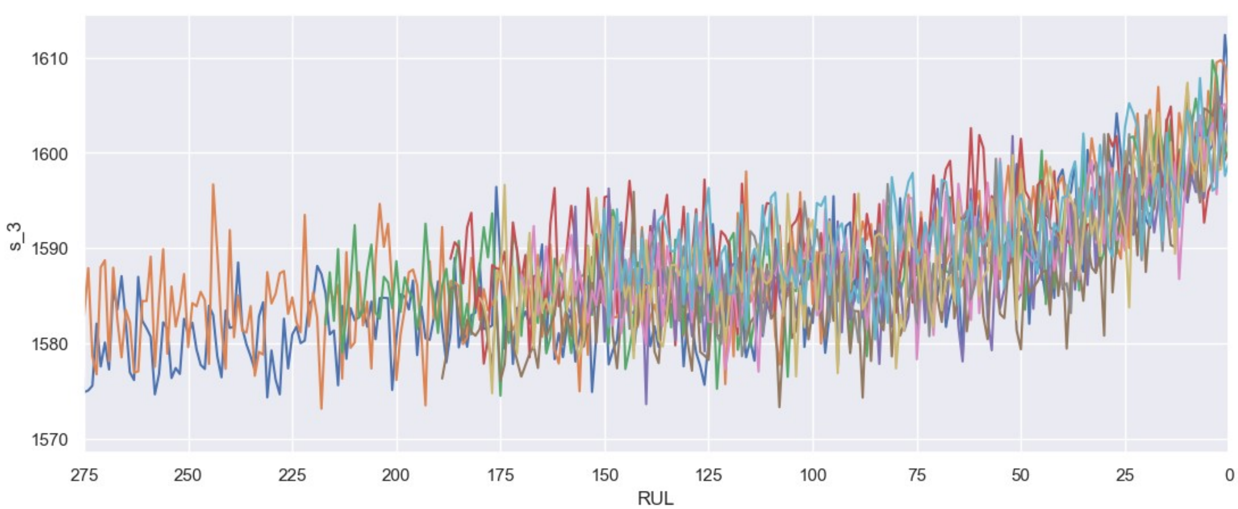


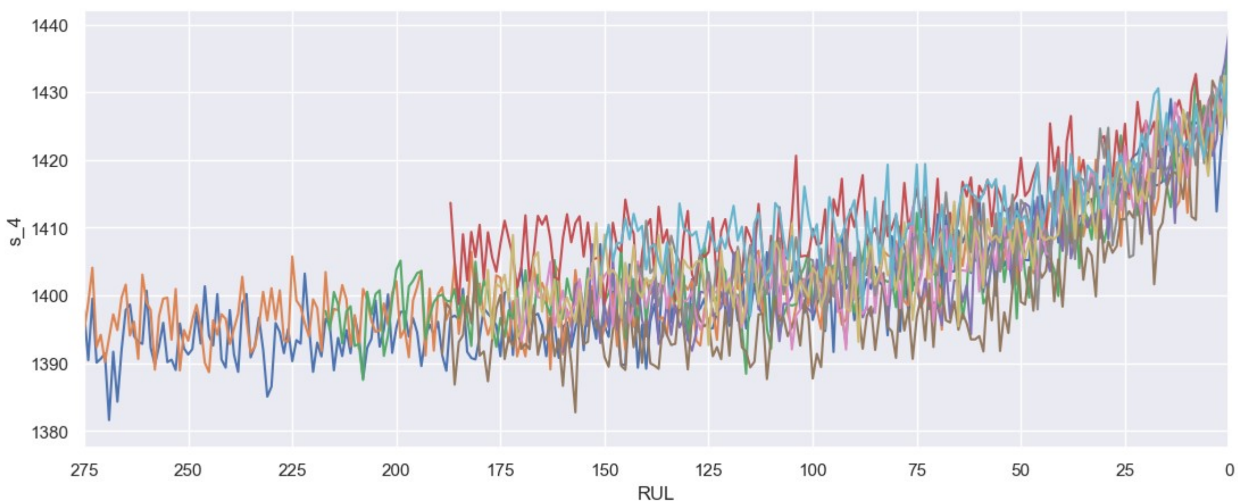
2. Plotando sinais

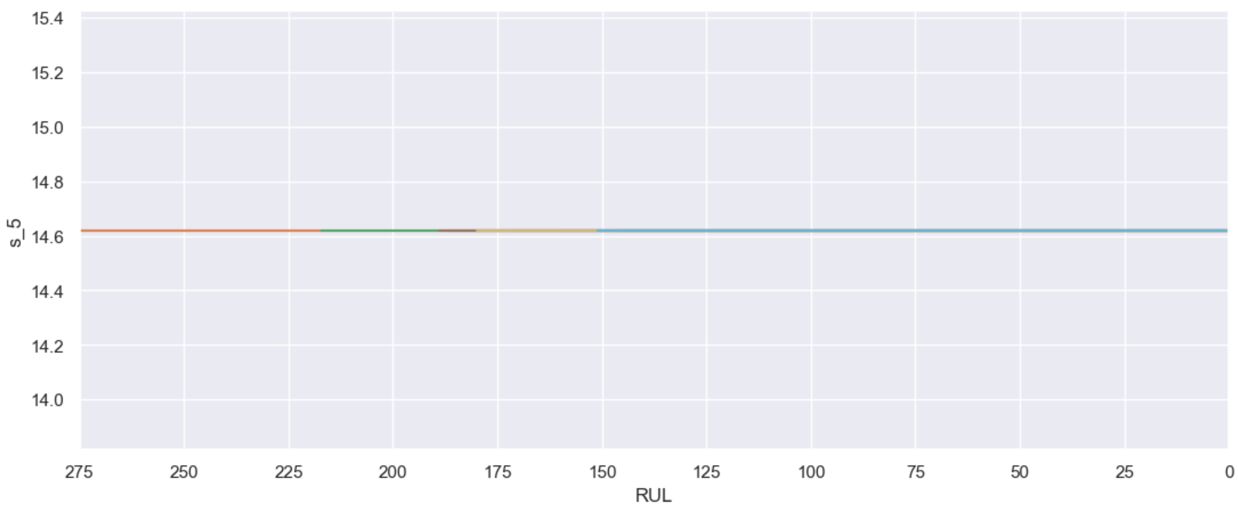
```
def plot_sinal(df, signal_name):
    plt.figure(figsize=(13,5))
    for i in df['unidade'].unique():
        if (i % 10 == 0):
            plt.plot('RUL', signal_name,
                     data=df[df['unidade']==i])
    plt.xlim(250, 0)  # Inverte o eixo x para ir de 250 ate 0
    plt.xticks(np.arange(0, 300, 25))
    plt.ylabel(signal_name)
    plt.xlabel('RUL')
    plt.show()

for sensor in sensor_names:
    plot_sinal(train, sensor)
```

