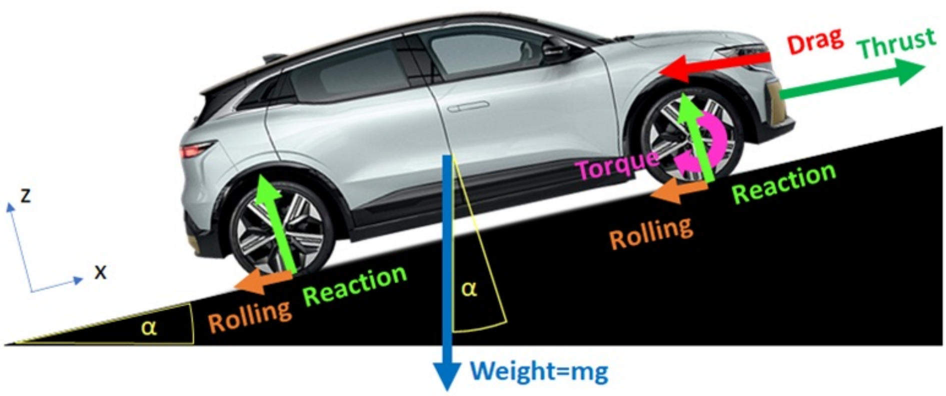
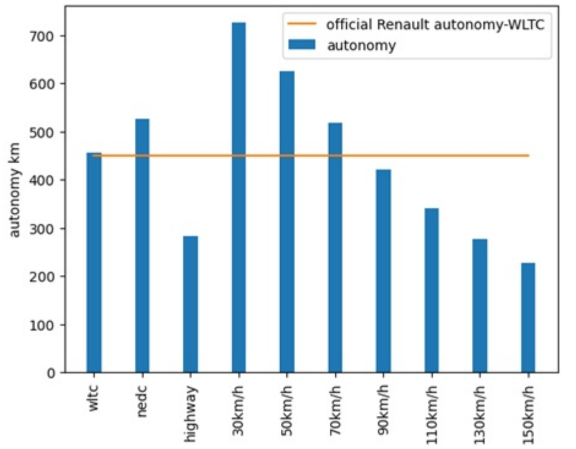
RENAULT Megane E-TECH 220Hp 60kWh (EV): Generate a Time Series Dataset with Matlab/Simulink simulation model

Introduction

The idea of this project is to generate a dataset of electric vehicle driving using a Matlab/simulink simulation model. The dataset will be published in many plateformes as kaggle and github to be accessible by others sudents / data scientist / analyst.

For this purpose, we will start by preparing the data (NEDC / WLTP and other driving data). In the second time we will discovering the Matlab subsystem by some plot of the elements test results. After that we will calculate the autonomy of each driving mode (WLTC, NEDC, HighWay, constant speed, ...). In the annexes you can see how we convert a matlab route to the right data of time, distance, speed, elevation, road gradient for Matlab simulation and also the Matlab/Simulink hypothesis and parameters





Abbreviation & keywords

Abbreviation

Below some abbreviation that well be used in this project

- EV : Electric vehicle
- SOC : State of charge
- Batt : Battery
- INV : Inverter
- NEDC : New European Driving Cycle
- WLTC : Worldwide harmonized Light vehicles Test procedure Cycle

Keywords

EV simulation, Matlab, Simulink, WLTP , NEDC, EV Dataset, Electric vehicle dataset, HV battery, EV Autonomy, electrical motor, Thrust, car drag, wheel rolling, Newton's second law, Highway driving

Links

- Github repository of this projet
- The main file as HTML
- The main file as notebook
- The ouput dataset link in Github
- The ouput dataset link in Kaggle

Table of contents

NEDC vs WLTC Cycles

Import of the libraries

In [214]:
```
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
import numpy as np
from scipy import interpolate
import scipy
import json
import requests
import plotly.express as px
import math
from scipy import interpolate
```

In [215]:
```
## Show all columns of a df
pd.set_option('display.max_columns', None)

#Save Plotly figures with the interactive mode in HTML file
import plotly
plotly.offline.init_notebook_mode()
```

NEDC vs WLTC

Read data

In [216]:
```
NEDC=pd.read_csv(r'../data/raw/NEDC.csv')
WLTC=pd.read_csv(r'../data/processed/WLTC_Class_3_vehicles_V2.csv')
NEDC.head(2)
```

