RandomForestRegressor_v1_seg_2

November 24, 2022

1 Random Forest regressor

1.1 Read the etl info results

1.2 Read the dataset

```
[]: df = pd.read_csv('../dataset_clean/PlatteRiverWeir_features_v1_clean.csv') df
```

```
[]:
                     SensorTime
                                          CaptureTime Stage Discharge
                                                                             grayMean \
     0
            2012-06-09 13:15:00
                                  2012-06-09T13:09:07
                                                         2.99
                                                                   916.0
                                                                            97.405096
     1
            2012-06-09 13:15:00
                                  2012-06-09T13:10:29
                                                         2.99
                                                                   916.0
                                                                           104.066757
     2
            2012-06-09 13:45:00
                                  2012-06-09T13:44:01
                                                         2.96
                                                                   873.0
                                                                           105.636831
     3
            2012-06-09 14:45:00
                                  2012-06-09T14:44:30
                                                         2.94
                                                                   846.0
                                                                           104.418949
     4
            2012-06-09 15:45:00
                                  2012-06-09T15:44:59
                                                         2.94
                                                                   846.0
                                                                           106.763541
     42054
            2019-10-11 09:00:00
                                  2019-10-11T08:59:53
                                                         2.54
                                                                   434.0
                                                                            82.872720
                                                                            89.028383
     42055
            2019-10-11 10:00:00
                                  2019-10-11T09:59:52
                                                         2.54
                                                                   434.0
     42056
            2019-10-11 11:00:00
                                  2019-10-11T10:59:52
                                                         2.54
                                                                            94.722097
                                                                   434.0
     42057
            2019-10-11 12:00:00
                                  2019-10-11T11:59:53
                                                         2.54
                                                                   434.0
                                                                            96.693270
     42058
            2019-10-11 12:45:00
                                  2019-10-11T12:59:52
                                                         2.54
                                                                   434.0
                                                                            98.738399
                       entropyMean
                                     entropySigma
            graySigma
                                                         hMean
                                                                   hSigma
     0
            39.623303
                           0.203417
                                         0.979825
                                                    105.368375
                                                                41.572939
     1
            40.179745
                           0.206835
                                         1.002624 112.399458
                                                                41.795584
     2
            40.533218
                           0.204756
                                         0.994246 114.021526
                                                                42.145582
     3
                                                    112.612830
            41.752678
                           0.202428
                                         0.983170
                                                                43.575351
     4
                                                    114.839424
            44.442097
                           0.202661
                                         0.989625
                                                                46.302008
     42054
            57.702652
                           0.221708
                                         1.076393
                                                    87.260572
                                                                61.485334
     42055
            55.840861
                           0.233168
                                         1.124774
                                                     94.175906
                                                                59.006132
     42056
            54.355753
                           0.240722
                                         1.151833
                                                    100.534577
                                                                56.921028
     42057
            52.787629
                           0.244789
                                         1.171987
                                                    102.891159
                                                                55.083532
     42058
            52.025453
                                                    105.292067
                           0.252812
                                         1.213278
                                                                53.994155
                 sMean
                           sSigma
                                        vMean
                                                   vSigma
     0
            124.520218
                        4.111846
                                   132.405971
                                                14.983367
     1
            124.317679
                        4.270429
                                   133.070221
                                                15.334166
     2
                        4.310293
                                   133.294541
            124.304621
                                                15.502448
     3
            124.369736
                        4.120586
                                   133.458381
                                                15.190064
     4
            124.283191
                        4.088480
                                                14.801143
                                   133.573595
                         •••
                 •••
     42054
            127.807813
                        2.564157
                                   124.073149
                                                13.757842
     42055
            127.336000
                        2.585121
                                   124.882812
                                                13.234735
     42056
            126.958768
                         2.774867
                                   126.145409
                                                13.408480
     42057
            126.679956
                         2.998683
                                   127.508063
                                                13.863205
     42058
            126.328075
                        3.258103
                                   128.788256
                                                14.353808
```

