Dataset_Z_Exploration

March 24, 2021

0.1 Dataset Prueba 1 - Tesis Javier-Uriel

0.1.1 Importamos algunas librerías que nos serán útiles más adelante

[1]:
```
import os
import time
import random

import pandas as pd # for dataframe operations.
import numpy as np #for linear algebra operations.
import seaborn as sns # data visualization library
import matplotlib.pyplot as plt # for plotting

from scipy.fftpack import fft, fftfreq

from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.stattools import pacf

pd.set_option('display.max_columns', None) #Para mostrar todas las columnas
random.seed(1)
```

0.1.2 Leemos el Dataset

[2]:
```
#Dataset solo movimientos en Z
rpm_list = ['RPM0', 'RPM1', 'RPM2', 'RPM3']
states_list_org = ["vz","az", "uvz",
                   "p", "q",
                   "wp", "wq",
                   "ap", "aq"]
#states_list_org = ["vz","az", "uvz"]
states_list_min = ["vz","az", "uvz"]
dataset_name = "Dataset_Z7_Disturbance_Z"
directory = "../logs/Datasets/"+dataset_name
ORDER = 3
dfs = []
states_list=states_list_org.copy()
```

0.1.3 Corregir la salida

El estado que entrega Pybullet de RPMs es la salida anterior, en este dataset se tomará RPMs como la salida actual. Si el primer elemento de RPMs es 0, es necesario hacer el shift

[3]:
```
for filename in os.listdir(directory):
    if not filename.endswith(".csv"):
        continue
    df = pd.read_csv(os.path.join(directory, filename))
    if any(df['z']<=1) or any(abs(df['vz'])>=10): #Eliminar si el dron se cae
        print(filename)
    else:
        if any(df[rpm_list].loc[0]==0): #Desplazar los estados de RPM si es␣
 ↪necesario
            df[rpm_list] = df[rpm_list].shift(periods=-1)
            df = df.dropna()
            df.to_csv(os.path.join(directory, filename), index=False)

        a = []
        ## Desplazamos estados anteriores
        for n in range(1,ORDER+1):
            for column in states_list:
                df[column+str(n)] = df[column].shift(periods=n, fill_value=0)
                a.append(column+str(n))
        dfs.append(df)
states_list+=a

dataset = pd.concat(dfs)
dataset.describe()
```

[3]:

	timestamps	x	y	z	Q1	\
count	4.007833e+06	4.007833e+06	4.007833e+06	4.007833e+06	4.007833e+06	
mean	4.999583e+01	1.232111e-01	-1.129199e-01	5.341394e+01	-1.124056e-04	
std	2.886631e+01	8.825598e-02	8.576300e-02	9.609585e+00	9.626432e-03	
min	0.000000e+00	-2.047597e-01	-4.811760e-01	2.697847e+01	-1.698321e-01	
25%	2.499583e+01	7.730229e-02	-1.592710e-01	5.008806e+01	-3.020625e-08	
50%	4.999583e+01	1.227265e-01	-1.127110e-01	5.048142e+01	2.370051e-19	
75%	7.499583e+01	1.779849e-01	-6.940946e-02	5.279696e+01	2.872166e-08	
max	9.999167e+01	4.597636e-01	2.173638e-01	1.539669e+02	1.563415e-01	

	Q2	Q3	Q4	p	q	\
count	4.007833e+06	4.007833e+06	4.007833e+06	4.007833e+06	4.007833e+06	
mean	-1.166851e-04	6.719640e-05	9.999114e-01	-2.303242e-04	-2.300284e-04	
std	9.127336e-03	8.662359e-04	6.002488e-04	1.938697e-02	1.821034e-02	
min	-1.457588e-01	-4.432610e-02	9.752161e-01	-3.536326e-01	-2.834447e-01	
25%	-2.448411e-08	-5.146146e-07	1.000000e+00	-6.436319e-08	-5.447548e-08	
50%	0.000000e+00	1.115153e-05	1.000000e+00	5.648435e-19	-0.000000e+00	
75%	2.405126e-08	1.971108e-05	1.000000e+00	6.241495e-08	5.148737e-08	

```
max    1.246893e-01  4.782059e-02  1.000000e+00  3.149456e-01  2.485051e-01

                r            vx            vy            vz            wp  \
count  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06
mean   1.836237e-04  1.468863e-03 -1.370043e-03  7.058128e-02  6.759972e-05
std    2.268712e-03  2.554577e-02  2.691607e-02  8.876363e-01  1.312313e-01
min   -8.505308e-02 -4.256045e-01 -5.883179e-01 -9.426658e+00 -2.441203e+00
25%   -9.294998e-07 -5.306351e-08 -8.073925e-08 -7.346576e-02 -4.127837e-07
50%    2.231696e-05 -6.482318e-17 -1.370919e-16  6.612490e-17  1.192785e-17
75%    3.946552e-05  6.332497e-08  6.395209e-08  1.286200e-01  4.945783e-07
max    9.873158e-02  5.853262e-01  5.074040e-01  9.720978e+00  2.744562e+00

                wq            wr            ax            ay            az  \
count  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06
mean  -6.813699e-05 -4.751161e-05  1.580413e-10  1.229393e-09  3.210177e-04
std    1.266916e-01  1.608981e-02  1.428626e-01  1.522444e-01  1.822109e+00
min   -2.568337e+00 -6.203632e-01 -4.023462e+00 -3.135487e+00 -9.800000e+00
25%   -3.408623e-07 -3.469616e-07 -4.160205e-07 -5.834920e-07 -7.146616e-03
50%    1.002047e-17 -1.814025e-07  9.363510e-18 -2.944722e-18  1.541975e-15
75%    3.984695e-07  4.894901e-08  4.825922e-07  5.296203e-07  4.185012e-03
max    2.167848e+00  8.109048e-01  3.499987e+00  4.139923e+00  1.610805e+01

                ap            aq            ar          RPM0          RPM1  \
count  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06
mean  -4.129174e-08 -1.073950e-09 -1.275564e-09  1.441872e+04  1.441844e+04
std    2.016054e+00  1.990444e+00  6.490893e-01  1.325549e+03  1.328543e+03
min   -1.762474e+01 -1.727289e+01 -1.572234e+01  9.440300e+03  9.440300e+03
25%   -3.930490e-06 -3.317791e-06 -1.070975e-09  1.442594e+04  1.442414e+04
50%   -7.111581e-27 -5.360310e-27  1.577592e-09  1.446843e+04  1.446843e+04
75%    3.629512e-06  2.922475e-06  4.010480e-09  1.451734e+04  1.451759e+04
max    1.725882e+01  1.708771e+01  1.558256e+01  2.166645e+04  2.166645e+04

               RPM2          RPM3         ux         uy         uz        uvx  \
count  4.007833e+06  4.007833e+06  4007833.0  4007833.0  4007833.0  4007833.0
mean   1.441873e+04  1.441900e+04        0.0        0.0       50.0        0.0
std    1.325717e+03  1.322718e+03        0.0        0.0        0.0        0.0
min    9.440300e+03  9.440300e+03        0.0        0.0       50.0        0.0
25%    1.442605e+04  1.442492e+04        0.0        0.0       50.0        0.0
50%    1.446843e+04  1.446843e+04        0.0        0.0       50.0        0.0
75%    1.451745e+04  1.451810e+04        0.0        0.0       50.0        0.0
max    2.166645e+04  2.166645e+04        0.0        0.0       50.0        0.0

              uvy           uvz         up         uq         ur         uwp  \
count  4007833.0  4.007833e+06  4007833.0  4007833.0  4007833.0  4007833.0
mean         0.0  5.302769e-02        0.0        0.0        0.0        0.0
std          0.0  9.432127e-01        0.0        0.0        0.0        0.0
min          0.0 -9.640079e+00        0.0        0.0        0.0        0.0
```

```
25%          0.0 -7.237447e-02        0.0        0.0        0.0        0.0
50%          0.0  0.000000e+00        0.0        0.0        0.0        0.0
75%          0.0  1.155227e-01        0.0        0.0        0.0        0.0
max          0.0  9.640079e+00        0.0        0.0        0.0        0.0

             uwq        uwr           vz1           az1          uvz1  \
count  4007833.0  4007833.0  4.007833e+06  4.007833e+06  4.007833e+06
mean         0.0        0.0  7.057994e-02  3.228008e-04  5.302917e-02
std          0.0        0.0  8.876180e-01  1.822077e+00  9.431880e-01
min          0.0        0.0 -9.426658e+00 -9.800000e+00 -9.640079e+00
25%          0.0        0.0 -7.344996e-02 -7.143027e-03 -7.237447e-02
50%          0.0        0.0  6.568330e-17  1.541974e-15  0.000000e+00
75%          0.0        0.0  1.286069e-01  4.183542e-03  1.154756e-01
max          0.0        0.0  9.720978e+00  1.610805e+01  9.640079e+00

                 p1            q1           wp1           wq1           ap1  \
count  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06
mean  -2.303242e-04 -2.300284e-04  6.759989e-05 -6.813698e-05 -4.142293e-08
std    1.938697e-02  1.821034e-02  1.312313e-01  1.266916e-01  2.016054e+00
min   -3.536326e-01 -2.834447e-01 -2.441203e+00 -2.568337e+00 -1.762474e+01
25%   -6.435992e-08 -5.447285e-08 -4.127670e-07 -3.408300e-07 -3.930290e-06
50%    5.543243e-19 -0.000000e+00  1.191775e-17  9.566621e-18 -6.863090e-27
75%    6.240801e-08  5.148517e-08  4.945490e-07  3.984622e-07  3.629396e-06
max    3.149456e-01  2.485051e-01  2.744562e+00  2.167848e+00  1.725882e+01

                aq1           vz2           az2          uvz2            p2  \
count  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06
mean  -1.133661e-09  7.057859e-02  3.245846e-04  5.303064e-02 -2.303243e-04
std    1.990444e+00  8.875997e-01  1.822046e+00  9.431632e-01  1.938697e-02
min   -1.727289e+01 -9.426658e+00 -9.800000e+00 -9.640079e+00 -3.536326e-01
25%   -3.317570e-06 -7.343642e-02 -7.140487e-03 -7.234720e-02 -6.435649e-08
50%   -5.182816e-27  6.544569e-17  1.541974e-15  0.000000e+00  5.427472e-19
75%    2.922272e-06  1.285923e-01  4.182457e-03  1.154372e-01  6.240276e-08
max    1.708771e+01  9.720978e+00  1.610805e+01  9.640079e+00  3.149456e-01

                 q2           wp2           wq2           ap2           aq2  \
count  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06
mean  -2.300284e-04  6.760007e-05 -6.813698e-05 -4.155414e-08 -1.193382e-09
std    1.821034e-02  1.312313e-01  1.266916e-01  2.016054e+00  1.990444e+00
min   -2.834447e-01 -2.441203e+00 -2.568337e+00 -1.762474e+01 -1.727289e+01
25%   -5.447123e-08 -4.127500e-07 -3.408117e-07 -3.930007e-06 -3.317059e-06
50%    0.000000e+00  1.179796e-17  9.482479e-18 -6.673763e-27 -4.975740e-27
75%    5.148300e-08  4.945288e-07  3.984494e-07  3.629268e-06  2.922085e-06
max    2.485051e-01  2.744562e+00  2.167848e+00  1.725882e+01  1.708771e+01

                vz3           az3          uvz3            p3            q3  \
count  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06
```

```
mean   7.057724e-02  3.263690e-04  5.303212e-02 -2.303243e-04 -2.300284e-04
std    8.875814e-01  1.822014e+00  9.431385e-01  1.938697e-02  1.821034e-02
min   -9.426658e+00 -9.800000e+00 -9.640079e+00 -3.536326e-01 -2.834447e-01
25%   -7.341829e-02 -7.137214e-03 -7.234720e-02 -6.435279e-08 -5.446777e-08
50%    6.520893e-17  1.541973e-15  0.000000e+00  5.325995e-19 -0.000000e+00
75%    1.285802e-01  4.181233e-03  1.154372e-01  6.239868e-08  5.147947e-08
max    9.720978e+00  1.610805e+01  9.640079e+00  3.149456e-01  2.485051e-01

                wp3           wq3           ap3           aq3
count  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06
mean   6.760024e-05 -6.813697e-05 -4.168538e-08 -1.253112e-09
std    1.312313e-01  1.266916e-01  2.016054e+00  1.990444e+00
min   -2.441203e+00 -2.568337e+00 -1.762474e+01 -1.727289e+01
25%   -4.127296e-07 -3.407898e-07 -3.929796e-06 -3.316981e-06
50%    1.110696e-17  9.426808e-18 -6.496270e-27 -4.798246e-27
75%    4.945138e-07  3.984406e-07  3.629094e-06  2.921943e-06
max    2.744562e+00  2.167848e+00  1.725882e+01  1.708771e+01
```

0.1.4 Estados repetidos

En este caso se eliminan estados repetidos y estados que se encuentren en estado transitorio mientras el dron despega o se estabiliza antes de introducir la señal de control.