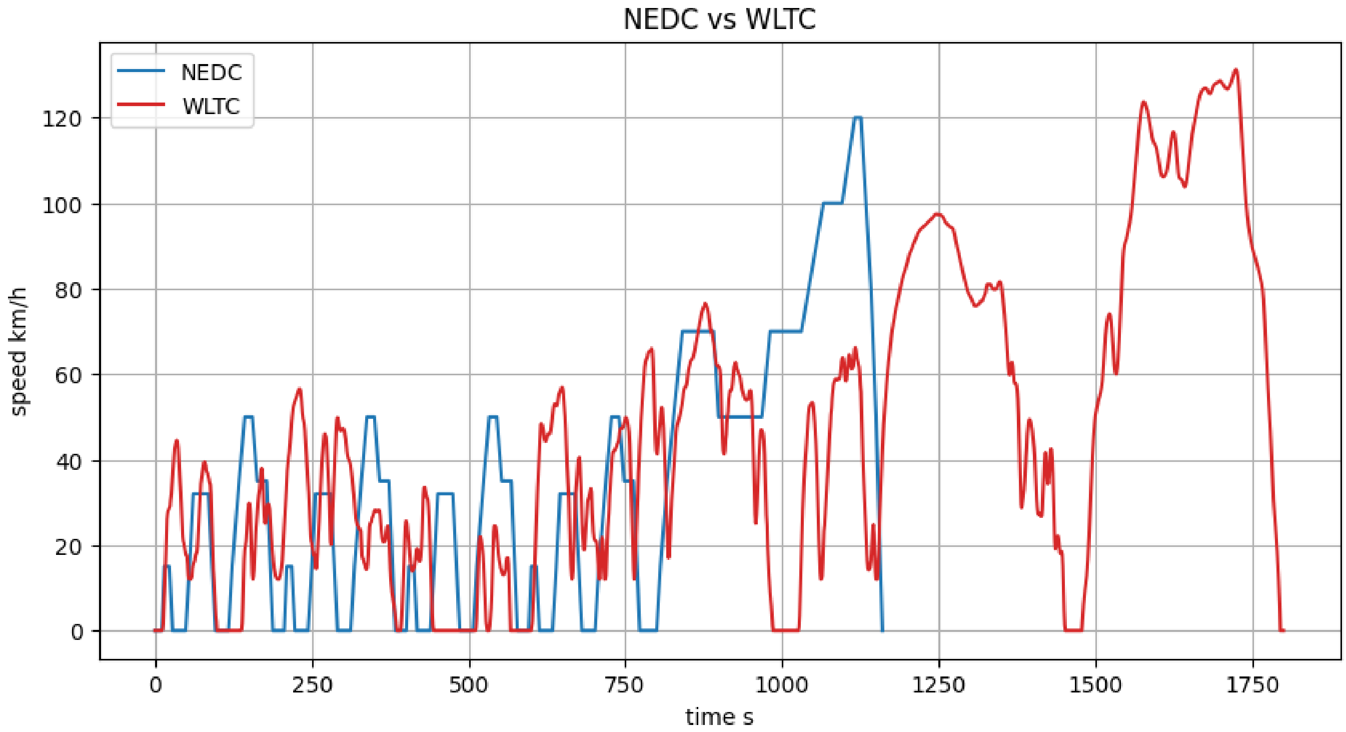
Out[216]:

	time	kmph
0	0	0
1	11	0

Plot the two cycles

In [217]:
```
# Color plot
r='#b7190f'
```

```
b='#26619c'
# Create a new figure
fig = plt.figure(figsize=(10,5))

plt.plot(NEDC.time,NEDC.kmph,label='NEDC',c='C0')
plt.plot(WLTC.time,WLTC.kmph,label='WLTC',c='C3')
plt.title('NEDC vs WLTC')
plt.xlabel('time s')
plt.ylabel('speed km/h')
plt.legend()
plt.grid()
#plt.savefig(r'../otherFiles/figures/NEDC_WLTC.png')
plt.show()
```



We can see that the WLTC is more realistic than the NEDC

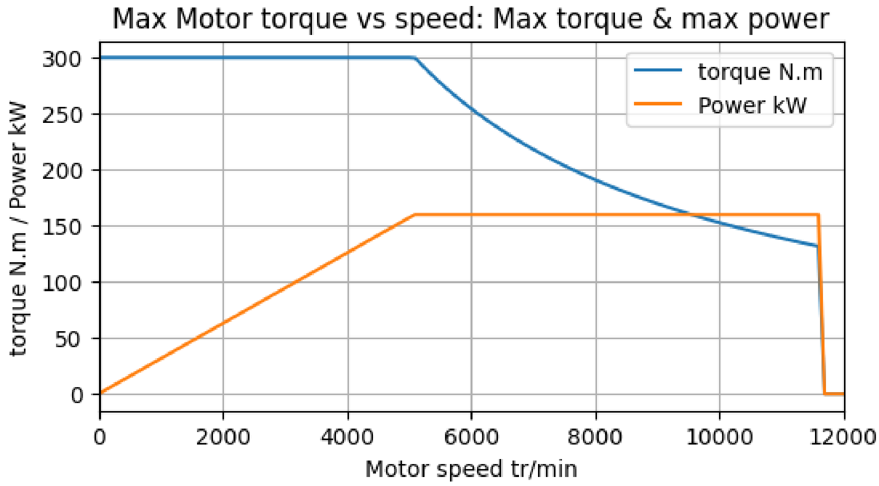
Simulation element tests

Motor

In [218]:
```
mat = scipy.io.loadmat('../matlabFiles/testSubSystems/motor_test_res.mat')
```

Torque vs speed

In [219]:
```
# motor speed rpm
motor_speed_rpmPM=mat['motor_speed_rpm']
motor_speed_rpmPM=motor_speed_rpmPM[0][0][1][0][0][0].flatten()

# motor torque
motor_torquePM=mat['motor_torque']
motor_torquePM=motor_torquePM[0][0][1][0][0][0].flatten()

# convert to dataFrame
dfm=pd.DataFrame(motor_speed_rpmPM,columns=['motor_speed_rpm'])
dfm['motor_torque']=motor_torquePM

# Power
powerKwPM=motor_torquePM*(motor_speed_rpmPM*2*np.pi/60)/1000


# Plot
figure(figsize=(6, 3))
plt.plot(motor_speed_rpmPM,motor_torquePM,label='torque N.m')
plt.plot(motor_speed_rpmPM,powerKwPM,label='Power kW')
plt.grid()
plt.ylabel('torque N.m / Power kW')
plt.xlabel('Motor speed tr/min')
plt.title('Max Motor torque vs speed: Max torque & max power')
plt.xlim([0,12000])
plt.legend()
plt.show()
```