[42059 rows x 14 columns]

```
[]: df['SensorTime'] = pd.to_datetime(df['SensorTime'])
     df['Year'] = df['SensorTime'].dt.year
     df['Month'] = df['SensorTime'].dt.month
[]: df.dtypes
[]: SensorTime
                     datetime64[ns]
     CaptureTime
                             object
     Stage
                            float64
    Discharge
                            float64
     grayMean
                            float64
     graySigma
                            float64
                            float64
     entropyMean
     entropySigma
                            float64
    hMean
                            float64
    hSigma
                            float64
     sMean
                            float64
     sSigma
                            float64
     vMean
                            float64
                            float64
     vSigma
    Year
                              int64
    Month
                              int64
     dtype: object
[]: df = df[(df.Stage > 0) & (df.Discharge > 0)]
[]: df.isna().sum()
[]: SensorTime
                     0
     CaptureTime
                     0
     Stage
                     0
     Discharge
                     0
     grayMean
                     0
     graySigma
                     0
     entropyMean
                     0
     entropySigma
    hMean
                     0
    hSigma
                     0
    sMean
                     0
    sSigma
                     0
    vMean
                     0
     vSigma
                     0
    Year
                     0
    Month
                     0
     dtype: int64
```

1.3 Divide dataset to X and Y

```
[]: np.random.seed(0)
    df_train = df[(df.Year >= 2012) & (df.Year <= 2017)]</pre>
    df_train = df_train.iloc[np.random.permutation(len(df_train))]
    df_test = df[(df.Year >= 2018) & (df.Year <= 2019)]</pre>
[]: df_train = df_train.drop(columns=["Year", "SensorTime", "CaptureTime"])
    #df_val = df_val.drop(columns=["Year", "SensorTime", "CaptureTime"])
    df_test = df_test.drop(columns=["Year", "SensorTime", "CaptureTime"])
[]: y_train = df_train["Stage"]
    X_train = df_train.drop(columns=["Stage", "Discharge"])
    y_test = df_test["Stage"]
    X_test = df_test.drop(columns=["Stage", "Discharge"])
[]: print(X_train.shape)
    print(y_train.shape)
    (27421, 11)
    (27421,)
[]: input_shape = X_train.shape
    output_shape = y_train.shape
    print(input_shape, output_shape)
    (27421, 11) (27421,)
    1.4 Train model
[]: pipeline = Pipeline([
        ('scaler', StandardScaler()),
        ('clf', RandomForestRegressor(random_state=0))
    ])
    param_grid = {'clf__n_estimators': np.arange(50, 300, 1), 'clf__max_features':u
     clf = RandomizedSearchCV(pipeline, param_distributions=param_grid, n_iter=20,__
     []: clf.fit(X_train, y_train)
```

Fitting 5 folds for each of 20 candidates, totalling 100 fits

```
[CV 4/5] END clf__max_features=log2, clf__n_estimators=193;, score=-0.206 total
time= 11.7s
[CV 3/5] END clf__max_features=log2, clf__n_estimators=193;, score=-0.190 total
time= 11.7s
[CV 5/5] END clf__max_features=log2, clf__n_estimators=193;, score=-0.186 total
time= 11.8s
[CV 1/5] END clf_max_features=log2, clf_n_estimators=193;, score=-0.201 total
time= 12.0s
[CV 2/5] END clf__max_features=log2, clf__n_estimators=193;, score=-0.187 total
time= 12.2s
[CV 2/5] END clf max features=log2, clf n estimators=206;, score=-0.187 total
time= 12.6s
[CV 3/5] END clf__max_features=log2, clf__n_estimators=206;, score=-0.190 total
time= 13.0s
[CV 1/5] END clf__max_features=log2, clf__n_estimators=206;, score=-0.201 total
time= 13.3s
[CV 2/5] END clf__max_features=log2, clf__n_estimators=118;, score=-0.188 total
      7.0s
[CV 1/5] END clf__max_features=log2, clf__n_estimators=118;, score=-0.201 total
      7.2s
[CV 3/5] END clf__max_features=log2, clf__n_estimators=118;, score=-0.190 total
      7.3s
[CV 4/5] END clf_max_features=log2, clf_n_estimators=118;, score=-0.206 total
      7.3s
[CV 5/5] END clf__max_features=log2, clf__n_estimators=118;, score=-0.187 total
       7.0s
[CV 4/5] END clf__max_features=log2, clf__n_estimators=206;, score=-0.206 total
time= 12.5s
[CV 5/5] END clf__max_features=log2, clf__n_estimators=206;, score=-0.186 total
time= 13.0s
[CV 1/5] END clf__max_features=log2, clf__n_estimators=91;, score=-0.201 total
[CV 3/5] END clf__max_features=log2, clf__n_estimators=91;, score=-0.191 total
time=
      5.1s
[CV 2/5] END clf__max_features=log2, clf__n_estimators=91;, score=-0.188 total
       6.1s
[CV 4/5] END clf__max_features=log2, clf__n_estimators=91;, score=-0.208 total
       5.1s
[CV 5/5] END clf__max_features=log2, clf__n_estimators=91;, score=-0.186 total
       5.1s
[CV 2/5] END clf__max_features=sqrt, clf__n_estimators=187;, score=-0.187 total
time= 11.4s
[CV 1/5] END clf__max_features=sqrt, clf__n_estimators=187;, score=-0.201 total
time= 12.3s
[CV 1/5] END clf__max_features=1.0, clf__n_estimators=162;, score=-0.195 total
time= 29.4s
[CV 3/5] END clf__max_features=sqrt, clf__n_estimators=187;, score=-0.190 total
time= 10.6s
```