[4]:
```
shape_b4 = dataset.drop(["timestamps"], axis=1).shape
shape_drop= dataset.drop(["timestamps"], axis=1).drop_duplicates().shape
print(f'shape (b4 drop) = {shape_b4}')
print(f'shape = {shape_drop}')
print(f'len (b4 drop) - len = {shape_b4[0]-shape_drop[0]}')
```

```
shape (b4 drop) = (4007833, 65)
shape = (3991268, 65)
len (b4 drop) - len = 16565
```

[5]:
```
states = dataset.drop(["timestamps"], axis=1).drop_duplicates()[states_list]
print(f'columns = {states.columns}')
print(f'shape = {states.shape}')
states.head()
```

```
columns = Index(['vz', 'az', 'uvz', 'p', 'q', 'wp', 'wq', 'ap', 'aq', 'vz1',
'az1',
       'uvz1', 'p1', 'q1', 'wp1', 'wq1', 'ap1', 'aq1', 'vz2', 'az2', 'uvz2',
       'p2', 'q2', 'wp2', 'wq2', 'ap2', 'aq2', 'vz3', 'az3', 'uvz3', 'p3',
       'q3', 'wp3', 'wq3', 'ap3', 'aq3'],
      dtype='object')
shape = (3991268, 36)
```

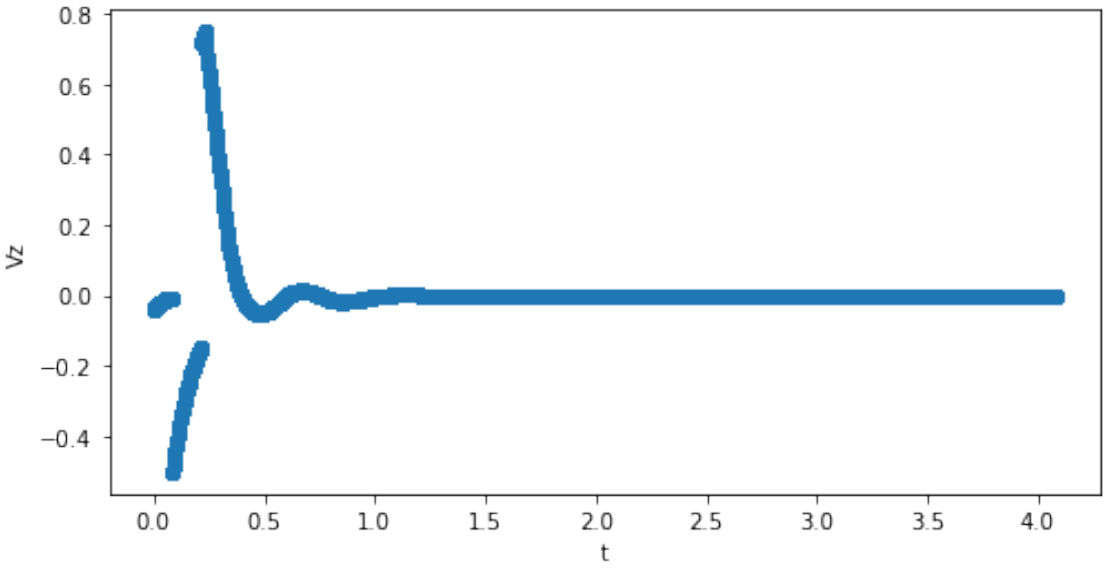
[5]:
```
         vz        az       uvz    p    q   wp   wq   ap   aq       vz1  \
0 -0.040833 -9.800000 -0.994789  0.0 -0.0  0.0  0.0  0.0  0.0  0.000000
```

```
1 -0.064276 -5.626198 -0.994789  0.0 -0.0  0.0  0.0  0.0  0.0 -0.040833
2 -0.087714 -5.625162 -0.994789  0.0 -0.0  0.0  0.0  0.0  0.0 -0.064276
3 -0.111148 -5.624082 -0.994789  0.0 -0.0  0.0  0.0  0.0  0.0 -0.087714
4 -0.134577 -5.622958 -0.994789  0.0 -0.0  0.0  0.0  0.0  0.0 -0.111148

        az1       uvz1   p1   q1  wp1  wq1  ap1  aq1       vz2       az2  \
0  0.000000  0.000000  0.0  0.0  0.0  0.0  0.0  0.0  0.000000  0.000000
1 -9.800000 -0.994789  0.0 -0.0  0.0  0.0  0.0  0.0  0.000000  0.000000
2 -5.626198 -0.994789  0.0 -0.0  0.0  0.0  0.0  0.0 -0.040833 -9.800000
3 -5.625162 -0.994789  0.0 -0.0  0.0  0.0  0.0  0.0 -0.064276 -5.626198
4 -5.624082 -0.994789  0.0 -0.0  0.0  0.0  0.0  0.0 -0.087714 -5.625162

       uvz2   p2   q2  wp2  wq2  ap2  aq2       vz3       az3       uvz3   p3  \
0  0.000000  0.0  0.0  0.0  0.0  0.0  0.0  0.000000  0.000000  0.000000  0.0
1  0.000000  0.0  0.0  0.0  0.0  0.0  0.0  0.000000  0.000000  0.000000  0.0
2 -0.994789  0.0 -0.0  0.0  0.0  0.0  0.0  0.000000  0.000000  0.000000  0.0
3 -0.994789  0.0 -0.0  0.0  0.0  0.0  0.0 -0.040833 -9.800000 -0.994789  0.0
4 -0.994789  0.0 -0.0  0.0  0.0  0.0  0.0 -0.064276 -5.626198 -0.994789  0.0

    q3  wp3  wq3  ap3  aq3
0  0.0  0.0  0.0  0.0  0.0
1  0.0  0.0  0.0  0.0  0.0
2  0.0  0.0  0.0  0.0  0.0
3 -0.0  0.0  0.0  0.0  0.0
4 -0.0  0.0  0.0  0.0  0.0
```

[6]:
```
states_duplicates = dataset[dataset.duplicated(keep='last')]
states_duplicates = states_duplicates.dropna()
```

[7]:
```
fig = plt.figure(figsize=(8, 4))
t = states_duplicates['timestamps']
y = states_duplicates['vz']
#y_ref = states_duplicates['uvz']
plt.scatter(t, y)
#plt.scatter(t, y_ref)
plt.ylabel('Vz')
plt.xlabel('t')
```

[7]:
```
Text(0.5, 0, 't')
```



[8]:
```
#Eliminar del dataset los estados repetidos entre 20 y 25 segundos
# for filename in os.listdir(directory):
#     if not filename.endswith(".csv"):
#         continue
#     df = pd.read_csv(os.path.join(directory, filename))
#     df = df[(df['timestamps']>20) & (df['timestamps']<25)]
#     df = pd.concat([df, states_duplicates])
#     df = df.reset_index(drop=True)
#     df_gpby = df.groupby(list(df.columns))
#     idx = [x[0] for x in df_gpby.groups.values() if len(x) > 1]
#     if len(idx)>1:
#         print(filename)
```

[27]:
```
df = pd.read_csv(os.path.join(directory, filename))
df = df[df['timestamps']>5]
df.describe()
```

[27]:

	timestamps	x	y	z	Q1	\
count	22798.000000	22798.000000	22798.000000	22798.000000	2.279800e+04	
mean	52.497917	0.213963	-0.068708	55.416453	1.019881e-05	
std	27.422334	0.043195	0.028817	3.834429	6.088466e-03	
min	5.004167	0.088270	-0.118016	50.934390	-5.899855e-02	
25%	28.751042	0.211788	-0.087524	52.904067	-6.527895e-09	
50%	52.497917	0.228379	-0.072161	53.091472	-1.585926e-19	
75%	76.244792	0.249480	-0.033927	58.664362	4.187087e-09	
max	99.991667	0.262985	-0.017267	63.877639	8.686141e-02	

	Q2	Q3	Q4	p	q	\

```
count  2.279800e+04  2.279800e+04  22798.000000  2.279800e+04  2.279800e+04
mean  -2.320382e-04  9.037240e-06      0.999945  2.006849e-05 -4.642801e-04
std    8.567149e-03  2.470256e-04      0.000316  1.220149e-02  1.713959e-02
min   -8.674468e-02 -4.739497e-03      0.994740 -1.183712e-01 -1.739674e-01
25%   -3.140996e-09 -8.093747e-07      1.000000 -1.305053e-08 -7.470571e-09
50%   -6.733801e-19 -4.048744e-07      1.000000  1.169691e-18 -1.902632e-18
75%    2.848567e-09 -3.331377e-07      1.000000  1.028379e-08  6.152859e-09
max    8.197384e-02  4.244254e-03      1.000000  1.740110e-01  1.641319e-01

                r            vx            vy            vz            wp  \
count  2.279800e+04  2.279800e+04  2.279800e+04  2.279800e+04  2.279800e+04
mean   2.291110e-05  1.300307e-03 -2.803249e-04  1.335566e-01 -1.313905e-06
std    6.116206e-04  2.215137e-02  1.357079e-02  2.172434e-01  8.523745e-02
min   -8.335807e-03 -1.534390e-01 -1.178540e-01 -4.953729e-01 -9.540215e-01
25%   -1.617737e-06 -5.113449e-09 -2.509279e-08  1.472631e-10 -7.158308e-08
50%   -8.089894e-07 -2.123666e-16  2.307827e-16  2.113164e-03 -1.919636e-18
75%   -6.657199e-07  9.294044e-09  8.371144e-09  2.162954e-01  8.847403e-08
max    8.578684e-03  2.634841e-01  1.226969e-01  1.531939e+00  1.021935e+00

                wq            wr            ax            ay            az  \
count  2.279800e+04  2.279800e+04  2.279800e+04  2.279800e+04  2.279800e+04
mean  -1.886191e-05 -1.271132e-05  6.285314e-10 -5.870805e-10 -3.188818e-03
std    1.224003e-01  9.954016e-03  1.340132e-01  8.120165e-02  1.274944e+00
min   -1.603630e+00 -2.390957e-01 -1.608419e+00 -7.039856e-01 -5.787428e+00
25%   -5.050098e-08  5.433390e-09 -4.999248e-08 -9.614242e-08 -2.287605e-04
50%   -1.031927e-17  6.819486e-09  1.444813e-17  1.766049e-18  2.259443e-10
75%    4.176720e-08  1.376374e-08  7.261314e-08  1.174926e-07  1.846656e-04
max    1.240884e+00  2.399215e-01  1.464879e+00  8.113460e-01  1.217651e+01

                ap            aq            ar          RPM0          RPM1  \
count  2.279800e+04  2.279800e+04  2.279800e+04  22798.000000  22798.000000
mean  -3.140801e-11  3.281040e-10 -6.926576e-09  14441.107336  14441.075299
std    1.735954e+00  2.012493e+00  5.720721e-01    960.019748    960.261655
min   -1.443714e+01 -1.487096e+01 -1.131256e+01   9440.300000   9440.300000
25%   -1.078042e-06 -3.351743e-07 -3.852363e-10  14467.434927  14467.388137
50%   -5.724179e-15  1.086454e-17 -5.890096e-11  14468.433843  14468.449513
75%    8.160492e-07  8.864161e-07  3.187153e-09  14488.003924  14487.611471
max    1.605764e+01  1.668113e+01  1.152098e+01  21666.447500  21666.447500

               RPM2          RPM3       ux       uy       uz       uvx  \
count  22798.000000  22798.000000  22798.0  22798.0  22798.0  22798.0
mean   14441.351558  14441.298640      0.0      0.0     50.0      0.0
std      956.145917    957.229090      0.0      0.0      0.0      0.0
min     9440.300000   9440.300000      0.0      0.0     50.0      0.0
25%    14467.379223  14467.464329      0.0      0.0     50.0      0.0
50%    14468.440113  14468.442277      0.0      0.0     50.0      0.0
75%    14486.691633  14486.832130      0.0      0.0     50.0      0.0
```

```
max    21666.447500  21666.447500      0.0      0.0     50.0      0.0

           uvy           uvz       up       uq       ur       uwp       uwq  \
count  22798.0  22798.000000  22798.0  22798.0  22798.0  22798.0  22798.0
mean       0.0      0.131265      0.0      0.0      0.0      0.0      0.0
std        0.0      0.218392      0.0      0.0      0.0      0.0      0.0
min        0.0     -0.064605      0.0      0.0      0.0      0.0      0.0
25%        0.0      0.000000      0.0      0.0      0.0      0.0      0.0
50%        0.0      0.000000      0.0      0.0      0.0      0.0      0.0
75%        0.0      0.216864      0.0      0.0      0.0      0.0      0.0
max        0.0      0.704802      0.0      0.0      0.0      0.0      0.0

           uwr
count  22798.0
mean       0.0
std        0.0
min        0.0
25%        0.0
50%        0.0
75%        0.0
max        0.0
```