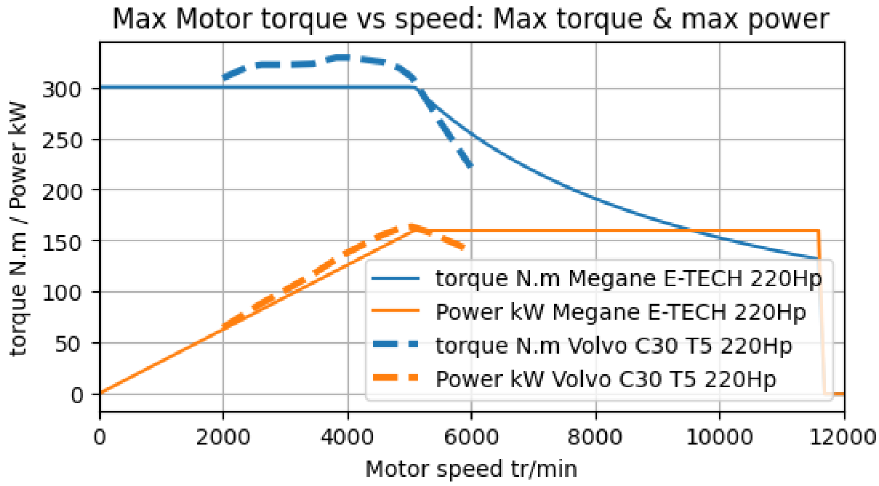


For this simulation, we will use the simple strategy: max torque util the power reached its max, and after that the power will be limited to its max

In the real control, the torque / speed is close to this cuve, but with a more complicated vector control strategy

Comparaison between the torque of the electrical Megane-E 220Hp and the gasoline Volvo C30 T5 220Hp

In [220]:
```
# The below data is extracted from the graph in the link below:
# https://en.bsr.se/tuning-kits/t/947/volvo-c30-t5-220hp-2007-2013-b-5254-t3
volvo='''2000 308.7209302
2255.578093 315.6976744
2385.395538 319.1860465
2624.74645 321.8023256
3050.709939 321.8023256
3448.275862 322.6744186
3829.614604 328.7790698
4016.227181 328.7790698
4356.997972 326.1627907
4588.235294 324.4186047
4851.926978 318.3139535
5046.653144 309.5930233
5342.799189 281.6860465
5513.184584 265.1162791
5805.273834 238.9534884
6000 221.5116279'''
volvo=volvo.split('\n')
volvo=[x.split('\t') for x in volvo]
volvo=np.array(volvo).T.astype(float)
rpm_vol=volvo[0]
torq_vol=volvo[1]
power_vol=torq_vol*(rpm_vol *2*np.pi/60)/1000

# Plot
figure(figsize=(6, 3))
plt.plot(motor_speed_rpmPM,motor_torquePM,label='torque N.m Megane E-TECH 220Hp',c='C0')
plt.plot(motor_speed_rpmPM,powerKwPM,label='Power kW Megane E-TECH 220Hp',c='C1')

plt.plot(rpm_vol,torq_vol,linestyle="--",linewidth=3,\
        label='torque N.m Volvo C30 T5 220Hp',c='C0')
plt.plot(rpm_vol,power_vol,linestyle="--",linewidth=3,\
        label='Power kW Volvo C30 T5 220Hp',c='C1')

plt.grid()
plt.ylabel('torque N.m / Power kW')
plt.xlabel('Motor speed tr/min')
plt.title('Max Motor torque vs speed: Max torque & max power')
plt.xlim([0,12000])
plt.legend()
plt.show()
```

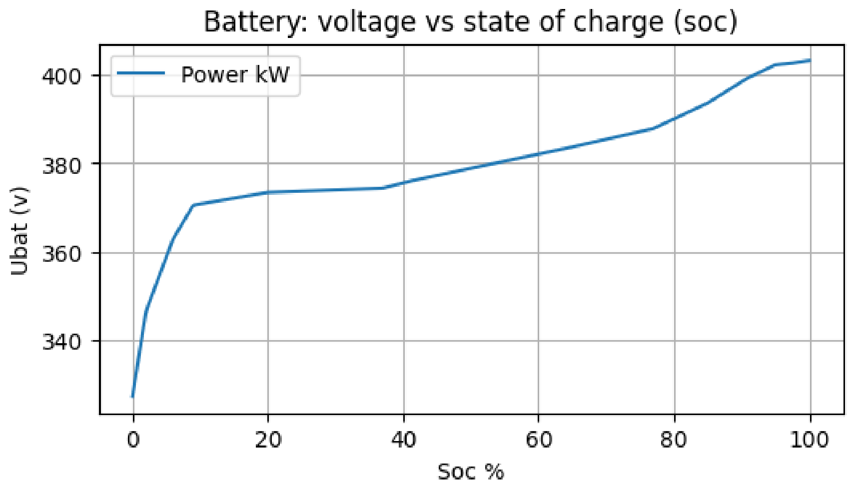


we can see that the Megane-E 220Hp and the gasoline Volvo C30 T5 220 Hp have the same peak power, but the speed range of the max torque is very short for the gasoline, because of that the conventional cars use a gearbox to adapt the speed, and the electrical vehicle use just a one level reductor.