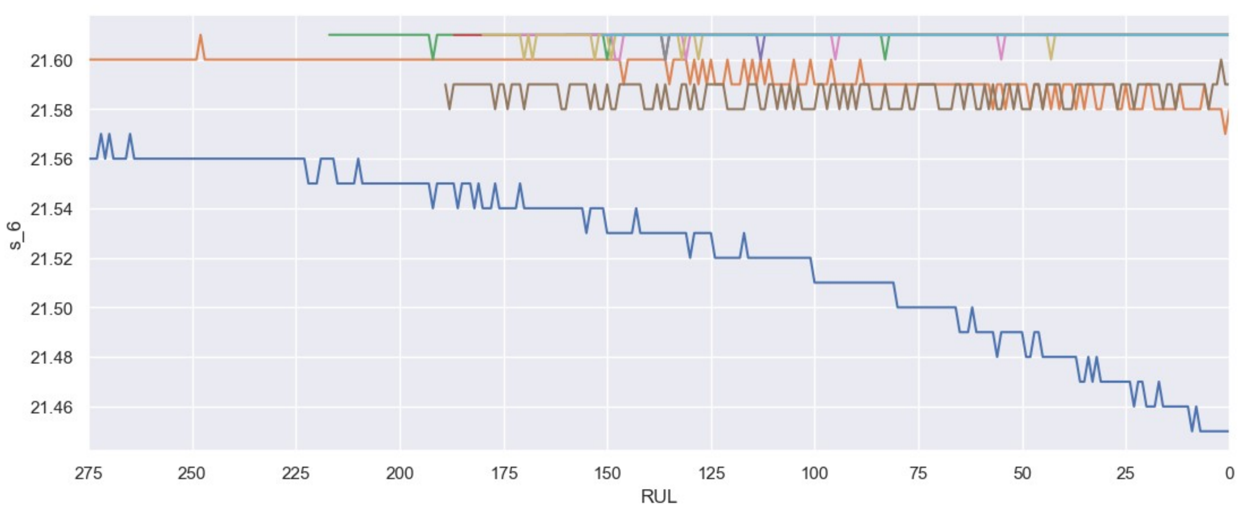

s_1
RUL

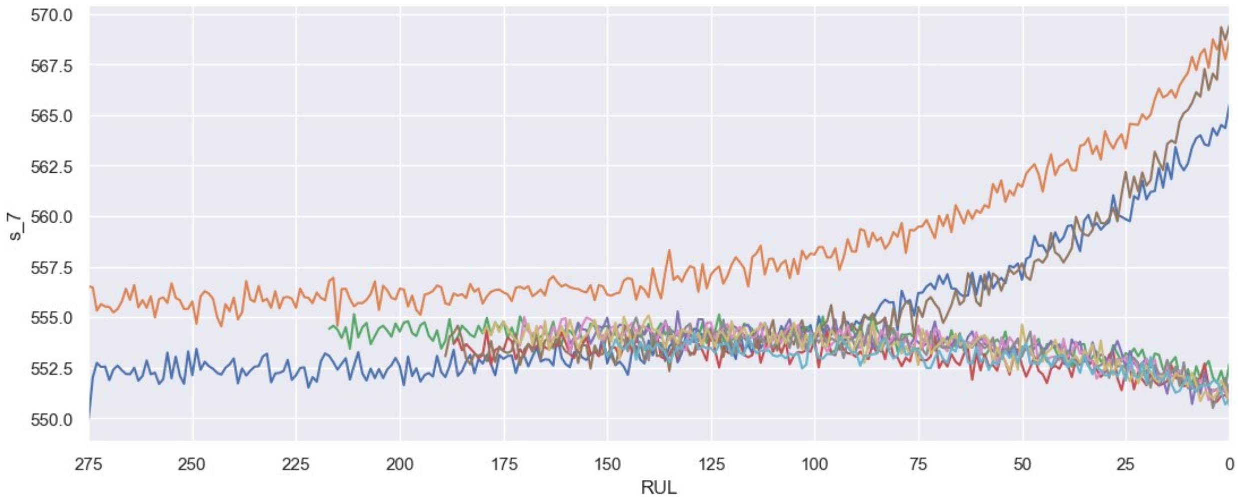

s_2
RUL

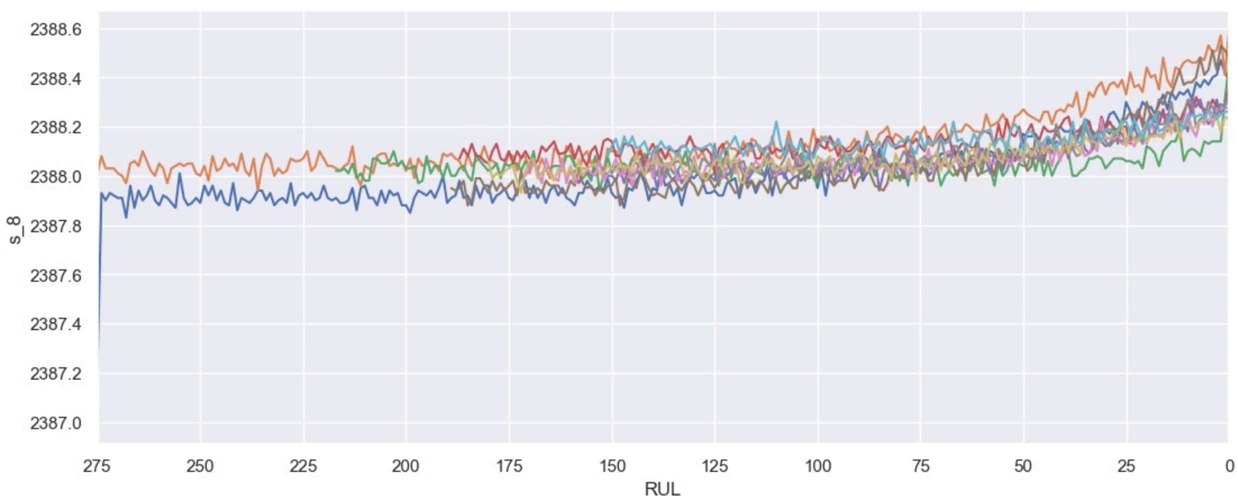

s_3
RUL

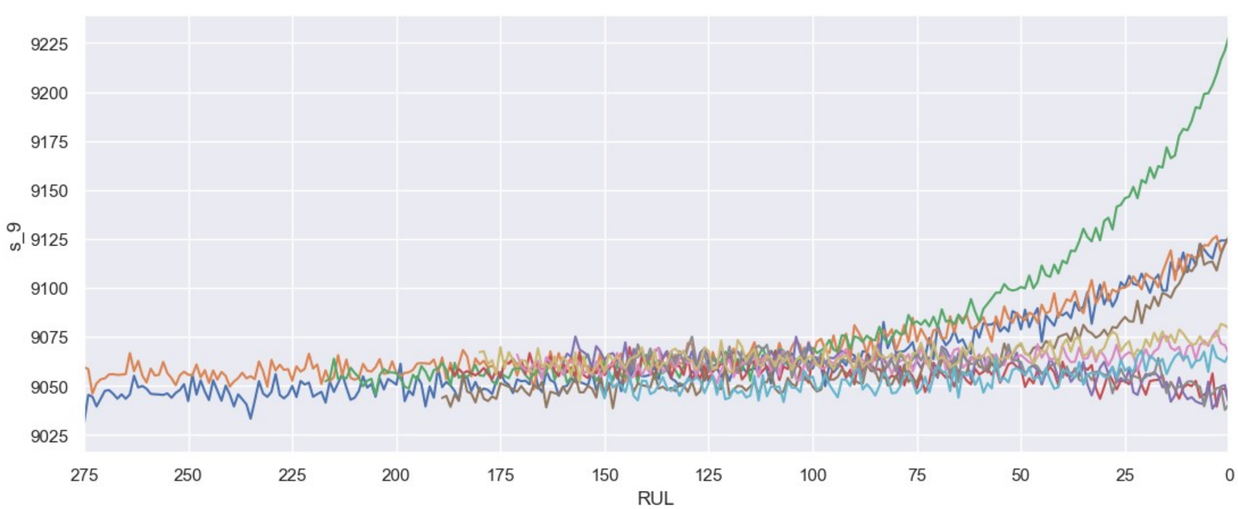

1440
1430
1420
1410
1400
1390
1380
s_4
275
250
225
200
175
150
125
100
75
50
25
0
RUL

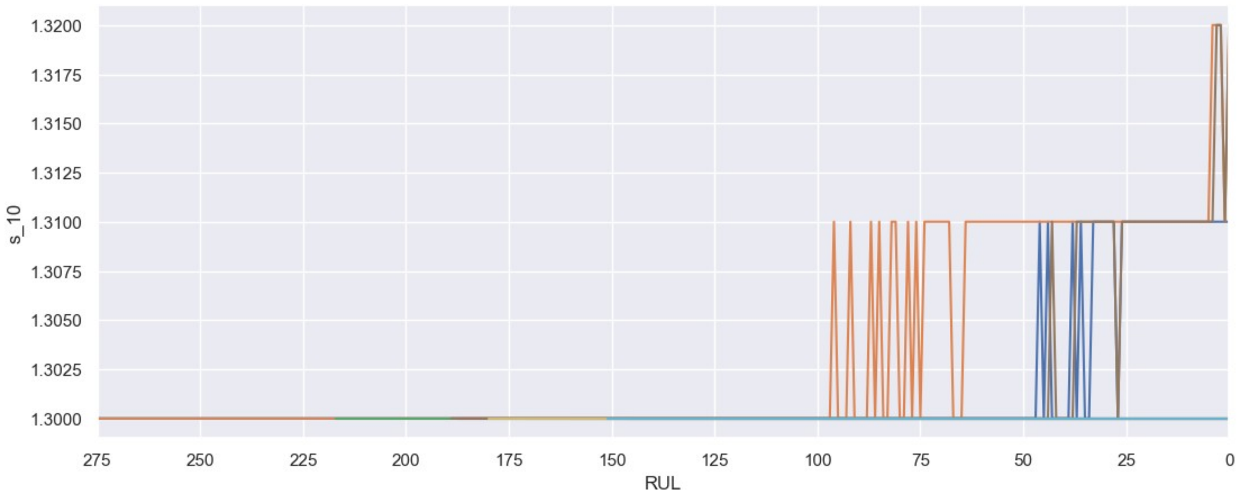

15.4
15.2
15.0
14.8
14.6
14.4
14.2
14.0
s_5
275
250
225
200
175
150
125
100
75
50
25
0
RUL