0.1.5 Se grafican los datos

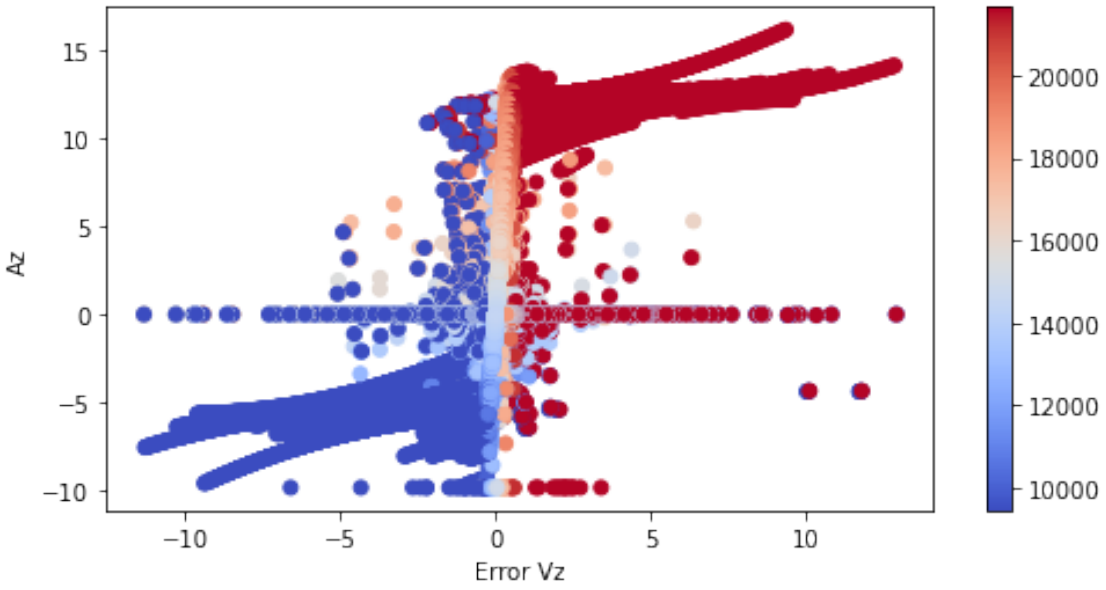
Se grafica un histograma de cada una de las propiedades los datos analizados individualmente por columnas, en el cual se observa que todos tienen distribuciones altamente apuntadas (curosis) y en algunos casos bimodales, pero de cualquier manera, no son uniformes

[10]:
```
n_bins = 50
#_ = dataset.hist(bins=n_bins, figsize=(30,30))
```

0.1.6 Análisis de estados

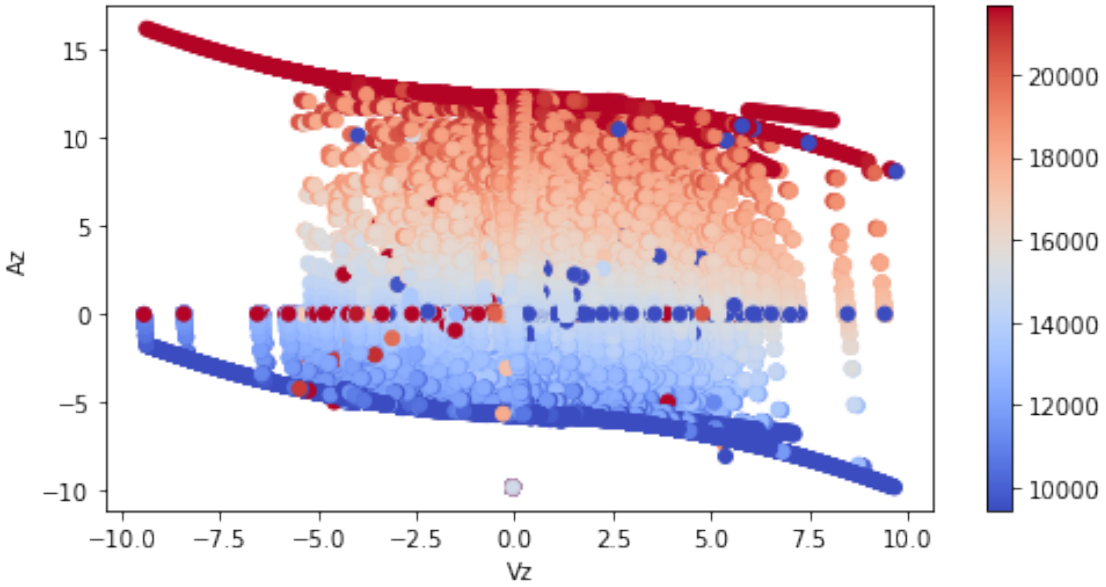
[11]:
```
fig = plt.figure(figsize=(8, 4))
x = dataset['uvz']-dataset['vz']
y = dataset['az']
c = dataset['RPM0']
plt.scatter(x, y, c=c, cmap='coolwarm')
plt.colorbar()
plt.ylabel('Az')
plt.xlabel('Error Vz')
```

[11]:
```
Text(0.5, 0, 'Error Vz')
```



[12]:
```
fig = plt.figure(figsize=(8, 4))
x = dataset['vz']
plt.scatter(x, y, c=c, cmap='coolwarm')
plt.colorbar()
plt.ylabel('Az')
plt.xlabel('Vz')
```

[12]:
```
Text(0.5, 0, 'Vz')
```

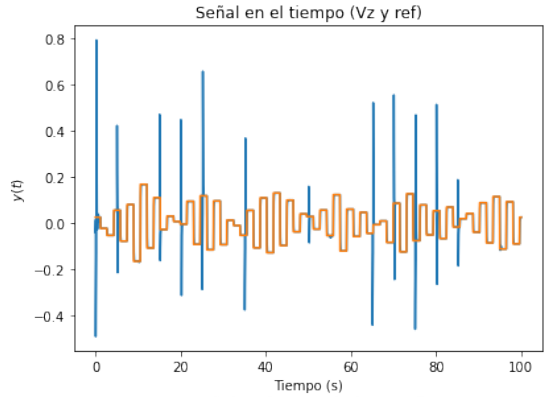


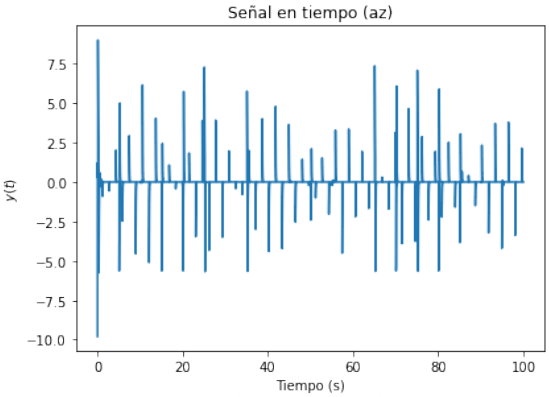
0.1.7 Análisis de Fourier

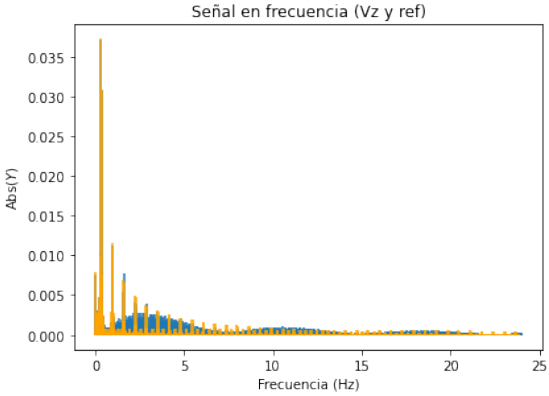
Gráfica de algunas señales

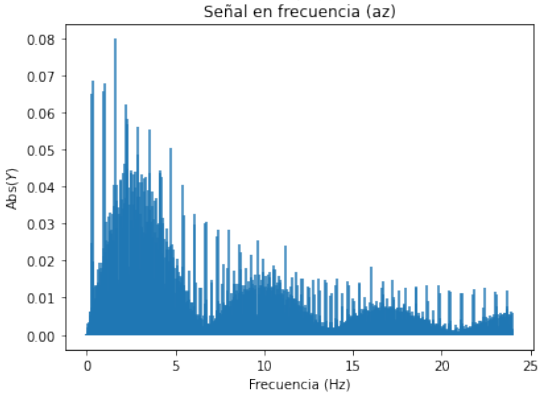
[13]:
```
def plot_fourier(df, states=['vz', 'uvz', 'az']):
    dt = df['timestamps'][1]-df['timestamps'][0]
    n = len(df['timestamps'])
    Y = fft(df[states[0]].to_numpy()) / n # Transformada normalizada
    Y_ref = fft(df[states[1]].to_numpy()) / n
    frq = fftfreq(n, dt)
    fig = plt.figure(figsize=(14, 10))
    ax1 = fig.add_subplot(221)
    ax1.plot(df['timestamps'], df[states[0]], df['timestamps'], df[states[1]])
    ax1.set_xlabel('Tiempo (s)')
    ax1.set_ylabel('$y(t)$')
    ax1.set_title('Señal en el tiempo (Vz y ref)')
    ax2 = fig.add_subplot(223)
    ax2.set_title('Señal en frecuencia (Vz y ref)')
    ax2.vlines(frq[0:int(n/10)], 0, abs(Y[0:int(n/10)]))
    ax2.vlines(frq[0:int(n/10)], 0, abs(Y_ref[0:int(n/10)]),  color='orange')
    plt.xlabel('Frecuencia (Hz)')
    plt.ylabel('Abs($Y$)')

    Y = fft(df[states[2]].to_numpy()) / n # Transformada normalizada
    ax1 = fig.add_subplot(222)
    ax1.plot(df['timestamps'], df[states[2]])
    ax1.set_xlabel('Tiempo (s)')
    ax1.set_ylabel('$y(t)$')
    ax1.set_title('Señal en tiempo (az)')
    ax2 = fig.add_subplot(224)
    ax2.set_title('Señal en frecuencia (az)')
    ax2.vlines(frq[0:int(n/10)], 0, abs(Y[0:int(n/10)]))
    plt.xlabel('Frecuencia (Hz)')
    plt.ylabel('Abs($Y$)')
```

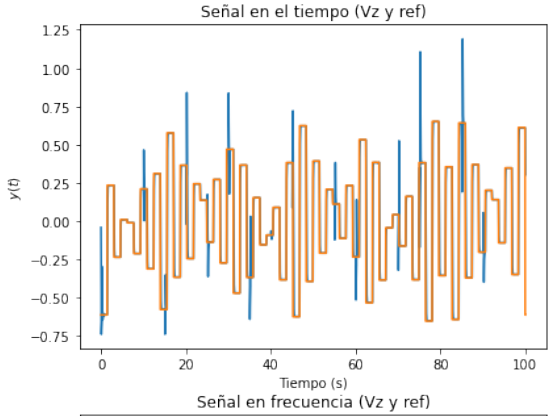
[14]:
```
for df in random.choices(dfs, k = 8):
    plot_fourier(df)
```

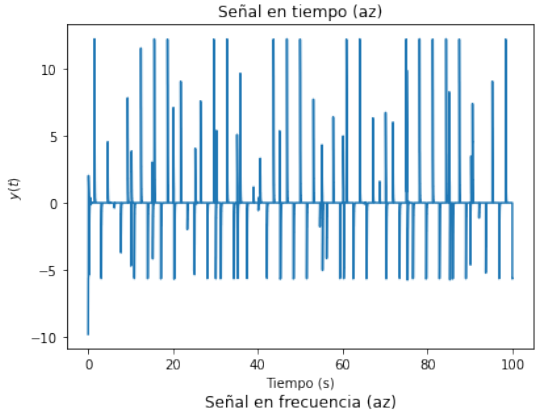

Señal en el tiempo (Vz y ref)
y(t)
Tiempo (s)

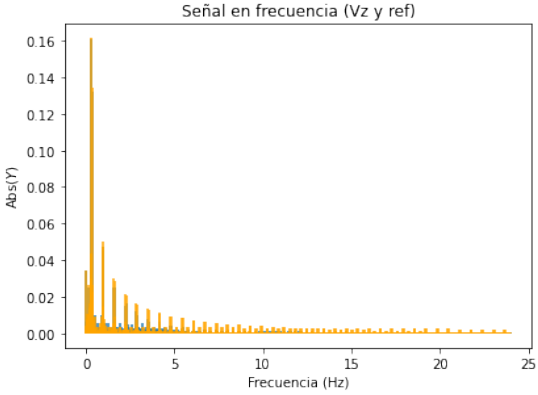

Señal en tiempo (az)
y(t)
Tiempo (s)

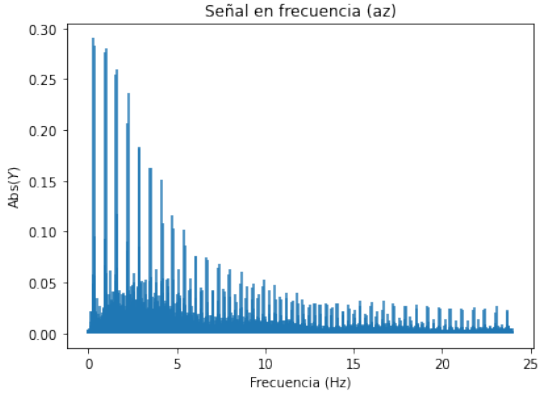

Señal en frecuencia (Vz y ref)
Abs(Y)
Frecuencia (Hz)