Battery

In [221]:
```
mat = scipy.io.loadmat('../matlabFiles/testSubSystems/battery_test_res.mat')
```

In [222]:
```
# battery Ubat
battery_Ubat=mat['battery_Ubat']
battery_Ubat=battery_Ubat[0][0][1][0][0][0].flatten()

# battery SOC
battery_soc=mat['battery_soc']
battery_soc=battery_soc[0][0][1][0][0][0].flatten()

# Plot
figure(figsize=(6, 3))
plt.plot(battery_soc,battery_Ubat,label='Power kW')
plt.grid()
plt.ylabel('Ubat (v)')
plt.xlabel('Soc %')
plt.title('Battery: voltage vs state of charge (soc)')
plt.legend()
plt.show()
```



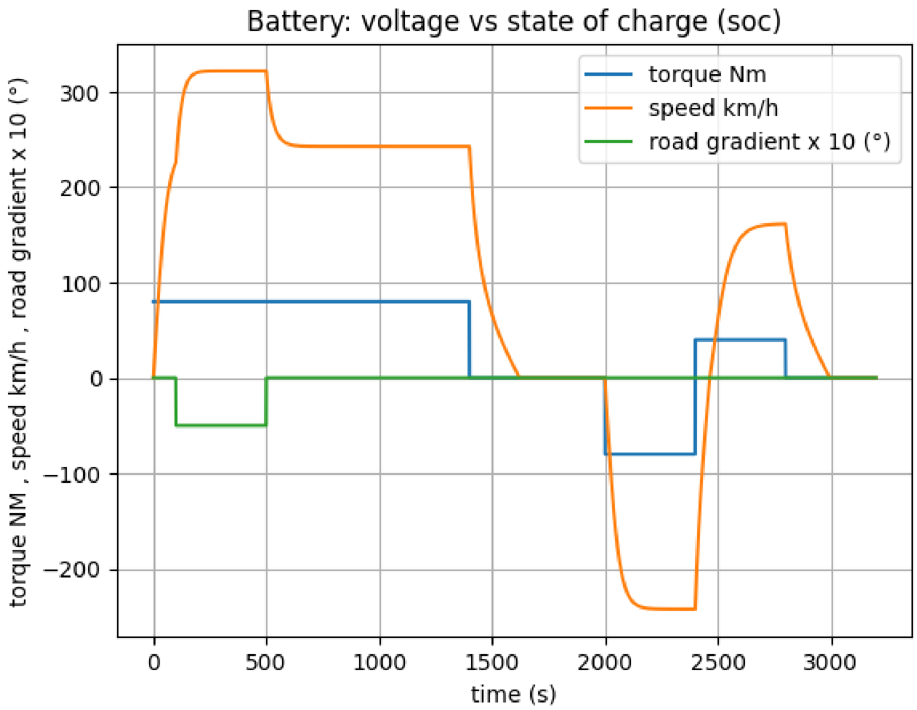
Body

In [223]:
```
# read matlab data
mat = scipy.io.loadmat('../matlabFiles/testSubSystems/body_test_res.mat')
```

Plot

In [224]:
```
# time
time  = mat['body_test_torque'][0][0][0].flatten()

# torque
body_test_torque=mat['body_test_torque']
body_test_torque=body_test_torque[0][0][1][0][0][0].flatten()

# speed
body_test_speedMeas=mat['body_test_speedMeas']
body_test_speedMeas=body_test_speedMeas[0][0][1][0][0][0].flatten()

# speed
```

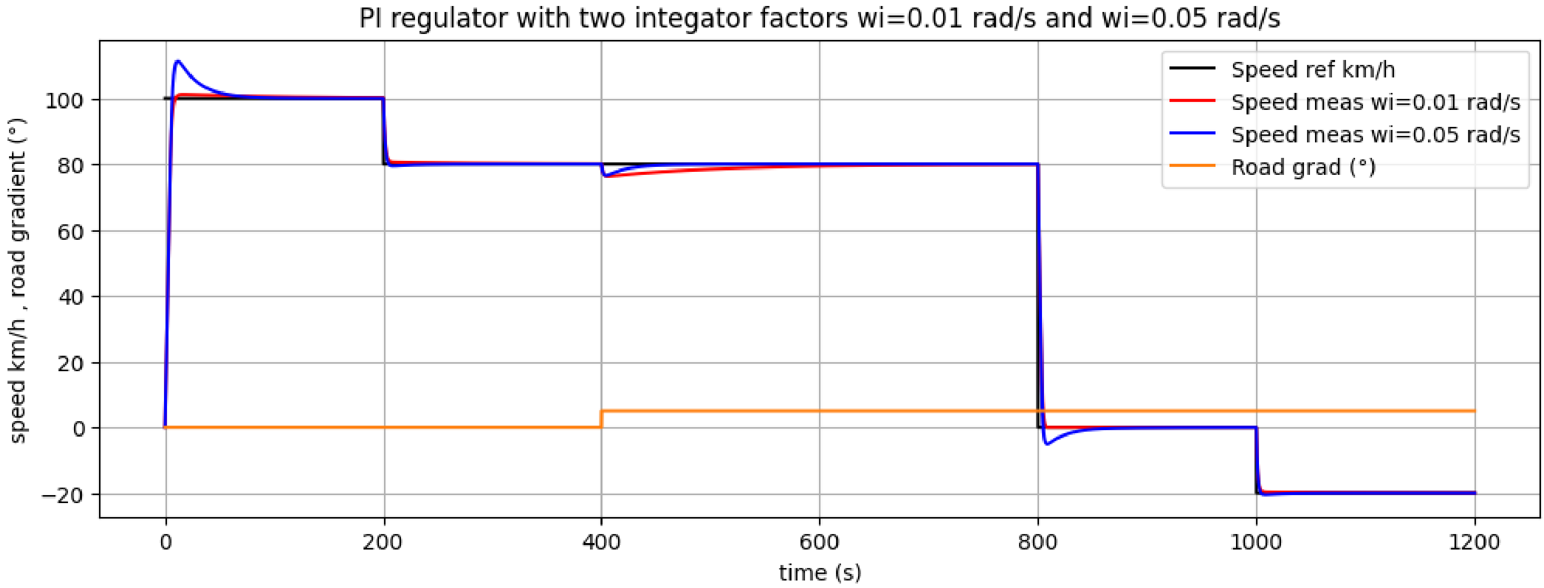
```
body_test_roadGrad=mat['body_test_roadGrad']
body_test_roadGrad=180*body_test_roadGrad[0][0][1][0][0][0].flatten()/np.pi

plt.plot(time,body_test_torque,label='torque Nm')
plt.plot(time,body_test_speedMeas,label='speed km/h')
plt.plot(time,10*body_test_roadGrad,label='road gradient x 10 (°)')

plt.ylabel('torque NM , speed km/h , road gradient x 10 (°)')
plt.xlabel('time (s)')
plt.title('Battery: voltage vs state of charge (soc)')
plt.grid()
plt.legend()
plt.show()
```