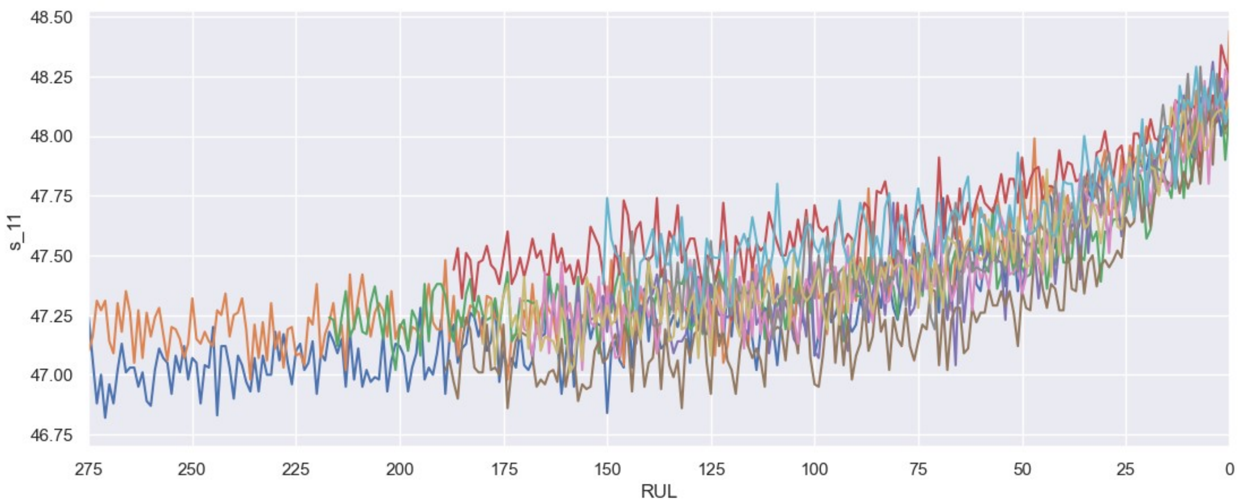

21.60
21.58
21.56
21.54
21.52
21.50
21.48
21.46
s_6
275
250
225
200
175
150
125
100
75
50
25
0
RUL

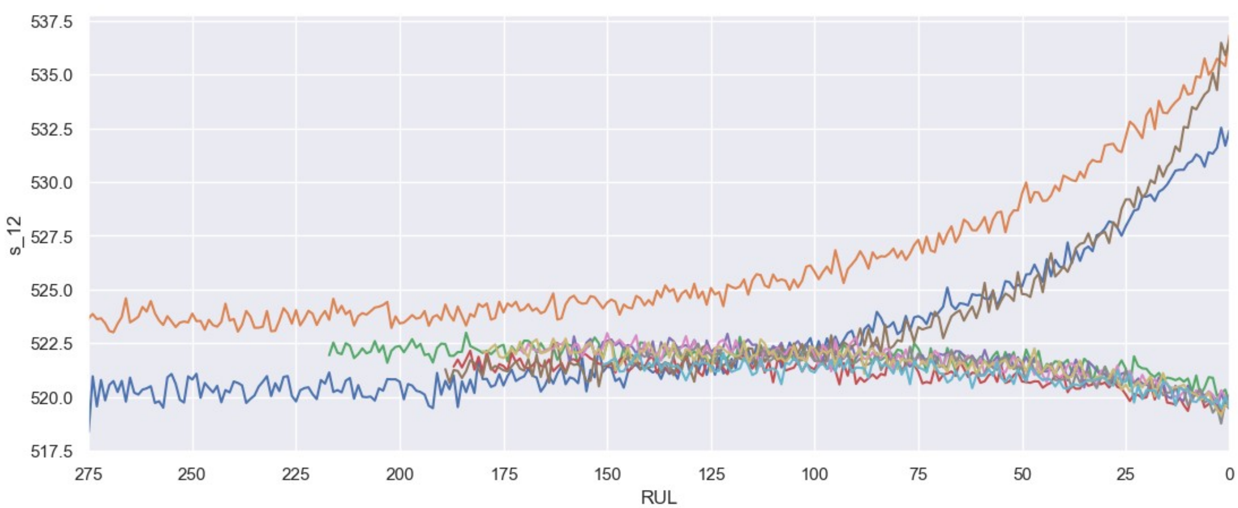

s_7
570.0
567.5
565.0
562.5
560.0
557.5
555.0
552.5
550.0
275
250
225
200
175
150
125
100
75
50
25
0
RUL

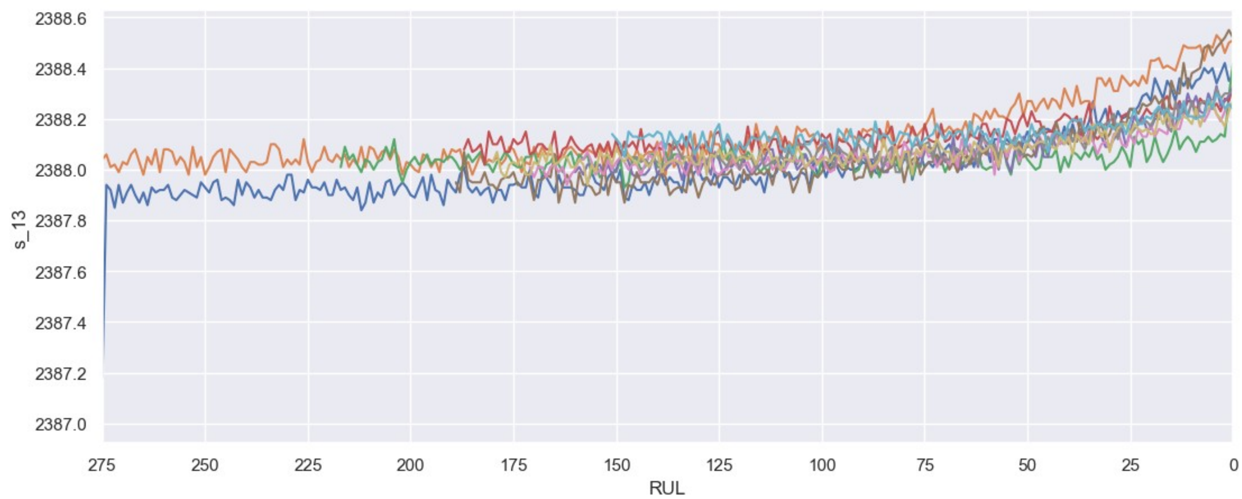

s_8
2388.6
2388.4
2388.2
2388.0
2387.8
2387.6
2387.4
2387.2
2387.0
275
250
225
200
175
150
125
100
75
50
25
0
RUL