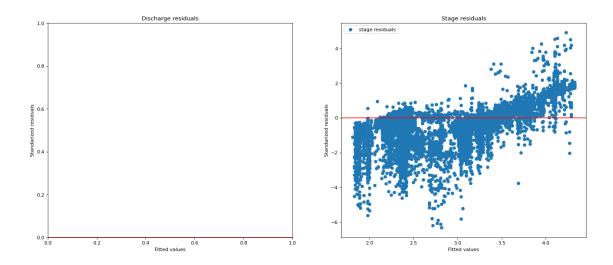
```
[CV 2/5] END clf__max_features=1.0, clf__n_estimators=162;, score=-0.185 total
time= 31.0s
[CV 3/5] END clf__max_features=1.0, clf__n_estimators=162;, score=-0.186 total
time= 31.4s
[CV 5/5] END clf__max_features=1.0, clf__n_estimators=162;, score=-0.182 total
time= 30.9s
[CV 4/5] END clf__max_features=1.0, clf__n_estimators=162;, score=-0.202 total
time= 32.0s
[CV 5/5] END clf__max_features=sqrt, clf__n_estimators=187;, score=-0.186 total
time= 10.8s
[CV 4/5] END clf max features=sqrt, clf n estimators=187;, score=-0.206 total
time= 11.4s
[CV 1/5] END clf__max_features=1.0, clf__n_estimators=150;, score=-0.195 total
time= 26.4s
[CV 2/5] END clf__max_features=1.0, clf__n_estimators=150;, score=-0.185 total
time= 28.6s
[CV 1/5] END clf__max_features=1.0, clf__n_estimators=118;, score=-0.195 total
time= 22.9s
[CV 2/5] END clf__max_features=1.0, clf__n_estimators=118;, score=-0.186 total
time= 22.5s
[CV 3/5] END clf__max_features=1.0, clf__n_estimators=150;, score=-0.186 total
time= 26.8s
[CV 3/5] END clf_max_features=1.0, clf_n_estimators=118;, score=-0.186 total
time= 23.3s
[CV 4/5] END clf__max_features=1.0, clf__n_estimators=150;, score=-0.202 total
time= 28.4s
[CV 5/5] END clf max features=1.0, clf n estimators=150;, score=-0.182 total
time= 28.3s
[CV 1/5] END clf__max_features=log2, clf__n_estimators=166;, score=-0.201 total
time= 10.4s
[CV 2/5] END clf__max_features=log2, clf__n_estimators=166;, score=-0.187 total
time= 10.4s
[CV 3/5] END clf__max_features=log2, clf__n_estimators=166;, score=-0.190 total
time= 10.2s
[CV 4/5] END clf_max_features=log2, clf_n_estimators=166;, score=-0.206 total
time= 10.4s
[CV 5/5] END clf__max_features=log2, clf__n_estimators=166;, score=-0.186 total
time= 10.2s
[CV 4/5] END clf__max_features=1.0, clf__n_estimators=118;, score=-0.203 total
time= 21.4s
[CV 1/5] END clf__max_features=sqrt, clf__n_estimators=209;, score=-0.201 total
time= 13.0s
[CV 5/5] END clf_max_features=1.0, clf_n_estimators=118;, score=-0.183 total
time= 21.5s
[CV 1/5] END clf__max_features=log2, clf__n_estimators=145;, score=-0.201 total
      8.2s
[CV 2/5] END clf__max_features=sqrt, clf__n_estimators=209;, score=-0.187 total
time= 12.9s
```