PI regulator, speed controller

In [225]:
```
# read matlab data for wi=0.01 rad/s
mat = scipy.io.loadmat('../matlabFiles/testSubSystems/pi_regulator_wi_0.01.mat')


# time
time  = mat['reg_kmph_ref'][0][0][0].flatten()

# road gradient
road_grad  = 180*mat['road_grad'][0][0][1][0][0][0].flatten()/np.pi

# Speed ref
reg_kmph_ref=mat['reg_kmph_ref'][0][0][1][0][0][0].flatten()

# speed measurement for wi=0.01 rad/s
reg_kmph_meas_w0_01=mat['reg_kmph_meas'][0][0][1][0][0][0].flatten()

# read matlab data for wi=0.01 rad/s
mat = scipy.io.loadmat('../matlabFiles/testSubSystems/pi_regulator_wi_0.05.mat')

# speed measurement for wi=0.05 rad/s
reg_kmph_meas_w0_05=mat['reg_kmph_meas'][0][0][1][0][0][0].flatten()

# the regulator output
reg_pi_output=mat['reg_pi_output'][0][0][1][0][0][0].flatten()

# Plot
figure(figsize=(12, 4))
plt.plot(time,reg_kmph_ref,label='Speed ref km/h',c='k')
plt.plot(time,reg_kmph_meas_w0_01,label='Speed meas wi=0.01 rad/s',c='r')
plt.plot(time,reg_kmph_meas_w0_05,label='Speed meas wi=0.05 rad/s',c='b')
plt.plot(time,road_grad,label='Road grad (°)',c='C1')
#plt.plot(time,20*reg_pi_output,label='regulator output',c='g')

plt.ylabel('speed km/h , road gradient (°)')
plt.xlabel('time (s)')
plt.title('PI regulator with two integator factors wi=0.01 rad/s and wi=0.05 rad/s')
```

```
plt.grid()
plt.legend()
plt.show()
```



We will conserve the integrator parameter wi=0.05 rad/s, because it give a best result in WLTC cycle.

in fact, in the real life we can use the soft start, we can use reference with a sloop and not a perfect step

Driving simulation WLTC / NEDC/ Heighway ...

In [226]:
```
# This dictionary will be used to store autonomy of each cycle/driving
dic_auto={}
```

WLTC Cycle

Read the matlab/simulink results

In [227]:
```
mat = scipy.io.loadmat('../matlabFiles/WLTC/WLTC_results.mat')
```

Select only variables that start with 'tws_...'

In [228]:
```
cols=[x for x in mat.keys() if 'tws_' in x]
```

Convert the selectionned variables to a dataFrame

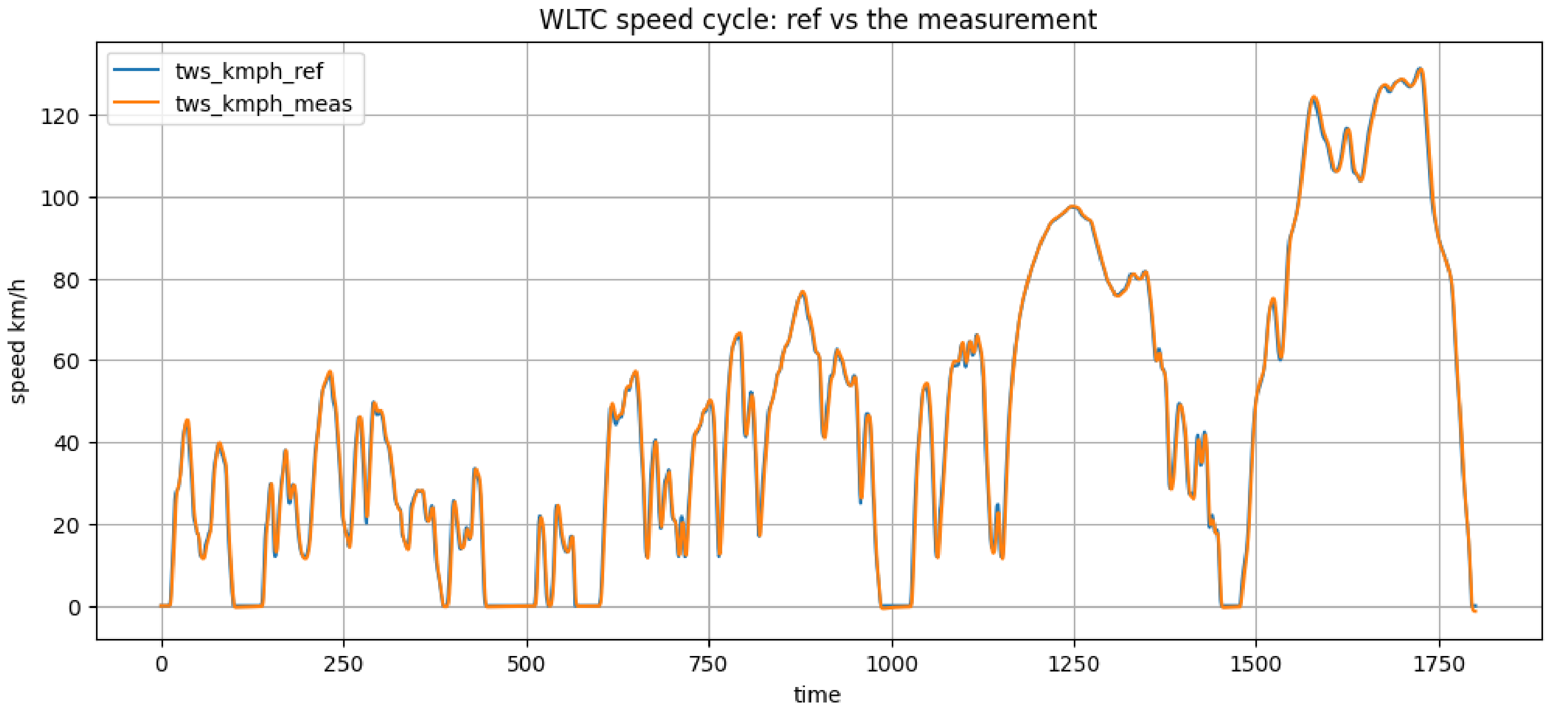
In [229]:
```
# Convert the selectionned variables to a dataFrame
c=cols[0]
# the time
time  = mat[c][0][0][0].flatten()
dfwltc=pd.DataFrame(time,columns=['time'])
# the other variables
for c in cols:
    value = mat[c][0][0][1][0][0][0].flatten()
    dfwltc[c]=value

# Display the head of the DF
dfwltc.head(2)
```