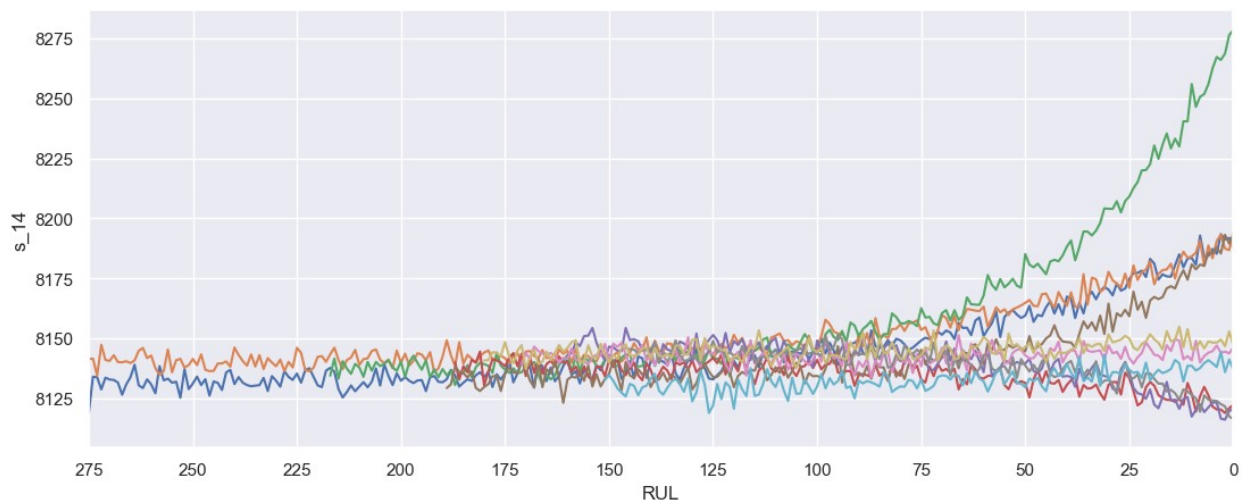

s_9
9225
9200
9175
9150
9125
9100
9075
9050
9025
275
250
225
200
175
150
125
100
75
50
25
0
RUL

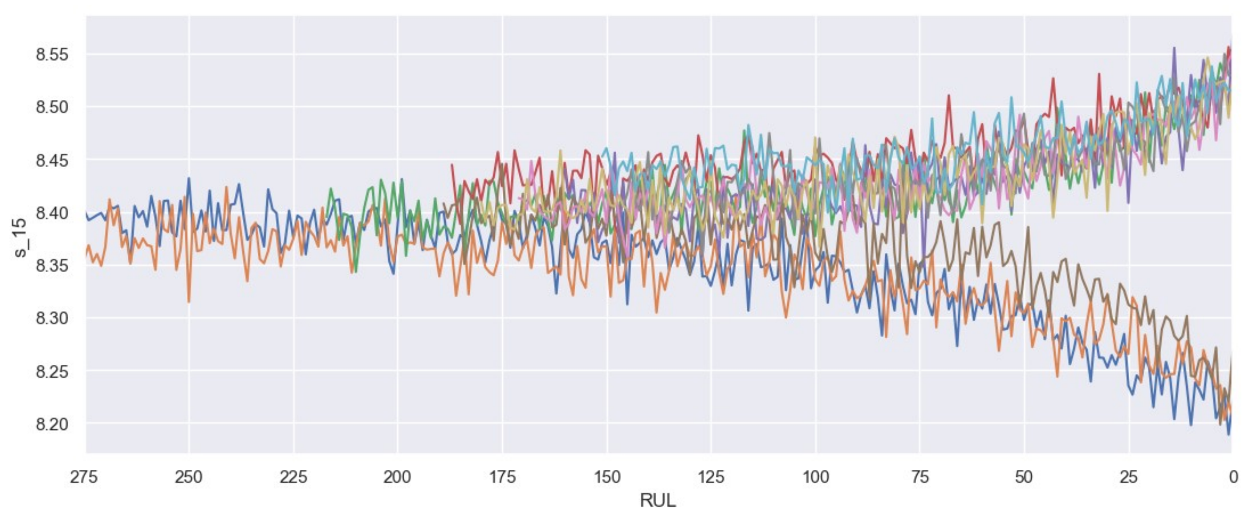

1.3200
1.3175
1.3150
1.3125
1.3100
1.3075
1.3050
1.3025
1.3000
s_10
275
250
225
200
175
150
125
100
75
50
25
0
RUL

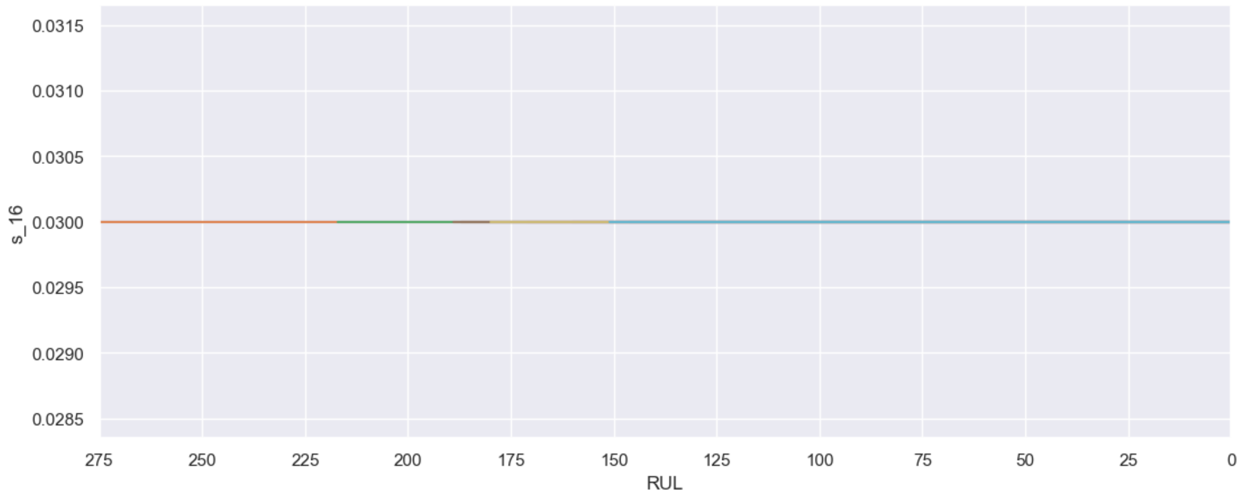

48.50
48.25
48.00
47.75
47.50
47.25
47.00
46.75
s_11
275
250
225
200
175
150
125
100
75
50
25
0
RUL

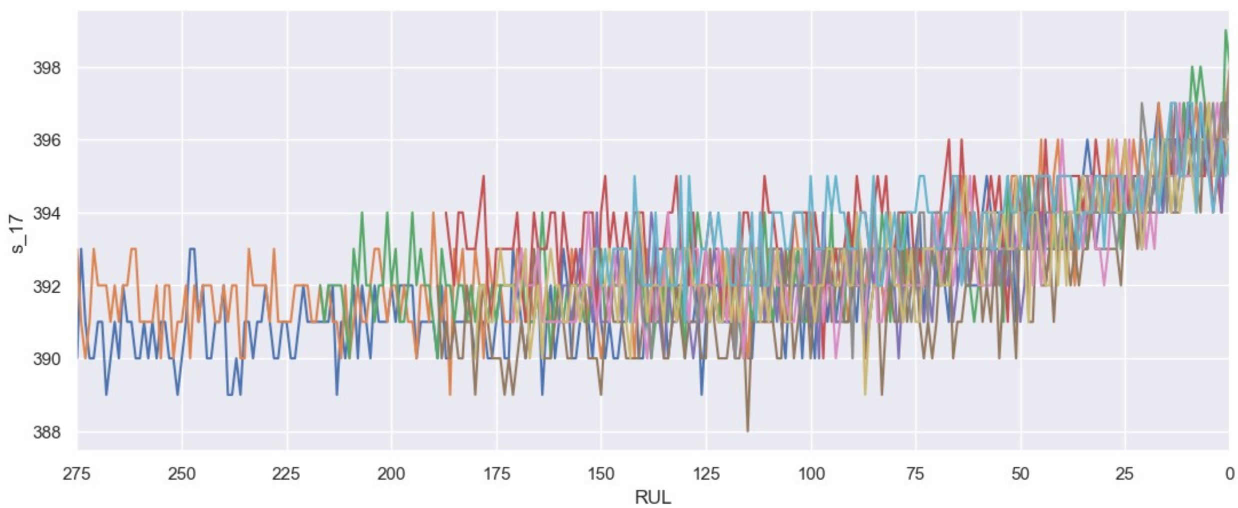

537.5
535.0
532.5
530.0
527.5
525.0
522.5
520.0
517.5
s_12
275
250
225
200
175
150
125
100
75
50
25
0
RUL