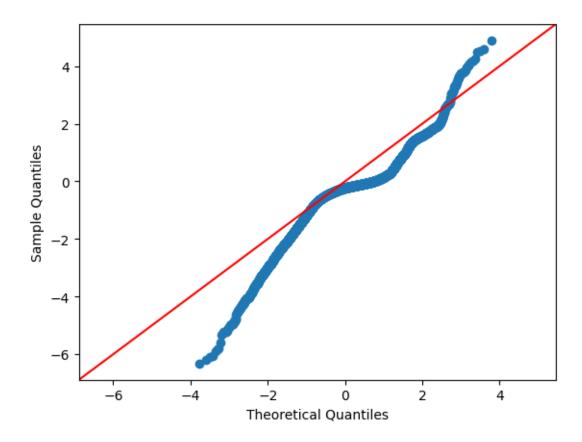
```
[CV 2/5] END clf max features=log2, clf n estimators=145;, score=-0.187 total
time=
      8.4s
[CV 3/5] END clf max features=sqrt, clf n estimators=209;, score=-0.190 total
time= 13.2s
[CV 4/5] END clf max features=sqrt, clf n estimators=209;, score=-0.206 total
time= 12.8s
[CV 5/5] END clf max features=sqrt, clf n estimators=209;, score=-0.186 total
time= 12.7s
[CV 3/5] END clf__max_features=log2, clf__n_estimators=145;, score=-0.190 total
time=
      8.8s
[CV 4/5] END clf max features=log2, clf n estimators=145;, score=-0.206 total
       8.7s
[CV 1/5] END clf_max_features=sqrt, clf_n_estimators=68;, score=-0.202 total
      4.1s
[CV 5/5] END clf_max_features=log2, clf_n_estimators=145;, score=-0.186 total
      8.3s
[CV 2/5] END clf_max_features=sqrt, clf_n_estimators=68;, score=-0.188 total
       4.3s
[CV 3/5] END clf__max_features=sqrt, clf__n_estimators=68;, score=-0.192 total
time=
[CV 4/5] END clf_max_features=sqrt, clf_n_estimators=68;, score=-0.208 total
      4.2s
[CV 5/5] END clf_max_features=sqrt, clf_n_estimators=68;, score=-0.188 total
time=
      4.2s
[CV 1/5] END clf__max_features=sqrt, clf__n_estimators=52;, score=-0.204 total
       3.2s
[CV 2/5] END clf max features=sqrt, clf n estimators=52;, score=-0.189 total
       3.2s
[CV 2/5] END clf max features=log2, clf n estimators=290;, score=-0.186 total
time= 16.3s
[CV 1/5] END clf__max_features=log2, clf__n_estimators=290;, score=-0.201 total
time= 17.6s
[CV 3/5] END clf max features=sqrt, clf n estimators=52;, score=-0.193 total
time=
      2.9s
[CV 5/5] END clf max features=sqrt, clf n estimators=52;, score=-0.190 total
       2.9s
[CV 4/5] END clf max features=sqrt, clf n estimators=52;, score=-0.209 total
       3.2s
[CV 5/5] END clf__max_features=log2, clf__n_estimators=290;, score=-0.185 total
time= 17.3s
[CV 3/5] END clf__max_features=log2, clf__n_estimators=290;, score=-0.189 total
time= 18.3s
[CV 4/5] END clf__max_features=log2, clf__n_estimators=290;, score=-0.206 total
time= 18.2s
[CV 1/5] END clf_max_features=sqrt, clf_n_estimators=97;, score=-0.201 total
       5.3s
[CV 2/5] END clf__max_features=sqrt, clf__n_estimators=97;, score=-0.188 total
time=
      5.5s
```

```
[CV 4/5] END clf max features=sqrt, clf n estimators=97;, score=-0.207 total
time=
      5.4s
[CV 3/5] END clf max features=sqrt, clf n estimators=97;, score=-0.190 total
time=
[CV 5/5] END clf max features=sqrt, clf n estimators=97;, score=-0.186 total
       6.0s
[CV 1/5] END clf max features=log2, clf n estimators=88;, score=-0.201 total
       5.0s
[CV 2/5] END clf__max_features=log2, clf__n_estimators=88;, score=-0.188 total
time=
       5.7s
[CV 3/5] END clf max features=log2, clf n estimators=88;, score=-0.191 total
       5.4s
[CV 4/5] END clf max features=log2, clf n estimators=88;, score=-0.208 total
       5.3s
[CV 5/5] END clf_max_features=log2, clf_n_estimators=88;, score=-0.187 total
      5.4s
[CV 1/5] END clf__max_features=sqrt, clf__n_estimators=146;, score=-0.201 total
time=
       8.7s
[CV 2/5] END clf__max_features=sqrt, clf__n_estimators=146;, score=-0.187 total
time=
      9.2s
[CV 3/5] END clf_max_features=sqrt, clf_n_estimators=146;, score=-0.190 total
time=
       9.0s
[CV 4/5] END clf_max_features=sqrt, clf_n_estimators=146;, score=-0.206 total
       8.5s
time=
[CV 5/5] END clf__max_features=sqrt, clf__n_estimators=146;, score=-0.186 total
       8.1s
[CV 1/5] END clf max features=1.0, clf n estimators=177;, score=-0.195 total
time= 32.3s
[CV 3/5] END clf max features=1.0, clf n estimators=177;, score=-0.186 total
time= 34.0s
[CV 4/5] END clf max features=1.0, clf n estimators=177;, score=-0.202 total
time= 31.8s
[CV 2/5] END clf max features=1.0, clf n estimators=177;, score=-0.185 total
time= 34.8s
[CV 5/5] END clf__max_features=1.0, clf__n_estimators=177;, score=-0.182 total
time= 33.2s
[CV 1/5] END clf_max_features=sqrt, clf_n_estimators=62;, score=-0.202 total
time=
       3.4s
[CV 2/5] END clf__max_features=sqrt, clf__n_estimators=62;, score=-0.188 total
       3.4s
[CV 3/5] END clf_max_features=sqrt, clf_n_estimators=62;, score=-0.192 total
time=
       3.8s
[CV 5/5] END clf_max_features=sqrt, clf_n_estimators=62;, score=-0.188 total
[CV 4/5] END clf_max_features=sqrt, clf_n_estimators=62;, score=-0.207 total
[CV 1/5] END clf_max_features=1.0, clf_n_estimators=163;, score=-0.195 total
time= 29.6s
```