Out[229]:

	time	tws_I_bat_ev	tws_Power_AC_ev	tws_Power_DC_ev	tws_Power_meca_ev	tws_Power_wheel_ev	tws_Ubat_ev	tws_acceleration_breake	tws_a
0	0.0	0.0	0.0	0.0	0.0	0.0	403.2	0.0	
1	0.5	0.0	0.0	0.0	0.0	0.0	403.2	0.0	

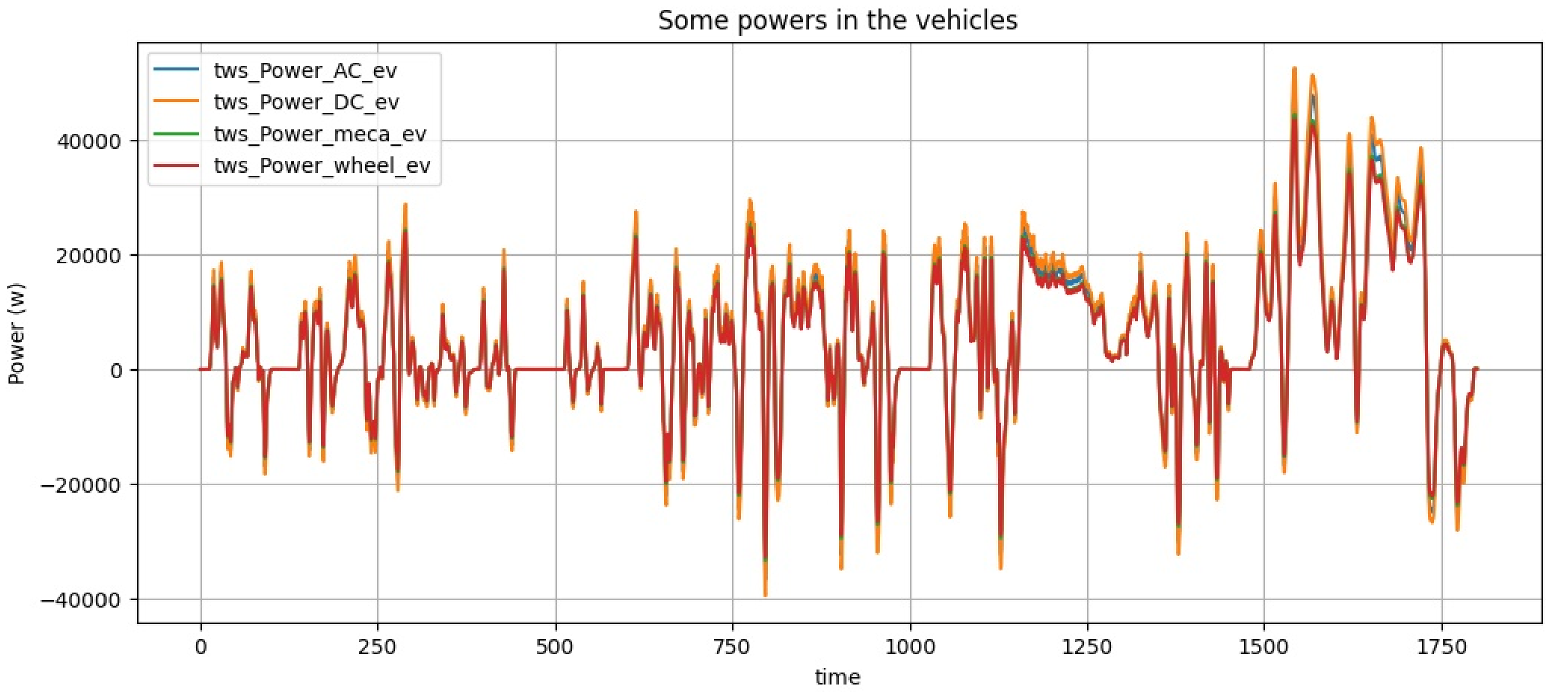
Plot the speed: ref and measurement

In [230]:
```
dfwltc.plot(x='time', y=['tws_kmph_ref','tws_kmph_meas'],figsize=(12, 5))
plt.grid()
plt.ylabel('speed km/h')
plt.title('WLTC speed cycle: ref vs the measurement')
plt.show()
```