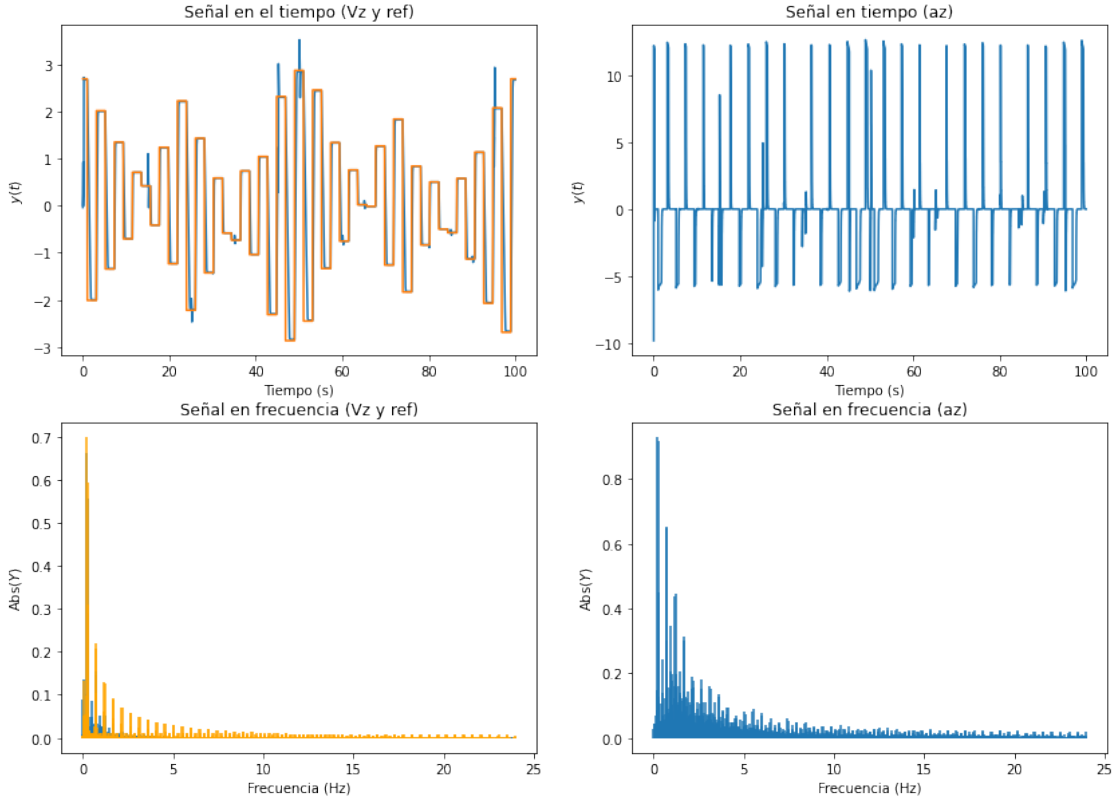

Señal en frecuencia (az)
Abs(Y)
Frecuencia (Hz)

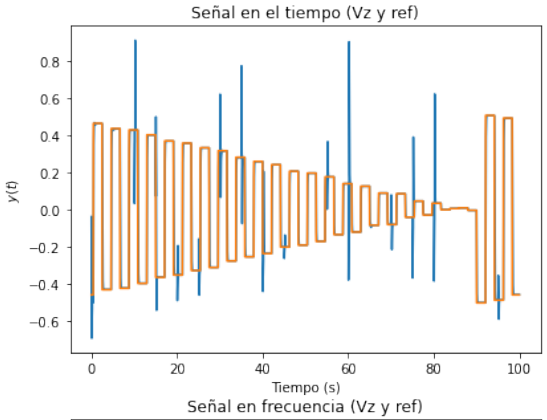

Señal en el tiempo (Vz y ref)
y(t)
Tiempo (s)

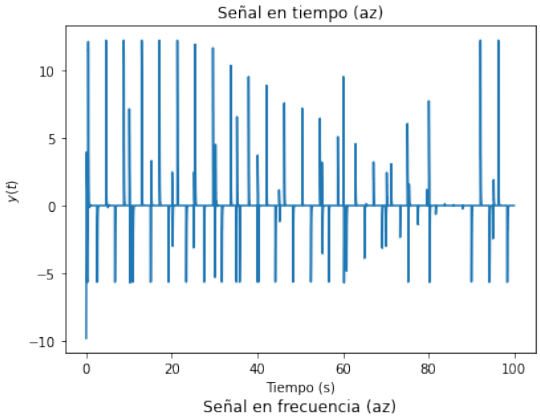

Señal en tiempo (az)
y(t)
Tiempo (s)

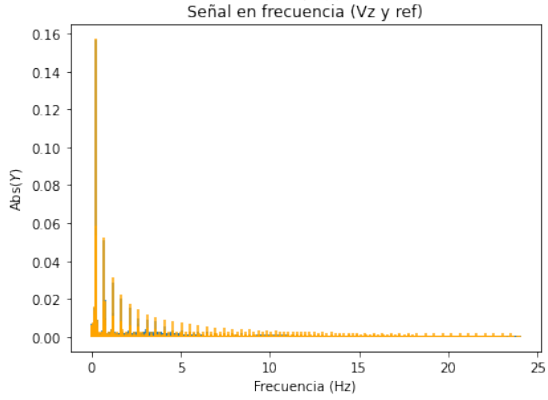

Señal en frecuencia (Vz y ref)
Abs(Y)
Frecuencia (Hz)

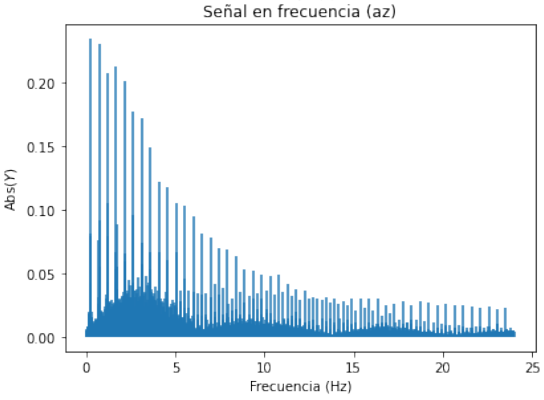

Señal en frecuencia (az)
Abs(Y)
Frecuencia (Hz)

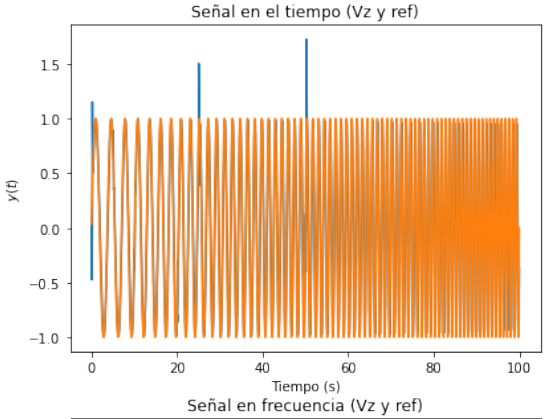

Señal en el tiempo (Vz y ref)
y(t)
Tiempo (s)
Señal en tiempo (az)
y(t)
Tiempo (s)
Señal en frecuencia (Vz y ref)
Abs(Y)
Frecuencia (Hz)
Señal en frecuencia (az)
Abs(Y)
Frecuencia (Hz)

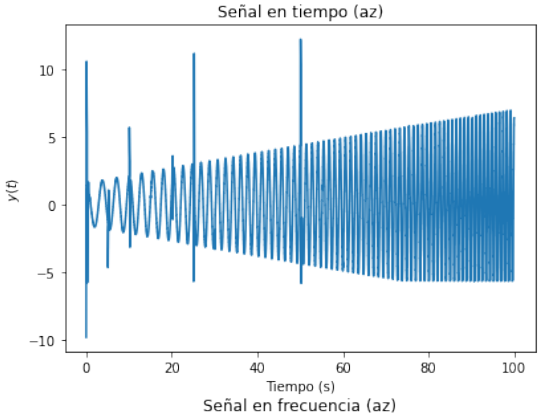

Señal en el tiempo (Vz y ref)
y(t)
Tiempo (s)

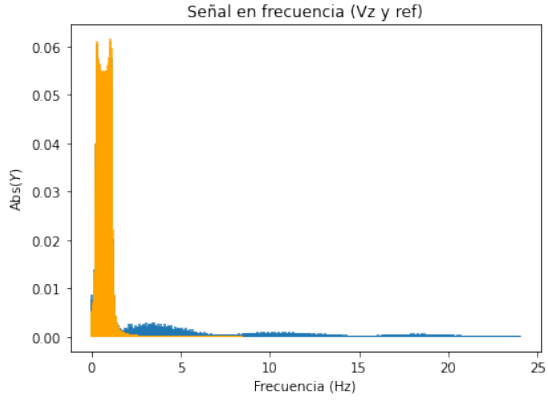

Señal en tiempo (az)
y(t)
Tiempo (s)

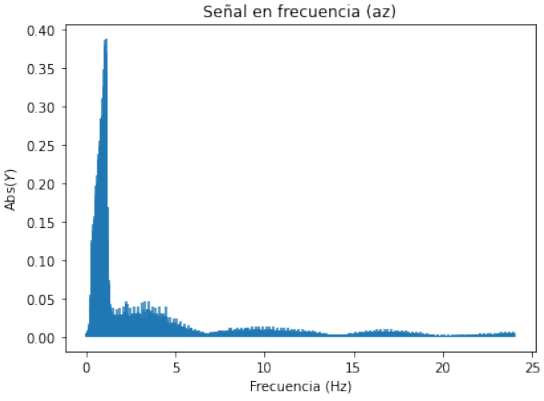

Señal en frecuencia (Vz y ref)
Abs(Y)
Frecuencia (Hz)

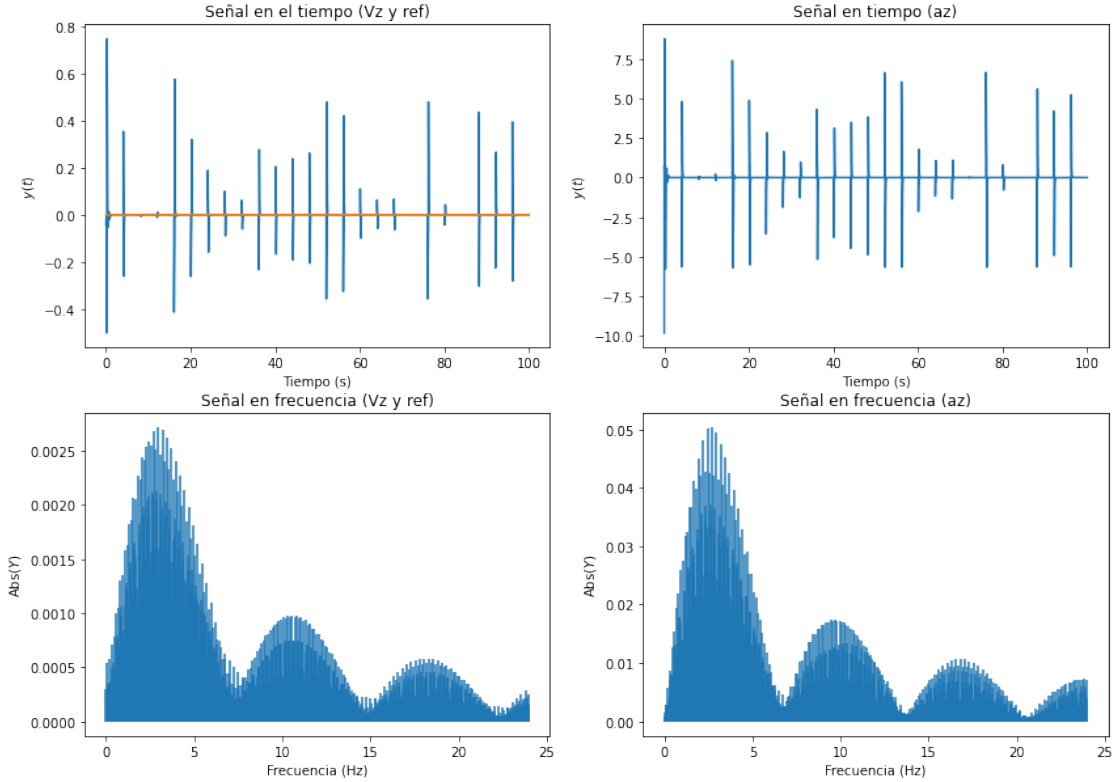

Señal en frecuencia (az)
Abs(Y)
Frecuencia (Hz)