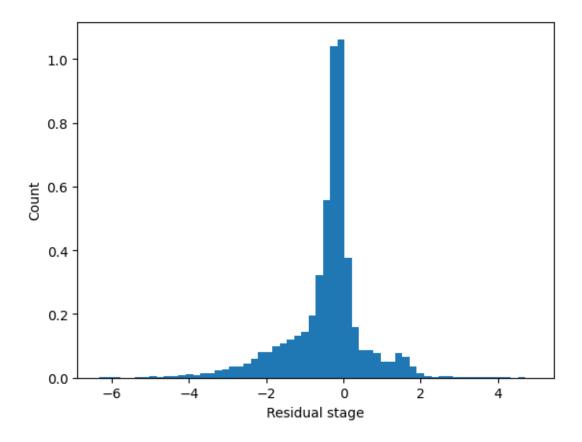
```
[CV 2/5] END clf max features=1.0, clf n estimators=163;, score=-0.185 total
    time= 29.2s
    [CV 3/5] END clf max features=1.0, clf n estimators=163;, score=-0.186 total
    time= 29.1s
    [CV 4/5] END clf__max_features=1.0, clf__n_estimators=163;, score=-0.202 total
    time= 28.6s
    [CV 5/5] END clf max features=1.0, clf n estimators=163;, score=-0.182 total
    time= 27.6s
[]: RandomizedSearchCV(estimator=Pipeline(steps=[('scaler', StandardScaler()),
                                                 ('clf',
    RandomForestRegressor(random_state=0))]),
                       n_iter=20, n_jobs=8,
                       param_distributions={'clf_max_features': ['sqrt', 1.0,
                                                                 'log2'],
                                            'clf__n_estimators': array([ 50, 51,
    52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62,
            63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75,
            76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88,
            89, 90...
           219, 220, 221, 222, 223, 224, 225, 226, 227, 228, 229, 230, 231,
           232, 233, 234, 235, 236, 237, 238, 239, 240, 241, 242, 243, 244,
           245, 246, 247, 248, 249, 250, 251, 252, 253, 254, 255, 256, 257,
           258, 259, 260, 261, 262, 263, 264, 265, 266, 267, 268, 269, 270,
           271, 272, 273, 274, 275, 276, 277, 278, 279, 280, 281, 282, 283,
           284, 285, 286, 287, 288, 289, 290, 291, 292, 293, 294, 295, 296,
           297, 298, 299])},
                       scoring='neg_mean_squared_error', verbose=3)
    1.5 Test model
[]: clf.best_score_
[]: -0.18974709842322832
[]: clf.best_params_
[]: {'clf_n_estimators': 177, 'clf_max_features': 1.0}
[]: clf.score(X_test, y_test)
[]: -0.346428887134744
[ ]: y_pred = clf.predict(X_test)
[]: print("R^2: ", r2_score(y_test, y_pred))
    print("mse: ", mean_squared_error(y_test, y_pred))
```

```
print("rmse: ", mean squared_error(y_test, y_pred, squared=False))
     print("mae: ", mean_absolute_error(y_test, y_pred))
     print("mape: ", mean_absolute_percentage_error(y_test, y_pred))
     print("Error estandar: ", stde(y_test.squeeze(),
          y_pred.squeeze(), ddof=2))
    R^2: 0.11294665850022367
    mse: 0.346428887134744
    rmse: 0.5885820988908378
    mae: 0.38203317916134527
    mape: 0.14412078605527165
    Error estandar: 0.5452671219668532
[]: residuals = y test - y pred
     residuals_std = residuals / residuals.std()
     y_real_stage = y_test
     residual_stage = residuals
     #y_real_discharge = np.array([i[-1] for i in y_test])
     \#residual\_discharge = np.array([i[-1] for i in residuals])
     figure, ax = plt.subplots(ncols=2, figsize=(20, 8), dpi=80)
     ax[1].scatter(y_real_stage, residual_stage / residual_stage.std(), label="stage_u
     ⇔residuals")
     #ax[0].scatter(y_real_discharge, residual_discharge / residual_discharge.std(),__
     → label="discharge residuals")
     ax[1].axhline(y=0.0, color='r', linestyle='-')
     ax[0].axhline(y=0.0, color='r', linestyle='-')
     ax[1].set title("Stage residuals")
     ax[0].set_title("Discharge residuals")
     ax[1].set_xlabel("Fitted values")
     ax[0].set_xlabel("Fitted values")
     ax[1].set_ylabel("Standarized residuals")
     ax[0].set_ylabel("Standarized residuals")
     plt.legend()
     plt.show()
```





```
[]: plt.hist(residual_stage / residual_stage.std(), density=True, bins = 60)
plt.ylabel('Count')
plt.xlabel('Residual stage');
plt.show()
```



```
[]: """plt.hist(residual_discharge / residual_discharge.std(), density=True, bins =

→60)

plt.ylabel('Count')

plt.xlabel('Residual discharge');

plt.show()"""
```