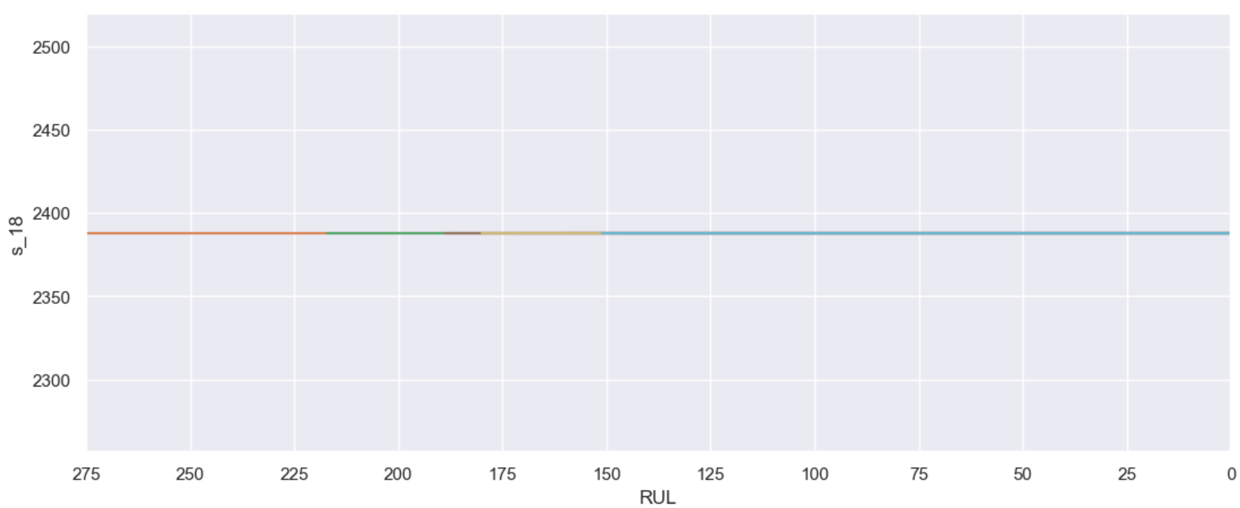

2388.6
2388.4
2388.2
2388.0
2387.8
2387.6
2387.4
2387.2
2387.0
s_13
275
250
225
200
175
150
125
100
75
50
25
0
RUL

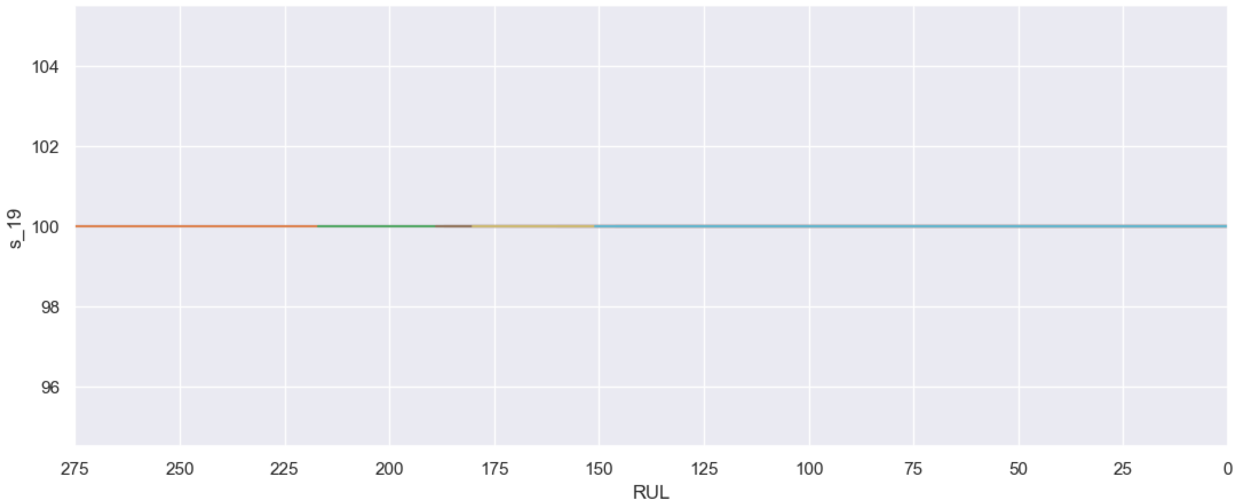

8275
8250
8225
8200
8175
8150
8125
s_14
275
250
225
200
175
150
125
100
75
50
25
0
RUL

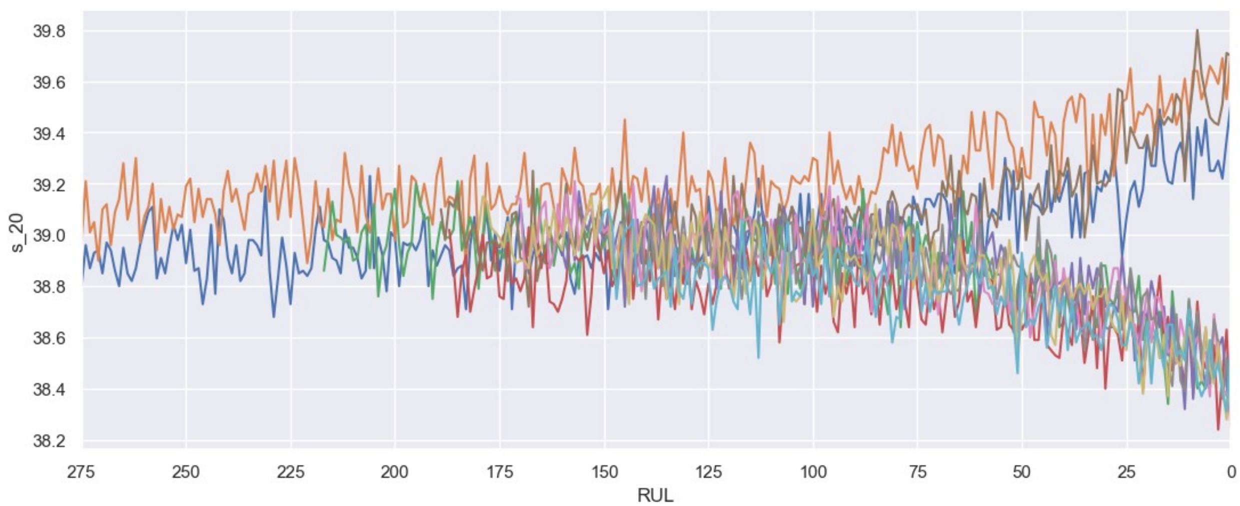

8.55
8.50
8.45
8.40
8.35
8.30
8.25
8.20
s_15
275
250
225
200
175
150
125
100
75
50
25
0
RUL

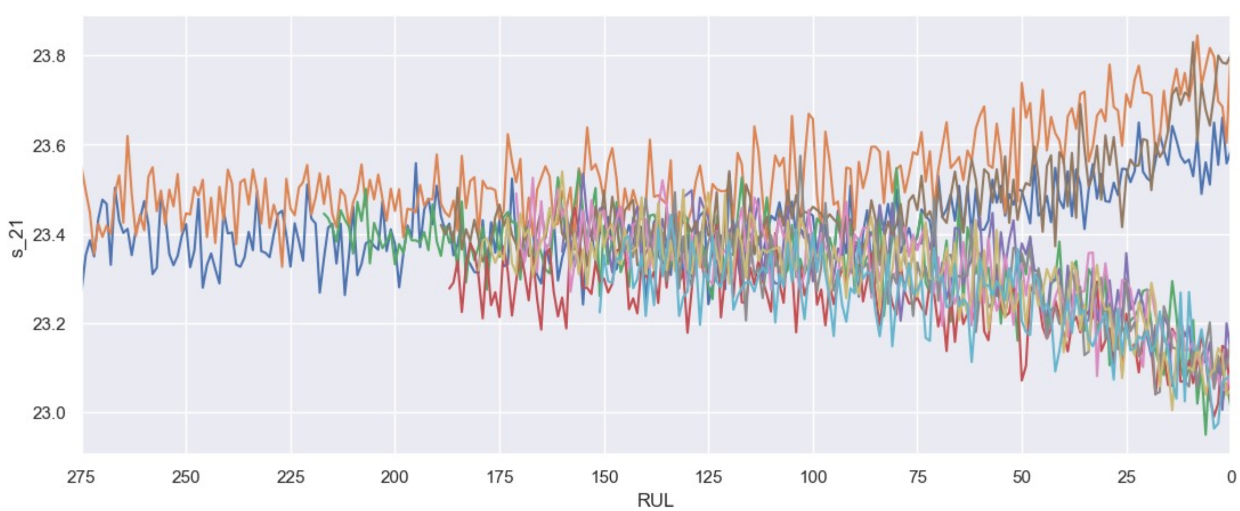

0.0315
0.0310
0.0305
0.0300
0.0295
0.0290
0.0285
s_16
275
250
225
200
175
150
125
100
75
50
25
0
RUL