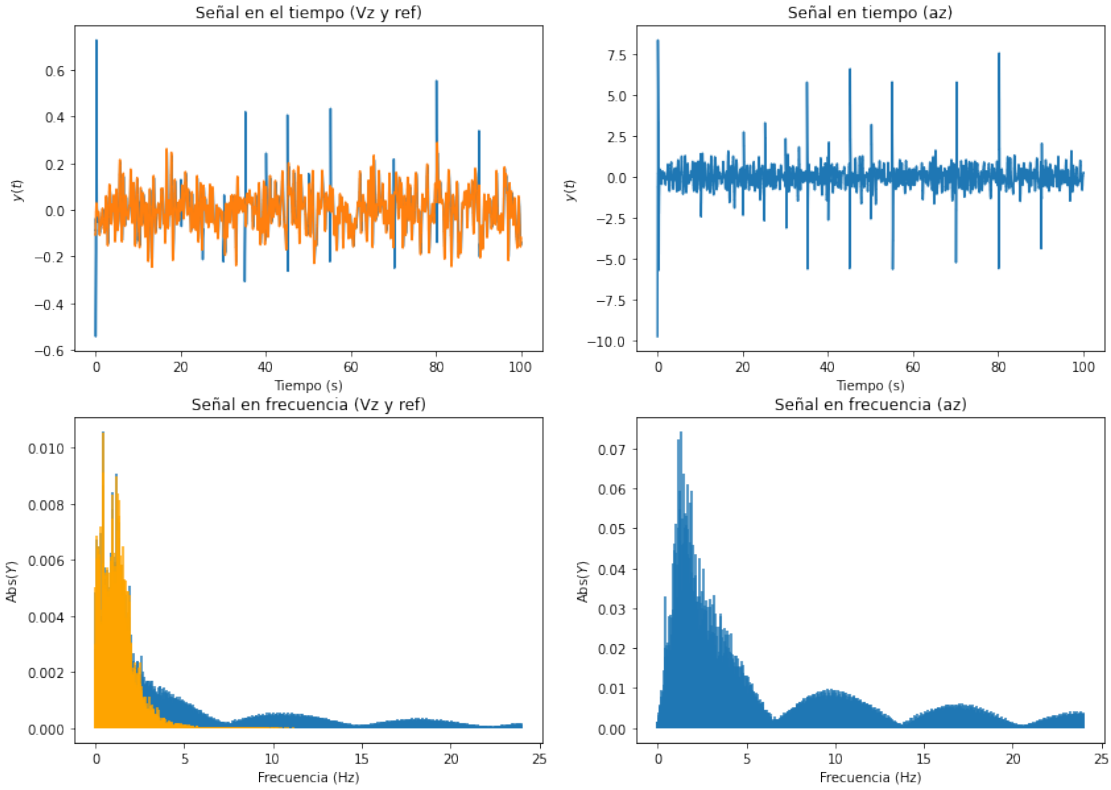

Señal en el tiempo (Vz y ref)
y(t)
Tiempo (s)

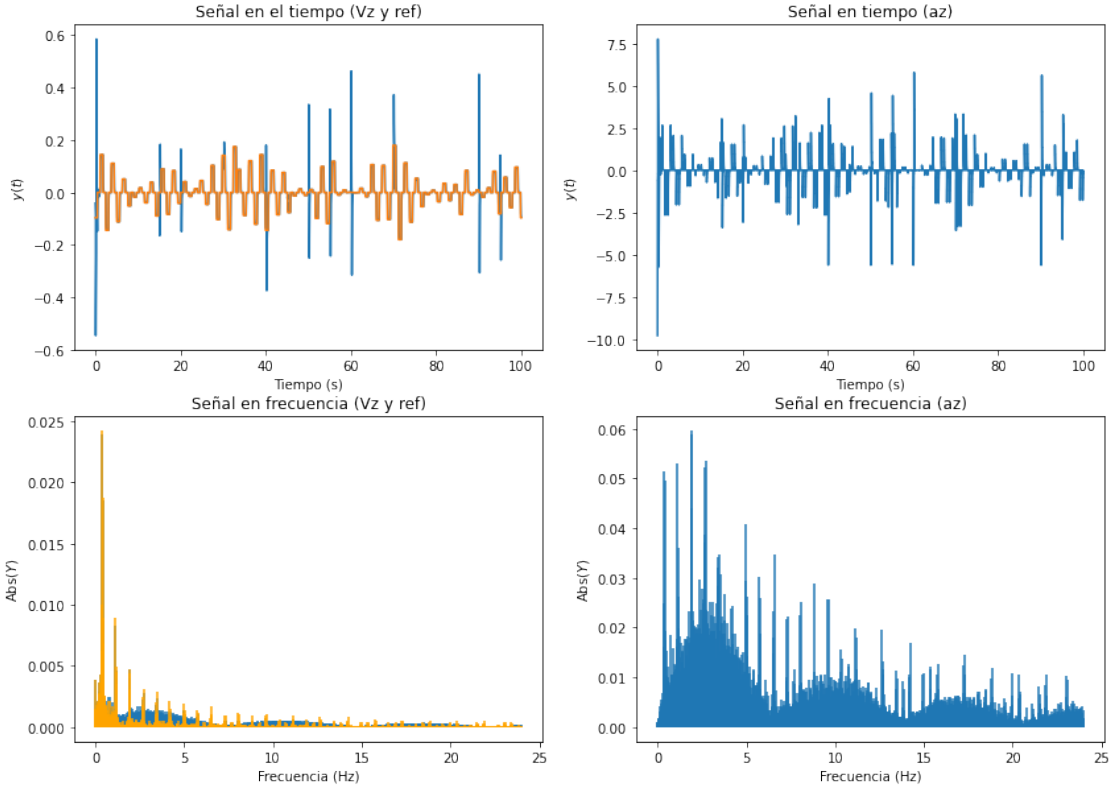

Señal en tiempo (az)
y(t)
Tiempo (s)


Señal en frecuencia (Vz y ref)
Abs(Y)
Frecuencia (Hz)

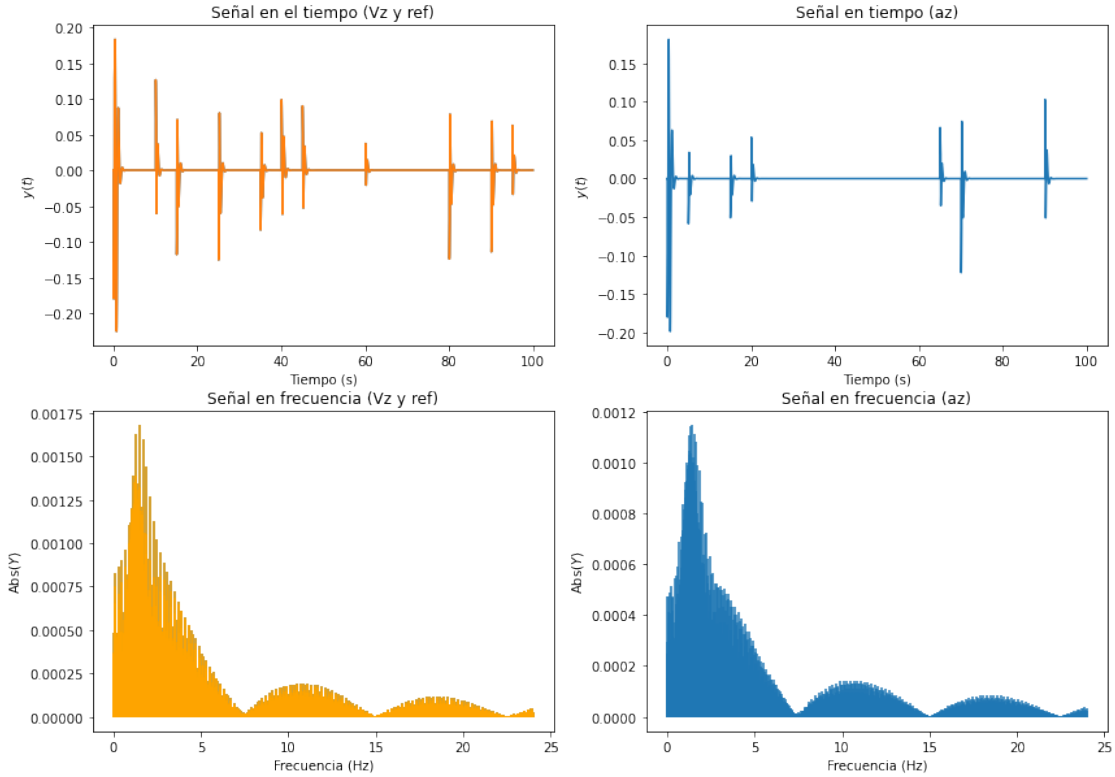

Señal en frecuencia (az)
Abs(Y)
Frecuencia (Hz)

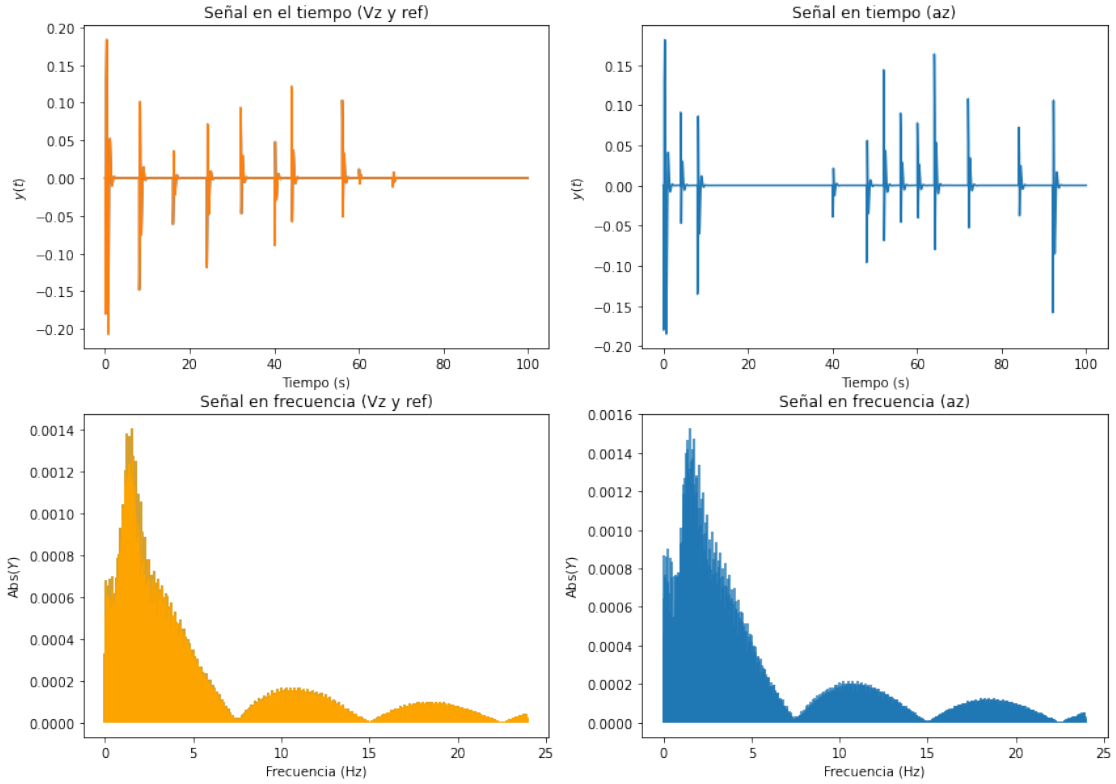

Señal en el tiempo (Vz y ref)
y(t)
Tiempo (s)
Señal en tiempo (az)
y(t)
Tiempo (s)
Señal en frecuencia (Vz y ref)
Abs(Y)
Frecuencia (Hz)
Señal en frecuencia (az)
Abs(Y)
Frecuencia (Hz)

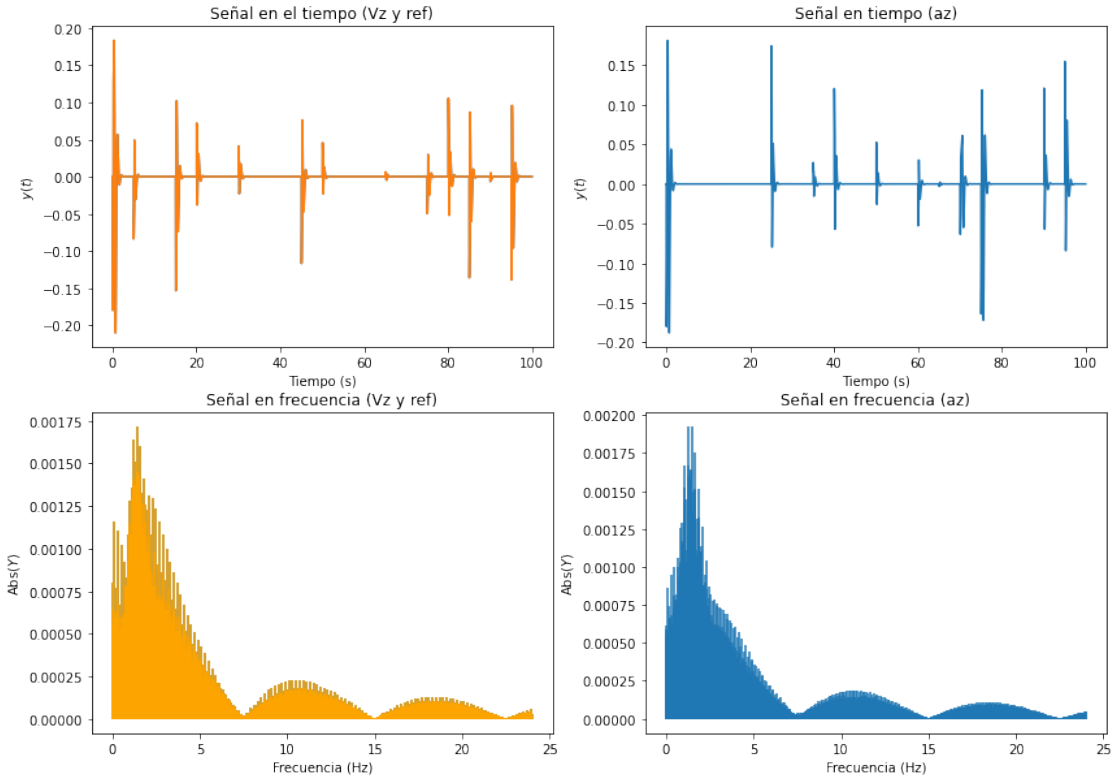

Señal en el tiempo (Vz y ref)
y(t)
Tiempo (s)
Señal en tiempo (az)
y(t)
Tiempo (s)
Señal en frecuencia (Vz y ref)
Abs(Y)
Frecuencia (Hz)
Señal en frecuencia (az)
Abs(Y)
Frecuencia (Hz)