[]: "plt.hist(residual_discharge / residual_discharge.std(), density=True, bins =
 60)\nplt.ylabel('Count')\nplt.xlabel('Residual discharge');\nplt.show()"

```
[]: stat, pval = normal_ad(residual_stage / residual_stage.std())
print("p-value:", pval)

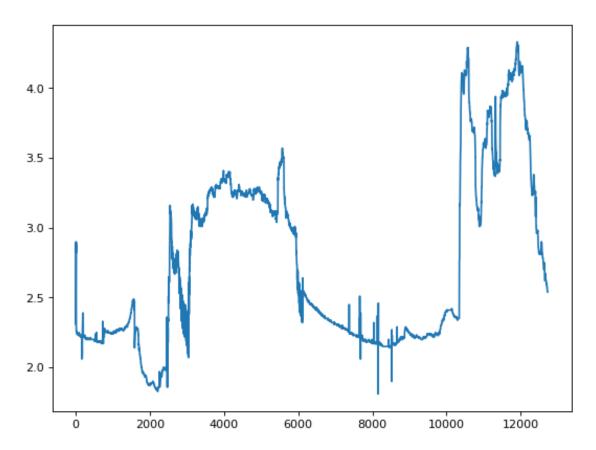
if pval < 0.05:
    print("Hay evidencia de que los residuos no provienen de una distribución
    →normal.")
else:
    print("No hay evidencia para rechazar la hipótesis de que los residuos
    →vienen de una distribución normal.")
```

p-value: 0.0

Hay evidencia de que los residuos no provienen de una distribución normal.

```
[]: plt.figure(figsize=(8, 6), dpi=80)
plt.plot(np.arange(len(y_test)), y_test, label="Stage real")
```

[]: [<matplotlib.lines.Line2D at 0x7f7bc2d64c40>]



```
[]: figure, ax = plt.subplots(ncols=2, figsize=(20, 8), dpi=80)

ax[0].plot(np.arange(len(y_test)), y_test, label="Stage real")
ax[0].plot(np.arange(len(y_test)), y_pred, label="Stage pred")

ax[0].set_title("Stage predictions")
ax[1].set_title("Discharge predictions")

ax[1].set_ylabel("Values")
ax[0].set_ylabel("Values")
ax[1].set_xlabel("Time")
ax[0].set_xlabel("Time")
```

No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.