398
396
394
392
390
388
s_17
275
250
225
200
175
150
125
100
75
50
25
0
RUL


2500
2450
2400
2350
2300
s_18
275
250
225
200
175
150
125
100
75
50
25
0
RUL


s_19
104
102
100
98
96
275
250
225
200
175
150
125
100
75
50
25
0
RUL


s_20
39.8
39.6
39.4
39.2
39.0
38.8
38.6
38.4
38.2
275
250
225
200
175
150
125
100
75
50
25
0
RUL


s_21
23.8
23.6
23.4
23.2
23.0
275
250
225
200
175
150
125
100
75
50
25
0
RUL

3. Modelo de Referência

```
# Preparando os dados

# Removendo os sensores desnecessarios
drop_sensors = ['s_1','s_5','s_16','s_18','s_19']  # Vou manter o s_6 
e s_10 por enquanto
drop_labels = index_names+setting_names+drop_sensors
remaining_sensors = ['s_2', 's_3', 's_4', 's_6', 's_7', 's_8', 's_9', 
's_10',
       's_11', 's_12', 's_13', 's_14', 's_15', 's_17', 's_20', 's_21']

# Separando o RUL do grupo de treino
X_train = train.drop(drop_labels, axis=1)
y_train = X_train.pop('RUL')
y_train_clipped = y_train.clip(upper=125)  # Cortando o RUL


# O valor real do RUL esta no ultimo ciclo de tempo de cada unidade
# Reorganizando o grupo de teste com esse ajuste
X_test = 
test.groupby('unidade').last().reset_index().drop(drop_labels, axis=1)

# Criando a funcao de avaliacao
def avaliar(y_verdadeiro, y_calculado, label='teste'):
    mse = mean_squared_error(y_verdadeiro, y_calculado)
    rmse = np.sqrt(mse)
    variancia = r2_score(y_verdadeiro, y_calculado)
    print('conjunto de {} -> RMSE:{}, R2:{}'.format(label, rmse, 
variancia))

# Criando e ajustando o modelo
lm = LinearRegression()
lm.fit(X_train, y_train)

# Testando e avaliando o modelo treinado
y_hat_train = lm.predict(X_train)
avaliar(y_train, y_hat_train, 'treino')

y_hat_test = lm.predict(X_test)
avaliar(y_test, y_hat_test)
```

```
conjunto de treino -> RMSE:63.494471921833146, R2:0.5873657567234036
conjunto de teste -> RMSE:57.05730530062128, R2:-0.8998253079767999
```

4. Floresta Aleatória - Random Forest

```
# Criando e ajustando o regressor de floresta aleatória sem qualquer 
alteracao
```

```
rf = RandomForestRegressor(n_estimators=100, max_features="sqrt",
random_state=42)
rf.fit(X_train, y_train_clipped)

# Testando e avaliando o modelo treinado
y_hat_train = rf.predict(X_train)
avaliar(y_train_clipped, y_hat_train, 'treino')

y_hat_test = rf.predict(X_test)
avaliar(y_test, y_hat_test)
```

```
conjunto de treino -> RMSE:5.9199939580022525, R2:0.9787661901585051
conjunto de teste -> RMSE:21.05308450085165, R2:0.7413439613827657
```

```
# Analisando a forma de uma das arvores da floresta
print(rf.estimators_[5].tree_.max_depth)  # Quantos nos no caminho
mais longo
rf.estimators_[5].tree_.n_node_samples    # Quantos samples nos
ultimos nos
```

```
33
```

```
array([15616, 11694,  7793, ...,     1,     1,     4], dtype=int64)
```

```
# Refazendo o modelo com alguns ajustes
rf = RandomForestRegressor(n_estimators=100, max_features="sqrt",
random_state=42,
                           max_depth=8, min_samples_leaf=50)
rf.fit(X_train, y_train_clipped)

# Testando e avaliando o modelo treinado
y_hat_train = rf.predict(X_train)
avaliar(y_train_clipped, y_hat_train, 'treino')

y_hat_test = rf.predict(X_test)
avaliar(y_test, y_hat_test)
```

```
conjunto de treino -> RMSE:15.706704198492831, R2:0.8505294865338602
conjunto de teste -> RMSE:20.994958823842456, R2:0.7427702419664686
```

5. Enxergando a RF

```
def export_rf_visual(estimator):
    # Criando representacao da arvore de decisao
    dot_data = export_graphviz(estimator,
        out_file=None,
        feature_names=X_train.columns,
        filled=True,
        special_characters=True,
```

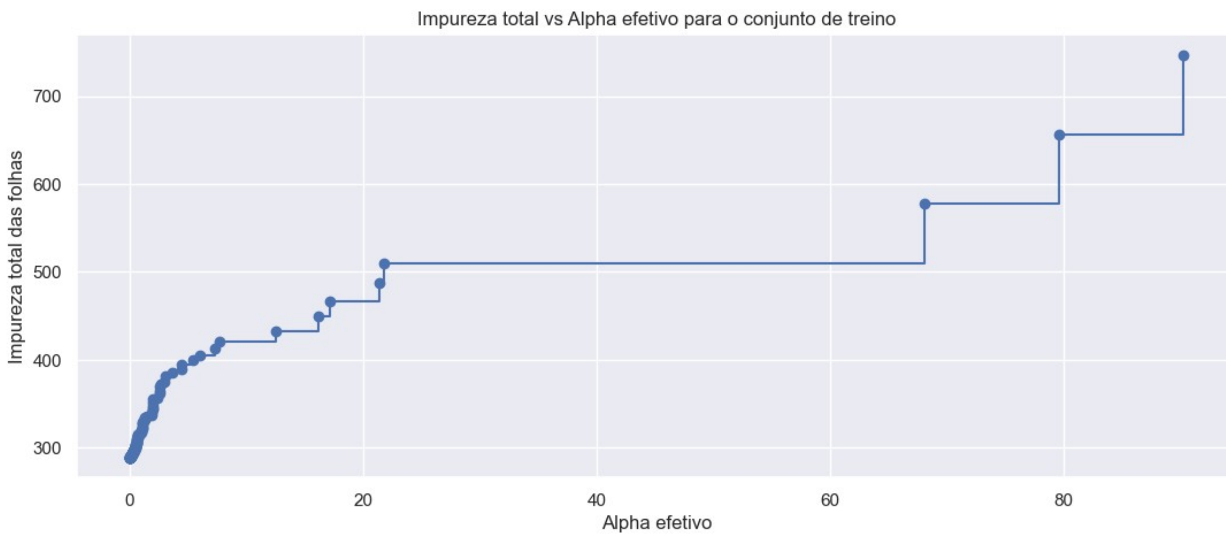
```
        rotate=True)

    graph = graphviz.Source(dot_data)
    return(graph)


# Exibindo no notebook
export_rf_visual(rf.estimators_[5])
```