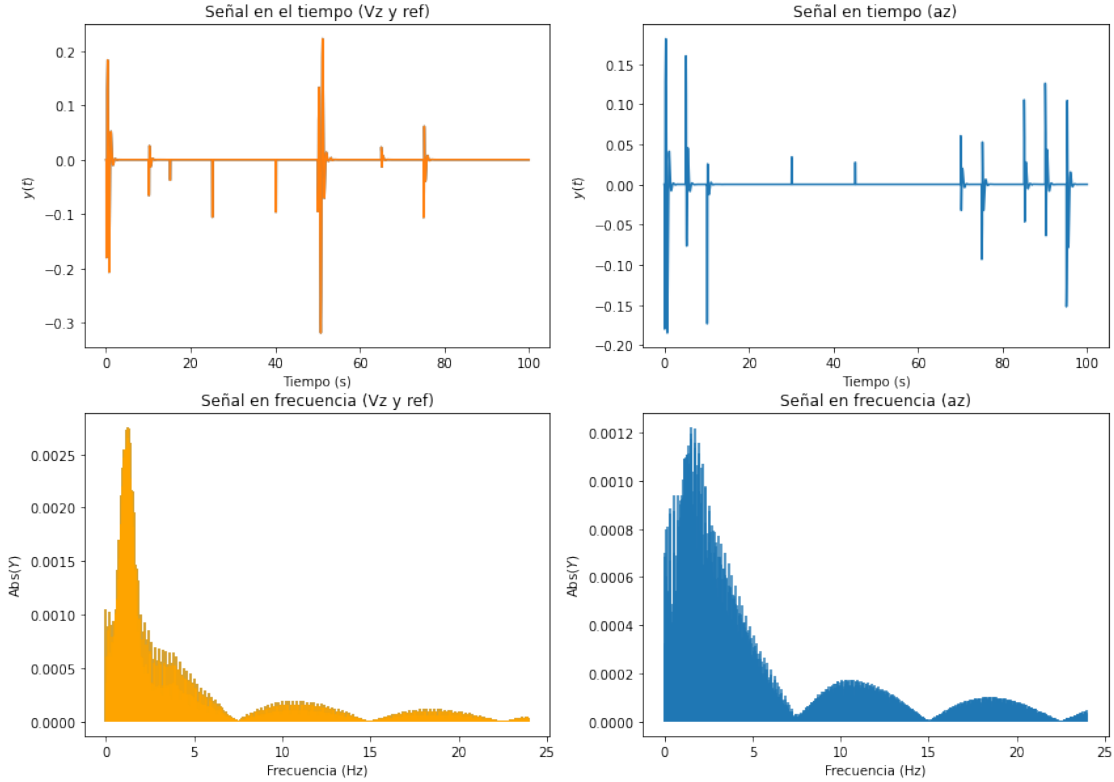

Señal en el tiempo (Vz y ref)
y(t)
Tiempo (s)
Señal en tiempo (az)
y(t)
Tiempo (s)
Señal en frecuencia (Vz y ref)
Abs(Y)
Frecuencia (Hz)
Señal en frecuencia (az)
Abs(Y)
Frecuencia (Hz)

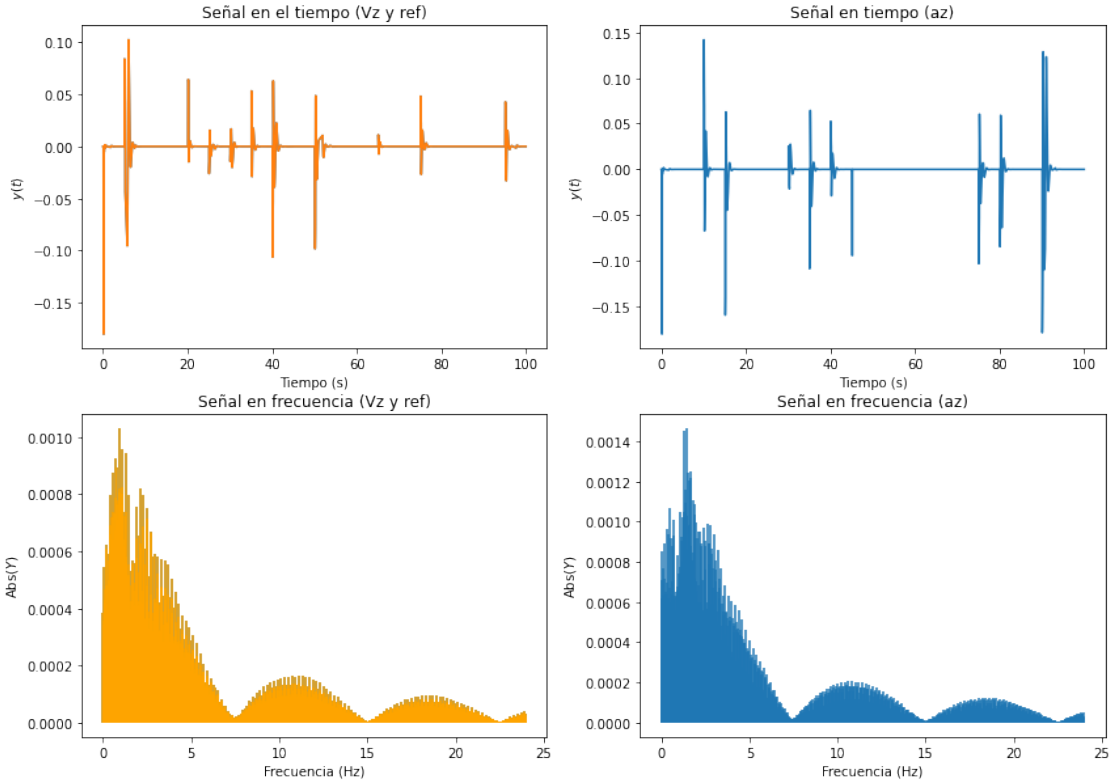
[15]:
```
for df in random.choices(dfs, k = 8):
    plot_fourier(df, states=['p', 'p', 'q'])
```

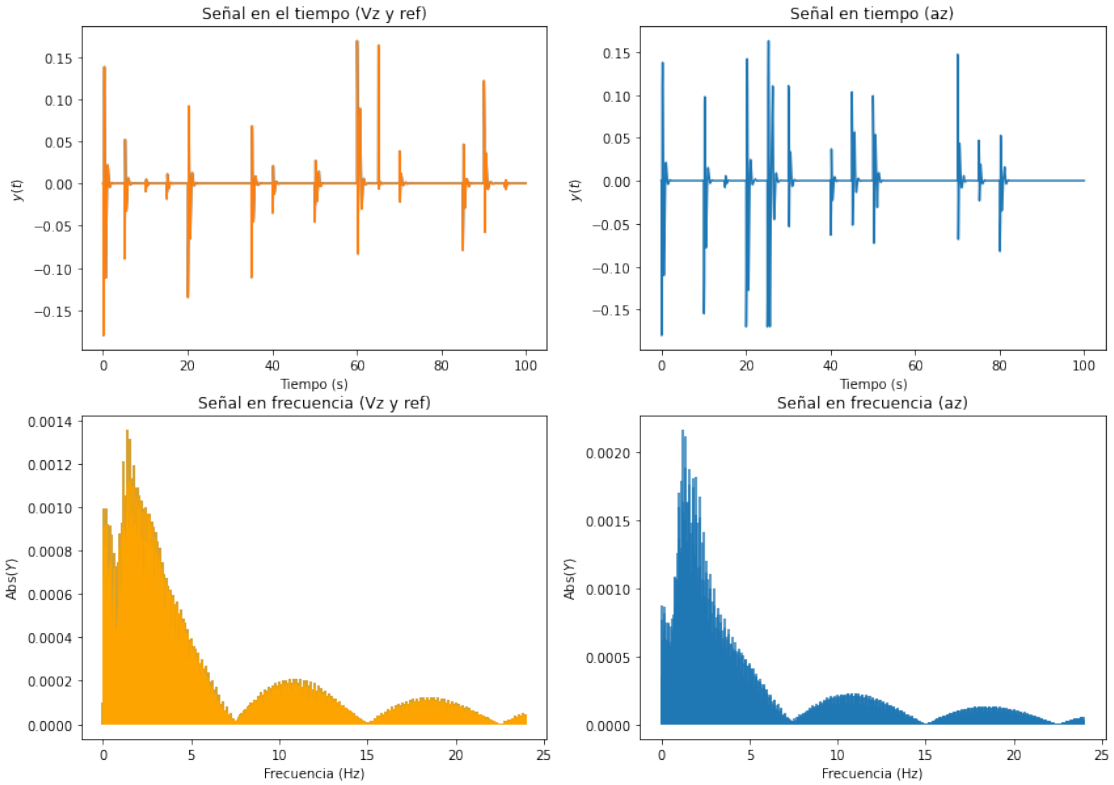


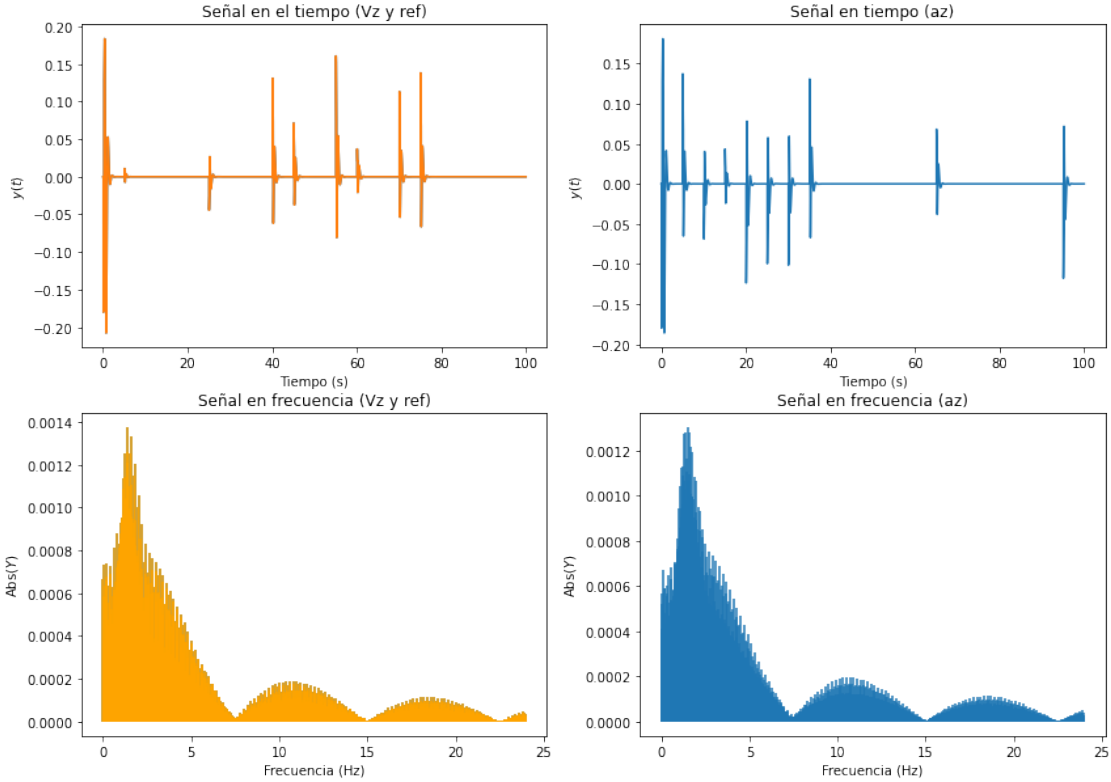

Señal en el tiempo (Vz y ref)
Señal en tiempo (az)
y(t)
Tiempo (s)
Señal en frecuencia (Vz y ref)
Señal en frecuencia (az)
Abs(Y)
Frecuencia (Hz)