Plot the different powers

```
In [231]:dfwltc.plot(x='time', y=['tws_Power_AC_ev', 'tws_Power_DC_ev',
            'tws_Power_meca_ev', 'tws_Power_wheel_ev'],figsize=(12, 5))
          plt.grid()
          plt.ylabel('Power (w)')
          plt.title('Some powers in the vehicles')
          plt.show()
```



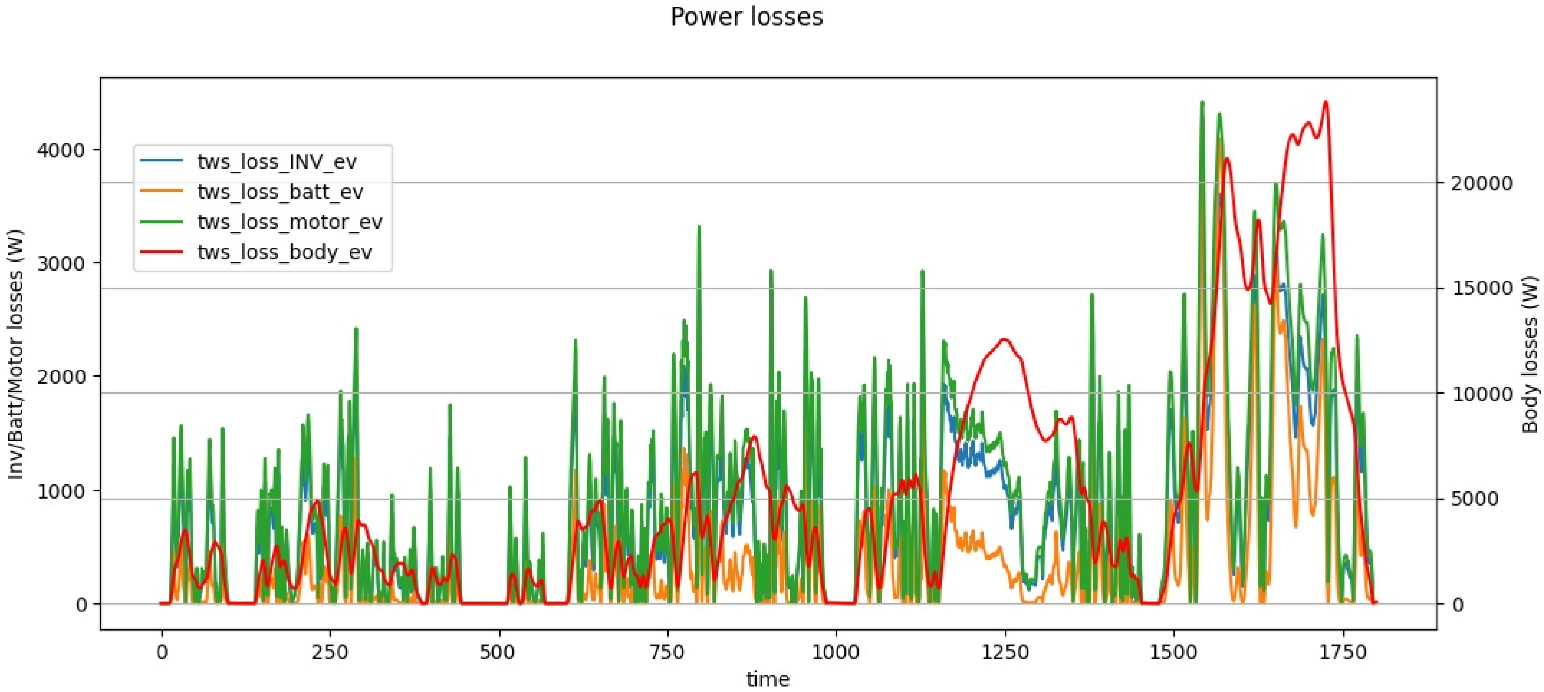
Change some errors in the nomination of the columns

```
In [232]:dfwltc.rename({'tws_battery_power': 'tws_battery_energy_j',
                'rmp_2_kmph':'rpm_2_kmph'},axis=1,inplace=True)
```

Plot the different losses

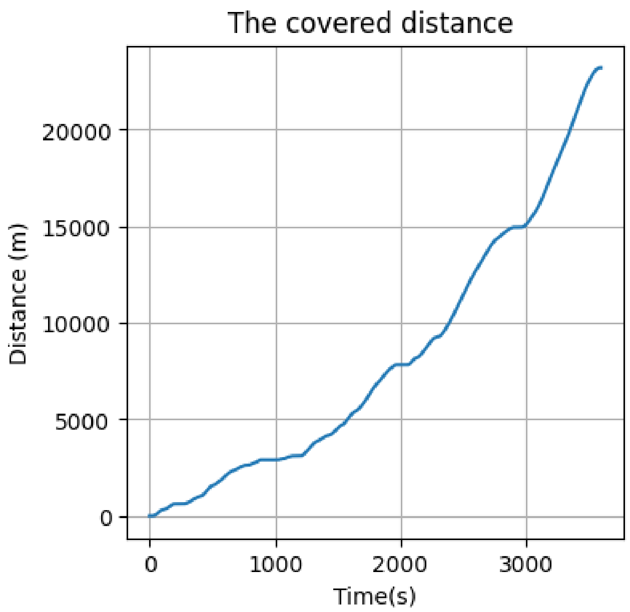
```
In [233]:# Create a new figure with two y-axes
          fig, ax1 = plt.subplots(figsize=(5,3))
          ax2 = ax1.twinx()


          # AX1
          dfwltc.plot(x='time', y=['tws_loss_INV_ev',
                      'tws_loss_batt_ev',
                      'tws_loss_motor_ev'],figsize=(12, 5),
                  ax=ax1)
          ax1.set_ylabel('Inv/Batt/Motor losses (W)')

          # AX2
          dfwltc.plot(x='time', y=['tws_loss_body_ev'],
                  ax=ax2,c='r')
```

```
ax2.set_ylabel('Body losses (W)')

# GENERAL SETTINGS
plt.suptitle('Power losses' )
ax1.legend().set_visible(False)
ax2.legend().set_visible(False)
fig.legend(loc='upper right', bbox_to_anchor=(0.3, 0.8))
plt.grid()
plt.show()
```