6. Hiperparâmetros

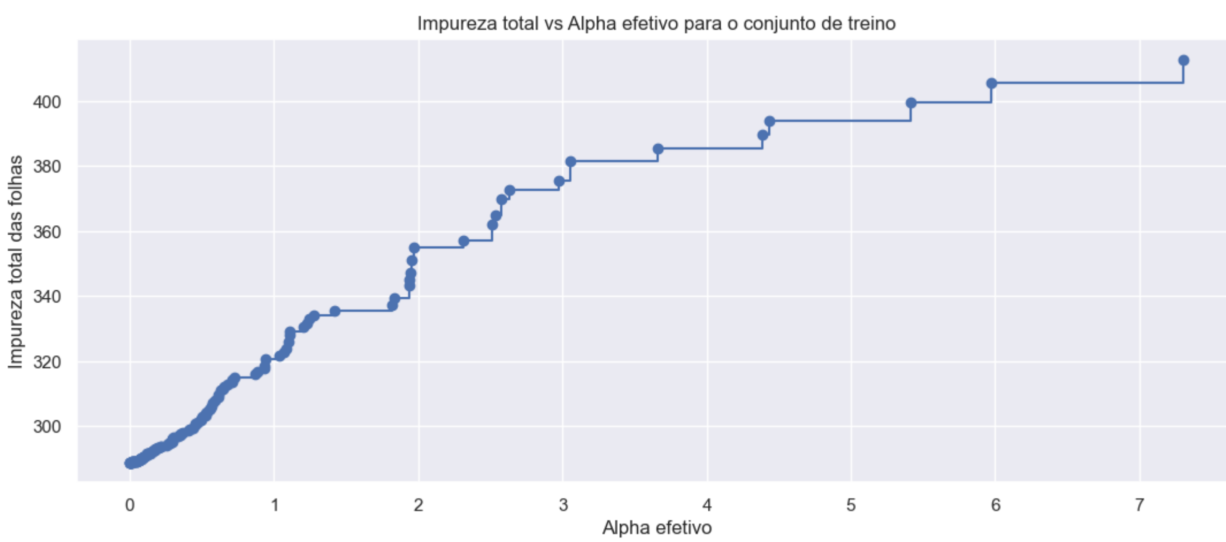
```
rf.get_params()
```

```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'criterion': 'squared_error',
 'max_depth': 8,
 'max_features': 'sqrt',
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 50,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 100,
 'n_jobs': None,
 'oob_score': False,
 'random_state': 42,
 'verbose': 0,
 'warm_start': False}
```

```
# Obtendo ccp_alphas
path = rf.estimators_[5].cost_complexity_pruning_path(X_train,
y_train_clipped)
ccp_alphas, impurities = path.ccp_alphas, path.impurities

fig, ax = plt.subplots(figsize=(13,5))
ax.plot(ccp_alphas[:-1], impurities[:-1], marker='o',
drawstyle="steps-post")
ax.set_xlabel("Alpha efetivo")
ax.set_ylabel("Impureza total das folhas")
ax.set_title("Impureza total vs Alpha efetivo para o conjunto de
treino")
plt.show()
```




```
# zoom in
fig, ax = plt.subplots(figsize=(13,5))
ax.plot(ccp_alphas[:-10], impurities[:-10], marker='o',
drawstyle="steps-post")
ax.set_xlabel("Alpha efetivo")
ax.set_ylabel("Impureza total das folhas")
ax.set_title("Impureza total vs Alpha efetivo para o conjunto de
treino")
plt.show()
```




```
rf_dict = {
    'id_node': list(range(rf.estimators_[5].tree_.node_count)),
    'impurity': rf.estimators_[5].tree_.impurity,
    'samples': rf.estimators_[5].tree_.n_node_samples,
    'id_left_child': rf.estimators_[5].tree_.children_left,
```

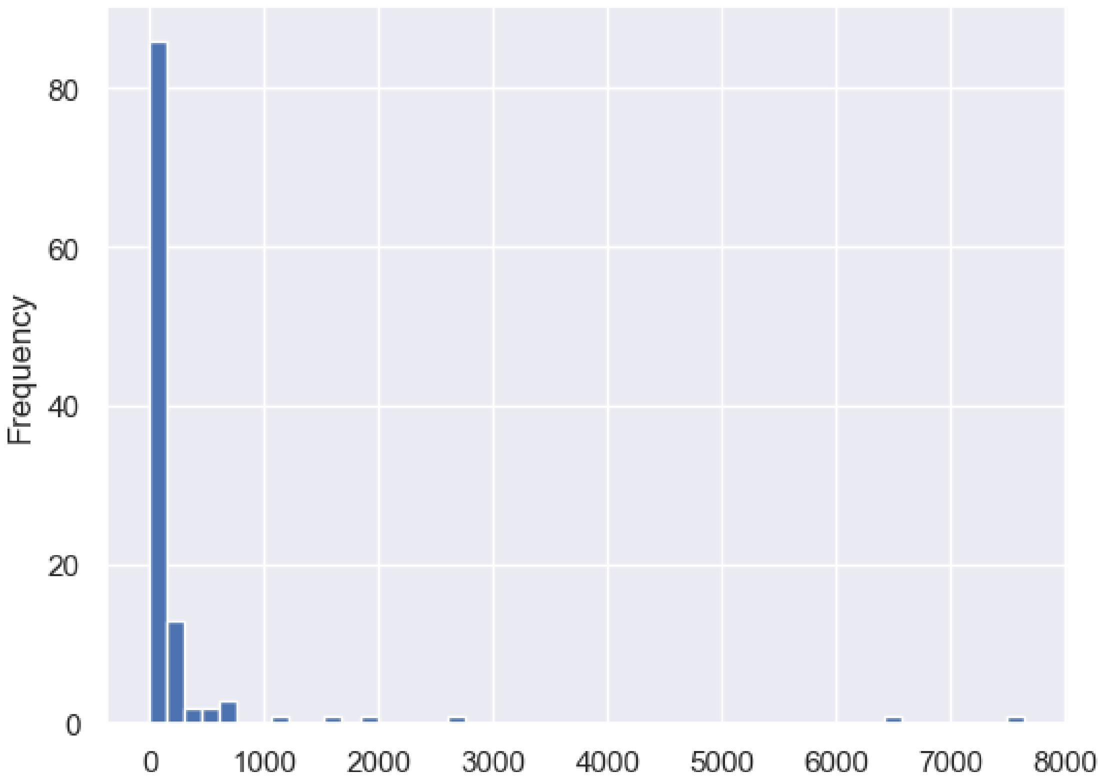
```python
    'id_right_child': rf.estimators_[5].tree_.children_right
}

impurity_df = pd.DataFrame(rf_dict)
print(impurity_df.shape)
impurity_df.head(10)
```

```
(227, 5)
```

	id_node	impurity	samples	id_left_child	id_right_child
0	0	1644.689840	15616	1	128
1	1	609.414829	11694	2	71
2	2	247.609863	7793	3	52
3	3	156.037153	6372	4	29
4	4	97.827624	4473	5	20
5	5	19.630575	1627	6	13
6	6	3.844416	765	7	10
7	7	10.192376	257	8	9
8	8	1.085113	143	-1	-1
9	9	21.980353	114	-1	-1

```python
# Calculando o min_impurity_decrease
impurity_df['impurity_decrease'] = np.nan
samples_total = rf.estimators_[5].tree_.node_count

for idx in impurity_df.index[1:]:  # Pulando o primeiro no, ja que n
ha divisoes antes dele
    if impurity_df.iloc[idx]['id_left_child'] == -1:
        continue  # n eh possivel calcular o decaimento da impureza
para folhas, ja que n ha divisoes apos elas
    else:
        impurity_P, samples_P = impurity_df.iloc[idx][['impurity',
'samples']]
        id_L, id_R = impurity_df.iloc[idx][['id_left_child',
'id_right_child']].astype(int)
        impurity_L, samples_L = impurity_df.iloc[id_L][['impurity',
'samples']]
        impurity_R, samples_R = impurity_df.iloc[id_R][['impurity',
'samples']]

        impurity_decrease = samples_P / samples_total * (
            impurity_P - samples_R / samples_P * impurity_R -
            samples_L / samples_P * impurity_L
            )
        impurity_df.at[idx, 'impurity_decrease'] = impurity_decrease

# Histograma do decaimento de impureza
impurity_df['impurity_decrease'].plot(kind='hist', bins=50)
```

```
<Axes: ylabel='Frequency'>
```