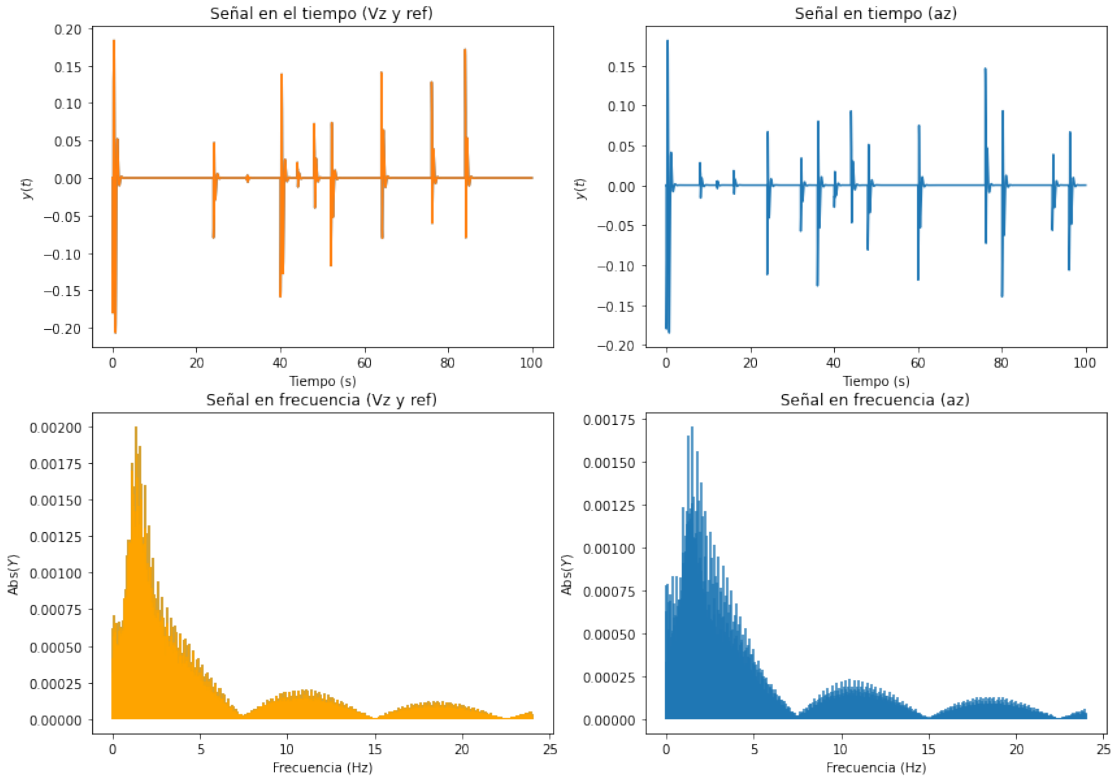

Señal en el tiempo (Vz y ref)
Señal en tiempo (az)
y(t)
Tiempo (s)
Señal en frecuencia (Vz y ref)
Señal en frecuencia (az)
Abs(Y)
Frecuencia (Hz)


Señal en el tiempo (Vz y ref)
y(t)
Tiempo (s)
Señal en tiempo (az)
y(t)
Tiempo (s)
Señal en frecuencia (Vz y ref)
Abs(Y)
Frecuencia (Hz)
Señal en frecuencia (az)
Abs(Y)
Frecuencia (Hz)


Señal en el tiempo (Vz y ref)
y(t)
Tiempo (s)
Señal en tiempo (az)
y(t)
Tiempo (s)
Señal en frecuencia (Vz y ref)
Abs(Y)
Frecuencia (Hz)
Señal en frecuencia (az)
Abs(Y)
Frecuencia (Hz)


Señal en el tiempo (Vz y ref)
y(t)
Tiempo (s)
Señal en tiempo (az)
y(t)
Tiempo (s)
Señal en frecuencia (Vz y ref)
Abs(Y)
Frecuencia (Hz)
Señal en frecuencia (az)
Abs(Y)
Frecuencia (Hz)


Señal en el tiempo (Vz y ref)
y(t)
Tiempo (s)
Señal en tiempo (az)
y(t)
Tiempo (s)
Señal en frecuencia (Vz y ref)
Abs(Y)
Frecuencia (Hz)
Señal en frecuencia (az)
Abs(Y)
Frecuencia (Hz)



Histograma

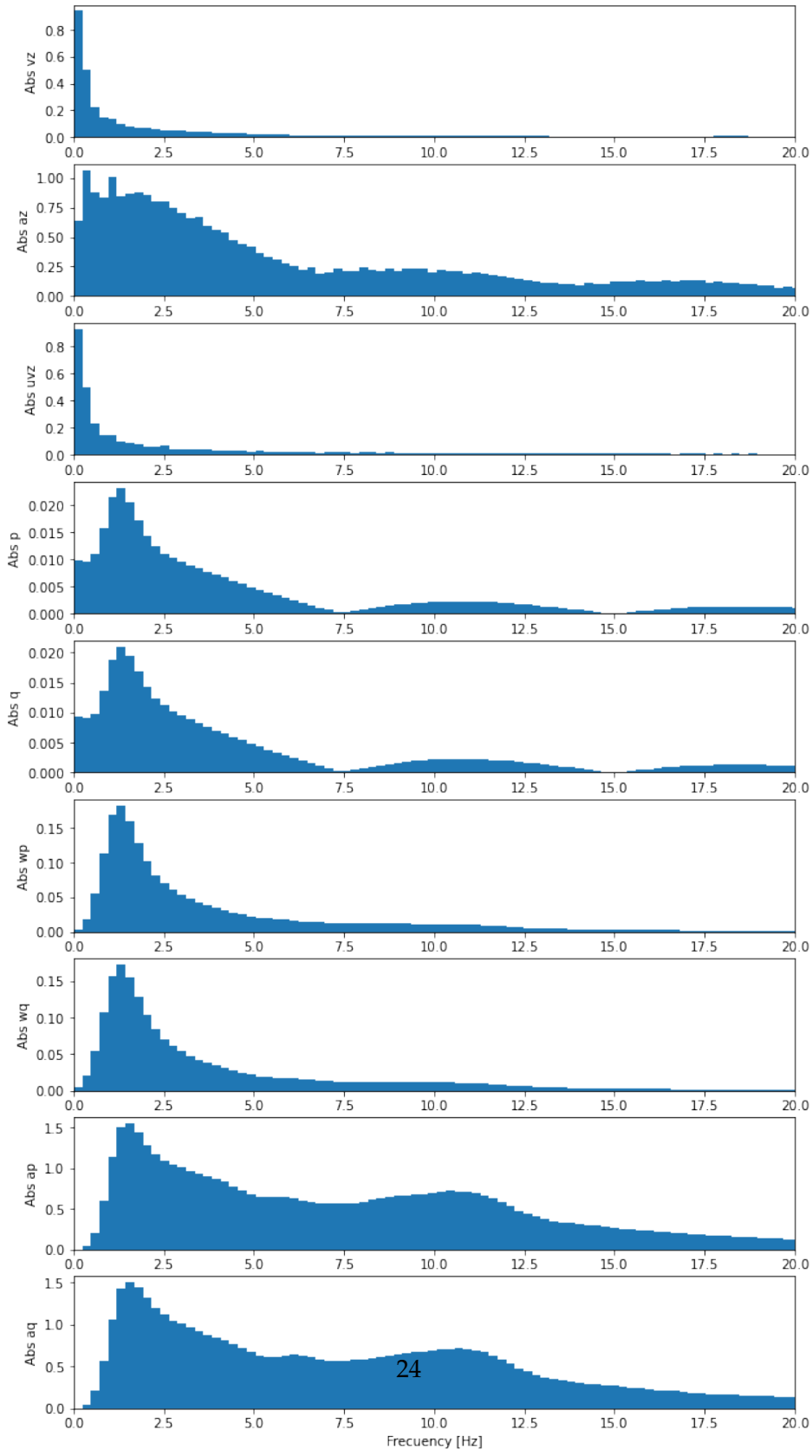
[16]:
```
Fourier = []
for i, df in enumerate(dfs):
    dt = df['timestamps'][1]-df['timestamps'][0]
    n = len(df['timestamps'])
    Fourier.append({})
    for state in states_list_org:
        Fourier[i][state]={}
        Fourier[i][state]['Y'] = abs(fft(df[state].to_numpy())/n)[0:int(n/2)] #␣
 ↪Transformada normalizada
        Fourier[i][state]['X'] = fftfreq(n, dt)[0:int(n/2)]
```

[17]:
```
F = {}
for state in states_list_org:
    F[state]={}
    F[state]['X'] = []
    F[state]['Y'] = []
    for f in Fourier:
        F[state]['X'] = np.concatenate([F[state]['X'], f[state]['X']])
        F[state]['Y'] = np.concatenate([F[state]['Y'], f[state]['Y']])
```

[18]:
```
fig, axs = plt.subplots(len(states_list_org), 1, figsize=(10, 20))
fig.suptitle('Fourier Transform Histogram per State')
for i, state in enumerate(states_list_org):
    axs[i].hist(F[state]['X'], bins=10*n_bins, weights=((F[state]['Y']+1e-7)/
 ↪len(Fourier)))
    axs[i].set_ylabel(f'Abs {state}')
    axs[i].set_xlim(0, 20)
axs[i].set_xlabel('Frecuency [Hz]')
```

[18]:
```
Text(0.5, 0, 'Frecuency [Hz]')
```

Fourier Transform Histogram per State



0.1.8 Análisis de Características - Método Estático

[19]:
```
dataset.describe()
```

[19]:

	timestamps	x	y	z	Q1	\
count	4.007833e+06	4.007833e+06	4.007833e+06	4.007833e+06	4.007833e+06	
mean	4.999583e+01	1.232111e-01	-1.129199e-01	5.341394e+01	-1.124056e-04	
std	2.886631e+01	8.825598e-02	8.576300e-02	9.609585e+00	9.626432e-03	
min	0.000000e+00	-2.047597e-01	-4.811760e-01	2.697847e+01	-1.698321e-01	
25%	2.499583e+01	7.730229e-02	-1.592710e-01	5.008806e+01	-3.020625e-08	
50%	4.999583e+01	1.227265e-01	-1.127110e-01	5.048142e+01	2.370051e-19	
75%	7.499583e+01	1.779849e-01	-6.940946e-02	5.279696e+01	2.872166e-08	
max	9.999167e+01	4.597636e-01	2.173638e-01	1.539669e+02	1.563415e-01	

	Q2	Q3	Q4	p	q	\
count	4.007833e+06	4.007833e+06	4.007833e+06	4.007833e+06	4.007833e+06	
mean	-1.166851e-04	6.719640e-05	9.999114e-01	-2.303242e-04	-2.300284e-04	
std	9.127336e-03	8.662359e-04	6.002488e-04	1.938697e-02	1.821034e-02	
min	-1.457588e-01	-4.432610e-02	9.752161e-01	-3.536326e-01	-2.834447e-01	
25%	-2.448411e-08	-5.146146e-07	1.000000e+00	-6.436319e-08	-5.447548e-08	
50%	0.000000e+00	1.115153e-05	1.000000e+00	5.648435e-19	-0.000000e+00	
75%	2.405126e-08	1.971108e-05	1.000000e+00	6.241495e-08	5.148737e-08	
max	1.246893e-01	4.782059e-02	1.000000e+00	3.149456e-01	2.485051e-01	

	r	vx	vy	vz	wp	\
count	4.007833e+06	4.007833e+06	4.007833e+06	4.007833e+06	4.007833e+06	
mean	1.836237e-04	1.468863e-03	-1.370043e-03	7.058128e-02	6.759972e-05	
std	2.268712e-03	2.554577e-02	2.691607e-02	8.876363e-01	1.312313e-01	
min	-8.505308e-02	-4.256045e-01	-5.883179e-01	-9.426658e+00	-2.441203e+00	
25%	-9.294998e-07	-5.306351e-08	-8.073925e-08	-7.346576e-02	-4.127837e-07	
50%	2.231696e-05	-6.482318e-17	-1.370919e-16	6.612490e-17	1.192785e-17	
75%	3.946552e-05	6.332497e-08	6.395209e-08	1.286200e-01	4.945783e-07	
max	9.873158e-02	5.853262e-01	5.074040e-01	9.720978e+00	2.744562e+00	

	wq	wr	ax	ay	az	\
count	4.007833e+06	4.007833e+06	4.007833e+06	4.007833e+06	4.007833e+06	
mean	-6.813699e-05	-4.751161e-05	1.580413e-10	1.229393e-09	3.210177e-04	
std	1.266916e-01	1.608981e-02	1.428626e-01	1.522444e-01	1.822109e+00	
min	-2.568337e+00	-6.203632e-01	-4.023462e+00	-3.135487e+00	-9.800000e+00	
25%	-3.408623e-07	-3.469616e-07	-4.160205e-07	-5.834920e-07	-7.146616e-03	
50%	1.002047e-17	-1.814025e-07	9.363510e-18	-2.944722e-18	1.541975e-15	
75%	3.984695e-07	4.894901e-08	4.825922e-07	5.296203e-07	4.185012e-03	
max	2.167848e+00	8.109048e-01	3.499987e+00	4.139923e+00	1.610805e+01	

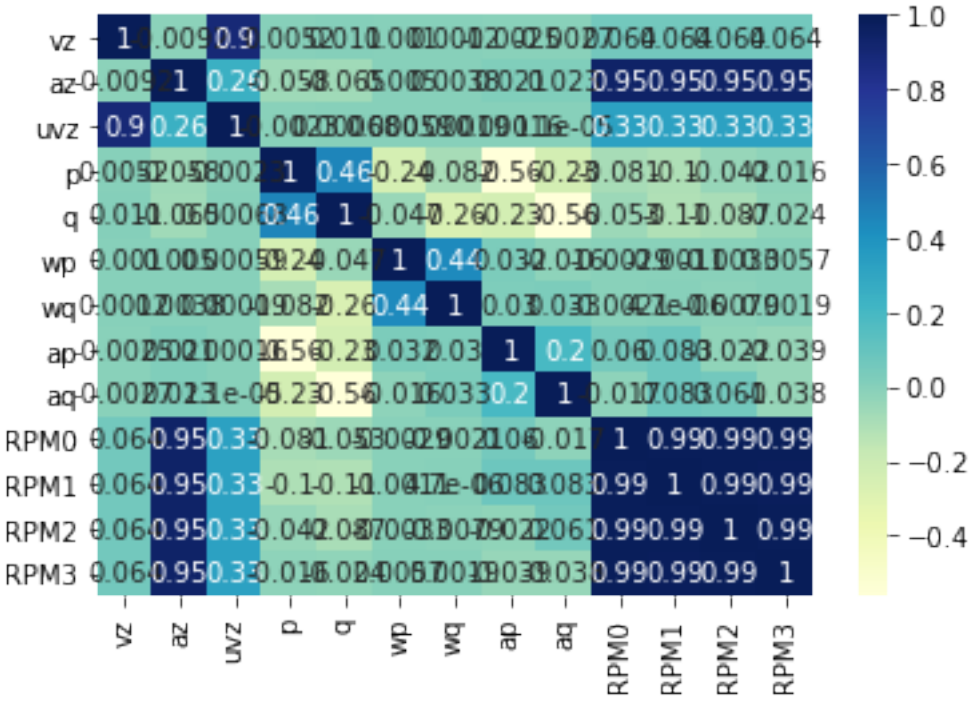
```
                ap            aq            ar          RPM0          RPM1  \
count  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06
mean  -4.129174e-08 -1.073950e-09 -1.275564e-09  1.441872e+04  1.441844e+04
std    2.016054e+00  1.990444e+00  6.490893e-01  1.325549e+03  1.328543e+03
min   -1.762474e+01 -1.727289e+01 -1.572234e+01  9.440300e+03  9.440300e+03
25%   -3.930490e-06 -3.317791e-06 -1.070975e-09  1.442594e+04  1.442414e+04
50%   -7.111581e-27 -5.360310e-27  1.577592e-09  1.446843e+04  1.446843e+04
75%    3.629512e-06  2.922475e-06  4.010480e-09  1.451734e+04  1.451759e+04
max    1.725882e+01  1.708771e+01  1.558256e+01  2.166645e+04  2.166645e+04

               RPM2          RPM3         ux         uy         uz        uvx  \
count  4.007833e+06  4.007833e+06  4007833.0  4007833.0  4007833.0  4007833.0
mean   1.441873e+04  1.441900e+04        0.0        0.0       50.0        0.0
std    1.325717e+03  1.322718e+03        0.0        0.0        0.0        0.0
min    9.440300e+03  9.440300e+03        0.0        0.0       50.0        0.0
25%    1.442605e+04  1.442492e+04        0.0        0.0       50.0        0.0
50%    1.446843e+04  1.446843e+04        0.0        0.0       50.0        0.0
75%    1.451745e+04  1.451810e+04        0.0        0.0       50.0        0.0
max    2.166645e+04  2.166645e+04        0.0        0.0       50.0        0.0

            uvy           uvz         up         uq         ur        uwp  \
count  4007833.0  4.007833e+06  4007833.0  4007833.0  4007833.0  4007833.0
mean         0.0  5.302769e-02        0.0        0.0        0.0        0.0
std          0.0  9.432127e-01        0.0        0.0        0.0        0.0
min          0.0 -9.640079e+00        0.0        0.0        0.0        0.0
25%          0.0 -7.237447e-02        0.0        0.0        0.0        0.0
50%          0.0  0.000000e+00        0.0        0.0        0.0        0.0
75%          0.0  1.155227e-01        0.0        0.0        0.0        0.0
max          0.0  9.640079e+00        0.0        0.0        0.0        0.0

            uwq        uwr           vz1           az1           uvz1  \
count  4007833.0  4007833.0  4.007833e+06  4.007833e+06  4.007833e+06
mean         0.0        0.0  7.057994e-02  3.228008e-04  5.302917e-02
std          0.0        0.0  8.876180e-01  1.822077e+00  9.431880e-01
min          0.0        0.0 -9.426658e+00 -9.800000e+00 -9.640079e+00
25%          0.0        0.0 -7.344996e-02 -7.143027e-03 -7.237447e-02
50%          0.0        0.0  6.568330e-17  1.541974e-15  0.000000e+00
75%          0.0        0.0  1.286069e-01  4.183542e-03  1.154756e-01
max          0.0        0.0  9.720978e+00  1.610805e+01  9.640079e+00

                p1            q1           wp1           wq1           ap1  \
count  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06
mean  -2.303242e-04 -2.300284e-04  6.759989e-05 -6.813698e-05 -4.142293e-08
std    1.938697e-02  1.821034e-02  1.312313e-01  1.266916e-01  2.016054e+00
min   -3.536326e-01 -2.834447e-01 -2.441203e+00 -2.568337e+00 -1.762474e+01
25%   -6.435992e-08 -5.447285e-08 -4.127670e-07 -3.408300e-07 -3.930290e-06
50%    5.543243e-19 -0.000000e+00  1.191775e-17  9.566621e-18 -6.863090e-27
```

```
75%    6.240801e-08  5.148517e-08  4.945490e-07  3.984622e-07  3.629396e-06
max    3.149456e-01  2.485051e-01  2.744562e+00  2.167848e+00  1.725882e+01

                aq1           vz2           az2           uvz2            p2  \
count  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06
mean  -1.133661e-09  7.057859e-02  3.245846e-04  5.303064e-02 -2.303243e-04
std    1.990444e+00  8.875997e-01  1.822046e+00  9.431632e-01  1.938697e-02
min   -1.727289e+01 -9.426658e+00 -9.800000e+00 -9.640079e+00 -3.536326e-01
25%   -3.317570e-06 -7.343642e-02 -7.140487e-03 -7.234720e-02 -6.435649e-08
50%   -5.182816e-27  6.544569e-17  1.541974e-15  0.000000e+00  5.427472e-19
75%    2.922272e-06  1.285923e-01  4.182457e-03  1.154372e-01  6.240276e-08
max    1.708771e+01  9.720978e+00  1.610805e+01  9.640079e+00  3.149456e-01

                q2           wp2           wq2           ap2           aq2  \
count  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06
mean  -2.300284e-04  6.760007e-05 -6.813698e-05 -4.155414e-08 -1.193382e-09
std    1.821034e-02  1.312313e-01  1.266916e-01  2.016054e+00  1.990444e+00
min   -2.834447e-01 -2.441203e+00 -2.568337e+00 -1.762474e+01 -1.727289e+01
25%   -5.447123e-08 -4.127500e-07 -3.408117e-07 -3.930007e-06 -3.317059e-06
50%    0.000000e+00  1.179796e-17  9.482479e-18 -6.673763e-27 -4.975740e-27
75%    5.148300e-08  4.945288e-07  3.984494e-07  3.629268e-06  2.922085e-06
max    2.485051e-01  2.744562e+00  2.167848e+00  1.725882e+01  1.708771e+01

                vz3           az3           uvz3            p3            q3  \
count  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06
mean   7.057724e-02  3.263690e-04  5.303212e-02 -2.303243e-04 -2.300284e-04
std    8.875814e-01  1.822014e+00  9.431385e-01  1.938697e-02  1.821034e-02
min   -9.426658e+00 -9.800000e+00 -9.640079e+00 -3.536326e-01 -2.834447e-01
25%   -7.341829e-02 -7.137214e-03 -7.234720e-02 -6.435279e-08 -5.446777e-08
50%    6.520893e-17  1.541973e-15  0.000000e+00  5.325995e-19 -0.000000e+00
75%    1.285802e-01  4.181233e-03  1.154372e-01  6.239868e-08  5.147947e-08
max    9.720978e+00  1.610805e+01  9.640079e+00  3.149456e-01  2.485051e-01

                wp3           wq3           ap3           aq3
count  4.007833e+06  4.007833e+06  4.007833e+06  4.007833e+06
mean   6.760024e-05 -6.813697e-05 -4.168538e-08 -1.253112e-09
std    1.312313e-01  1.266916e-01  2.016054e+00  1.990444e+00
min   -2.441203e+00 -2.568337e+00 -1.762474e+01 -1.727289e+01
25%   -4.127296e-07 -3.407898e-07 -3.929796e-06 -3.316981e-06
50%    1.110696e-17  9.426808e-18 -6.496270e-27 -4.798246e-27
75%    4.945138e-07  3.984406e-07  3.629094e-06  2.921943e-06
max    2.744562e+00  2.167848e+00  1.725882e+01  1.708771e+01
```

Mapa de Correlación

[20]:
```
correlation = dataset[states_list_org + rpm_list].corr() #corr() method of␣
 ↪pandas library calculates correlation between columns of dataframe
```

```
sns.heatmap(correlation,cmap="YlGnBu",annot=True)
plt.show()
```



Análisis de Correlaciones

[21]:
```
# Comentado porque se demora mucho procesando
# for i in states_list_org:
#     sns.lmplot(x=i, y=rpm_list[0], data=dataset,line_kws={'color': 'red'})
#     text="Relation between RPM0 and " + i
#     plt.title(text)
#     plt.show()
```

[22]:
```
corr_df = pd.DataFrame()
for i in rpm_list:
    correlation = dataset.corr()[i] # convert series to dataframe so it can be␣
 ↪sorted
    correlation_df = pd.DataFrame(correlation) # correct column label from␣
 ↪Points to correlation
    correlation_df.columns = [f"Correlation_{i}"] # sort correlation
    corr_df = pd.concat([correlation_df, corr_df], axis=1)
corr_df = corr_df.dropna(how='all')
corr_df = corr_df.sort_values(by=[f'Correlation_{rpm_list[0]}'], ascending=False)
corr_df.head(30)
```

[22]:

	Correlation_RPM3	Correlation_RPM2	Correlation_RPM1	Correlation_RPM0
RPM0	0.991461	0.990278	0.991656	1.000000
RPM1	0.985660	0.991275	1.000000	0.991656
RPM3	1.000000	0.991579	0.985660	0.991461
RPM2	0.991579	1.000000	0.991275	0.990278
az	0.949121	0.950150	0.949392	0.950166
az1	0.922955	0.923834	0.923384	0.923842
az2	0.896776	0.897504	0.897362	0.897505
az3	0.870584	0.871161	0.871328	0.871154
uvz	0.333734	0.332963	0.332300	0.333040
uvz1	0.333448	0.332674	0.332010	0.332752
uvz2	0.333162	0.332386	0.331720	0.332465
uvz3	0.332875	0.332097	0.331429	0.332177
vz	0.064389	0.063967	0.063664	0.064020
ap	-0.038952	-0.021516	0.082525	0.060006
vz1	0.056814	0.056426	0.056170	0.056479
ap1	-0.033630	-0.017449	0.078524	0.056303
ap2	-0.028307	-0.013382	0.074520	0.052600
Q3	0.022745	0.052761	0.045461	0.050919
vz2	0.049462	0.049109	0.048897	0.049161
ap3	-0.022983	-0.009313	0.070514	0.048896
vz3	0.042333	0.042016	0.041846	0.042067
ay	-0.027869	-0.002373	0.058659	0.034701
x	0.014280	0.015866	0.016667	0.015379
wr	0.032213	0.015626	-0.014720	0.014709
vy	0.015088	0.010697	0.012418	0.011226
Q4	0.012948	0.012649	-0.002284	0.010424
r	-0.011369	0.006751	0.002947	0.006344
wq3	0.008263	-0.018993	-0.015563	0.000505
wq2	0.006456	-0.015563	-0.010634	-0.000099
wq1	0.004324	-0.011856	-0.005444	-0.000957

0.1.9 Análisis de Características - Método Dinámico

Autocorrelación Parcial

[23]:
```
# N_df = 3
# nlags = 15
# fig, axs = plt.subplots(N_df, len(states_list_min), figsize=(15, 15))
# for k, df in enumerate(random.choices(dfs, k = N_df)):
#     for j, i in enumerate(states_list_min):
#         plot_pacf(df[i], lags=nlags, ax = axs[j, k])
#         axs[j, k].set_title(i)
```

[24]:
```
# pacf_df = [pd.DataFrame()]*len(states_list_min)
# for k, df in enumerate(dfs):
#     for j, i in enumerate(states_list_min):
#         tmp = pd.DataFrame(pacf(df[i], nlags=nlags), columns=[str(k)])
```

```
#         pacf_df[j] = pd.concat([pacf_df[j], tmp], axis=1)
# pacf_df_dict = {}
# for j, i in enumerate(states_list_min):
#     pacf_df_dict[i] =  pd.DataFrame()
#     pacf_df_dict[i]['mean'] = pacf_df[j].T.mean()
#     pacf_df_dict[i]['min'] = pacf_df[j].T.min()
#     pacf_df_dict[i]['max'] = pacf_df[j].T.max()
#     pacf_df_dict[i]['abs'] = np.maximum(pacf_df[j].T.max(), abs(pacf_df[j].T.
 ↪min()))
```

[25]:
```
# fig, axes = plt.subplots(nrows=len(states_list_min), ncols=1, figsize=(10, 10))
# crt = 'mean'
# for j, i in enumerate(states_list_min):
#     pacf_df_dict[i][crt].plot(kind="bar", ax=axes[j])
#     axes[j].set_ylabel('Autocorrelación')
#     axes[j].set_title(f'Autocorrelación_{i}_{crt}')
```

[26]:
```
# fig, axes = plt.subplots(nrows=len(states_list_min), ncols=1, figsize=(10, 10))
# crt = 'abs'
# for j, i in enumerate(states_list_min):
#     pacf_df_dict[i][crt].plot(kind="bar", ax=axes[j])
#     axes[j].set_ylabel('Autocorrelación')
#     axes[j].set_title(f'Autocorrelación_{i}_{crt}')
```

[ ]:
```

```