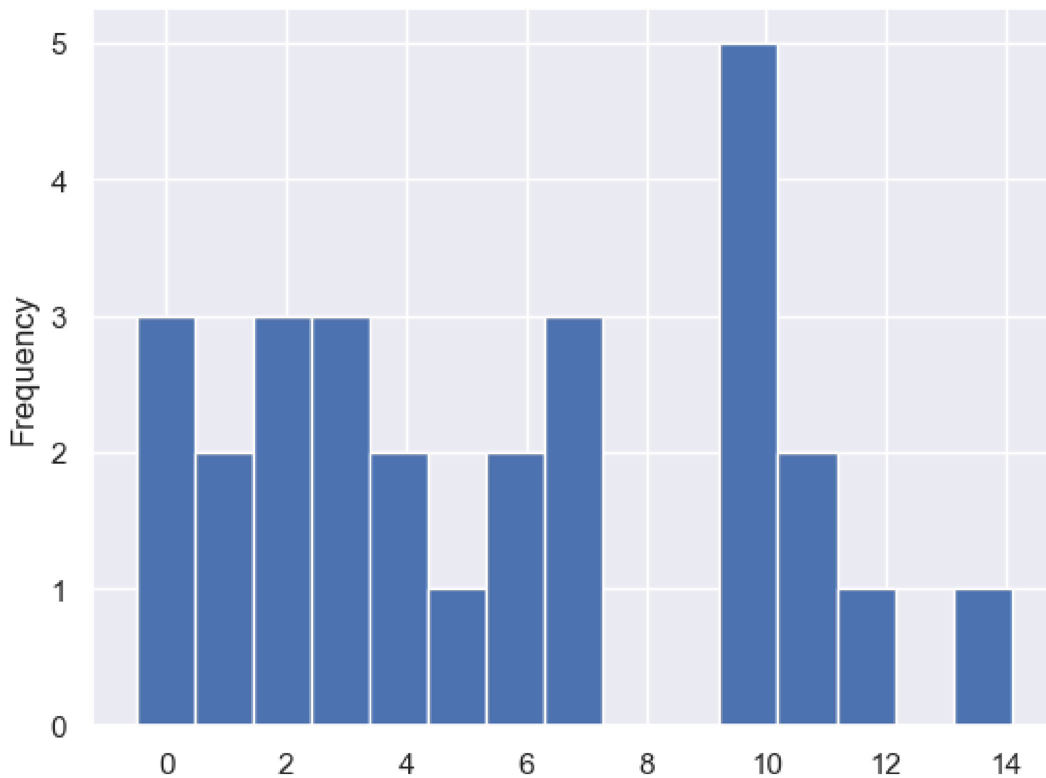



```python
# Dados estatísticos
impurity_df['impurity_decrease'].describe()
```

```
count     112.000000
mean      282.515265
std       994.407842
min        -0.506232
25%        14.589094
50%        47.024819
75%       129.095879
max      7639.300570
Name: impurity_decrease, dtype: float64
```

```python
# Zoom no histograma
impurity_df.loc[impurity_df['impurity_decrease'] < 14.59,
'impurity_decrease'].plot(kind='hist', bins=15)
```

```
<Axes: ylabel='Frequency'>
```



7. Procura aleatória - Randomsearch

```
# Definindo os limites de cada parametro para a randomsearch
max_depth = [None] + list(range(3, 34, 3))
min_samples_leaf = list(range(1, 102, 10))
min_impurity_decrease = list(np.arange(0,147)/10)
ccp_alpha = list(np.round(np.linspace(0, 2, 81), decimals=3))

parameters = {
    'max_depth': max_depth,
    'min_samples_leaf': min_samples_leaf,
    'min_impurity_decrease': min_impurity_decrease,
    'ccp_alpha': ccp_alpha
}

tuning_options = len(max_depth) * len(min_samples_leaf) *
len(min_impurity_decrease) * len(ccp_alpha)
print(tuning_options)
```

```
1571724
```

```
# Criando um conjunto de validação e evitando o vazamento dos dados
com o uso do GroupKFold
```

```
from sklearn.model_selection import RandomizedSearchCV, GroupKFold

ITERATIONS = 300

rf = RandomForestRegressor(n_estimators=100, max_features="sqrt",
random_state=42)
gkf = GroupKFold(n_splits=3)


regressor = RandomizedSearchCV(rf,
                               parameters,
                               cv = gkf.split(train,
groups=train['unidade']),
                               verbose=2,
                               error_score='raise',
                               n_iter=ITERATIONS,
                               n_jobs=-2,
                               # scoring
https://scikit-learn.org/stable/modules/model_evaluation.html#scoring-
parameter
                               scoring= 'neg_root_mean_squared_error')

regressor.fit(X_train, y_train_clipped)
```

```
Fitting 3 folds for each of 300 candidates, totalling 900 fits
```

```
RandomizedSearchCV(cv=<generator object _BaseKFold.split at
0x00000189DD648740>,
                   error_score='raise',

estimator=RandomForestRegressor(max_features='sqrt',
                                                   random_state=42),
                   n_iter=300, n_jobs=-2,
                   param_distributions={'ccp_alpha': [0.0, 0.025,
0.05, 0.075,
                                                      0.1, 0.125,
0.15, 0.175,
                                                      0.2, 0.225,
0.25, 0.275,
                                                      0.3, 0.325,
0.35, 0.375,
                                                      0.4, 0.425,
0.45, 0.475,
                                                      0.5, 0.525,
0.55, 0.575,
                                                      0.6, 0.625,
0.65, 0.675,
                                                      0.7,
0.725, ...],
                                        'max_depth': [None, 3, 6, 9,
```

```
12, 15, 18,
                                                    21, 24, 27, 30,
33],
                                    'min_impurity_decrease': [0.0,
0.1, 0.2,
                                                                0.3,
0.4, 0.5,
                                                                0.6,
0.7, 0.8,
                                                                0.9,
1.0, 1.1,
                                                                1.2,
1.3, 1.4,
                                                                1.5,
1.6, 1.7,
                                                                1.8,
1.9, 2.0,
                                                                2.1,
2.2, 2.3,
                                                                2.4,
2.5, 2.6,
                                                                2.7,
2.8, 2.9, ...],
                                    'min_samples_leaf': [1, 11,
21, 31, 41,
                                                         51, 61,
71, 81, 91,
                                                         101]},
                   scoring='neg_root_mean_squared_error', verbose=2)
```

```
resultado = pd.DataFrame(regressor.cv_results_)
columns = ['param_min_samples_leaf', 'param_min_impurity_decrease',
'param_max_depth', 'param_ccp_alpha',
           'mean_test_score', 'std_test_score', 'rank_test_score']
resultado[columns].sort_values('mean_test_score', ascending=False)
```

```
    param_min_samples_leaf param_min_impurity_decrease param_max_depth
\
26                      21                         0.1              21

277                     31                         0.2              33

299                      1                         0.0              15

123                     31                         0.8               9

4                       11                         1.2              24

..                     ...                         ...             ...
```

```
295                       101                            8.6               3
84                         31                            9.1               3
223                        71                           10.4               3
3                          11                           11.4               3
212                        71                           13.7               3

    param_ccp_alpha  mean_test_score  std_test_score  rank_test_score
26            0.475       -16.669104        0.316564                1
277            0.35       -16.744735        0.332176                2
299           0.875       -16.813201        0.281859                3
123           0.175       -16.942223        0.298950                4
4              0.85       -17.041977        0.291904                5
..              ...              ...             ...              ...
295           0.925       -19.089300        0.524540              296
84            1.275       -19.090969        0.523144              297
223            0.85       -19.098670        0.521663              298
3             0.475       -19.106038        0.521172              299
212             1.9       -19.122912        0.513109              300

[300 rows x 7 columns]
```

```
# Melhores parametros
print(regressor.best_params_)
print(regressor.best_score_)
```

```
{'min_samples_leaf': 21, 'min_impurity_decrease': 0.1, 'max_depth':
21, 'ccp_alpha': 0.475}
-16.669103655003024
```

8. Modelo Final

```
# Usando os melhores parametros para treinar o modelo final
rf = RandomForestRegressor(n_estimators=100, max_features="sqrt",
```

```
random_state=42,
                                  min_samples_leaf=11,
min_impurity_decrease=0.0,
                                  max_depth=15, ccp_alpha=0.125)
rf.fit(X_train, y_train_clipped)

# Testando e avaliando o modelo
y_hat_train = rf.predict(X_train)
avaliar(y_train_clipped, y_hat_train, 'treino')

y_hat_test = rf.predict(X_test)
avaliar(y_test, y_hat_test)
```

```
conjunto de treino -> RMSE:13.95446880579081, R2:0.8820190156933622
conjunto de teste -> RMSE:20.61288923394374, R2:0.7520472702746352
```