Plot the covered distance

```
In [234]:dfwltc[ 'tws_distance_ev'].plot(figsize=(4, 4))
         plt.grid()
         plt.ylabel('Distance (m)')
         plt.xlabel('Time(s)')
         plt.title('The covered distance ')
         plt.show()
```



The autonomy of this simulation

```
In [235]:delta_soc=dfwltc['tws_soc_ev'].iloc[0]-dfwltc['tws_soc_ev'].iloc[-1]
         delta_dist=dfwltc['tws_distance_ev'].iloc[-1]-dfwltc[ 'tws_distance_ev'].iloc[0]
         autonomy = 100*delta_dist/(delta_soc*1000)
         matlab_auto=mat['autonomy'].item()
         print('The autonomy of the WLTC cycle is: ','{:.2f}'.format(autonomy),'km')
         print('The autonomy calculated by matlab is: ',  '{:.2f}'.format(matlab_auto),'km')
```

```
The autonomy of the WLTC cycle is:  456.96 km
The autonomy calculated by matlab is:  456.99 km
```

```
In [236]:# Store the autonomy in the dic_auto dictionary
         dic_auto['wltc']=autonomy
```

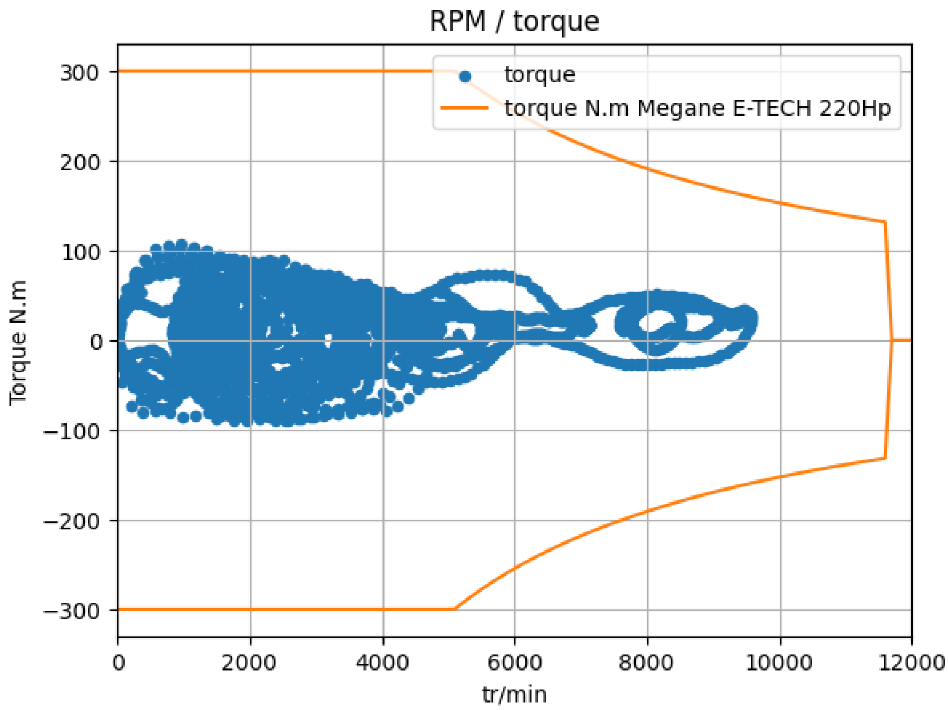
Calculate the RPM

In [237]:
```
rpm_2_kmph=mat['rmp_2_kmph'].item()
dfwltc['tws_rpm']=dfwltc['tws_kmph_meas']/rpm_2_kmph
```

Plot the RPM / torque

In [238]:
```
x=motor_speed_rpmPM.tolist()
xPM=x+x
yPM=motor_torquePM.tolist()+(-motor_torquePM).tolist()
```

In [239]:
```
dfwltc.plot(x='tws_rpm',y='tws_torque_motor_ev',kind='scatter',c='C0',label='torque')
plt.plot(motor_speed_rpmPM,motor_torquePM,label='torque N.m Megane E-TECH 220Hp',c='C1')
plt.plot(motor_speed_rpmPM,-motor_torquePM,c='C1')
plt.xlim([0,12000])
plt.grid()
plt.legend()
plt.xlabel('tr/min')
plt.ylabel('Torque N.m')
plt.title('RPM / torque')
plt.show()
```



In [240]:
```
dfwltc=dfwltc.astype('float32')
```

NEDC Cycle

Read the matlab/simulink results

In [241]:
```
mat = scipy.io.loadmat('../matlabFiles/NEDC/nedc.mat')
```

Select only variables that start with 'tws_...'

In [242]:
```
cols=[x for x in mat.keys() if 'tws_' in x]
```

Convert the selectionned variables to a dataFrame

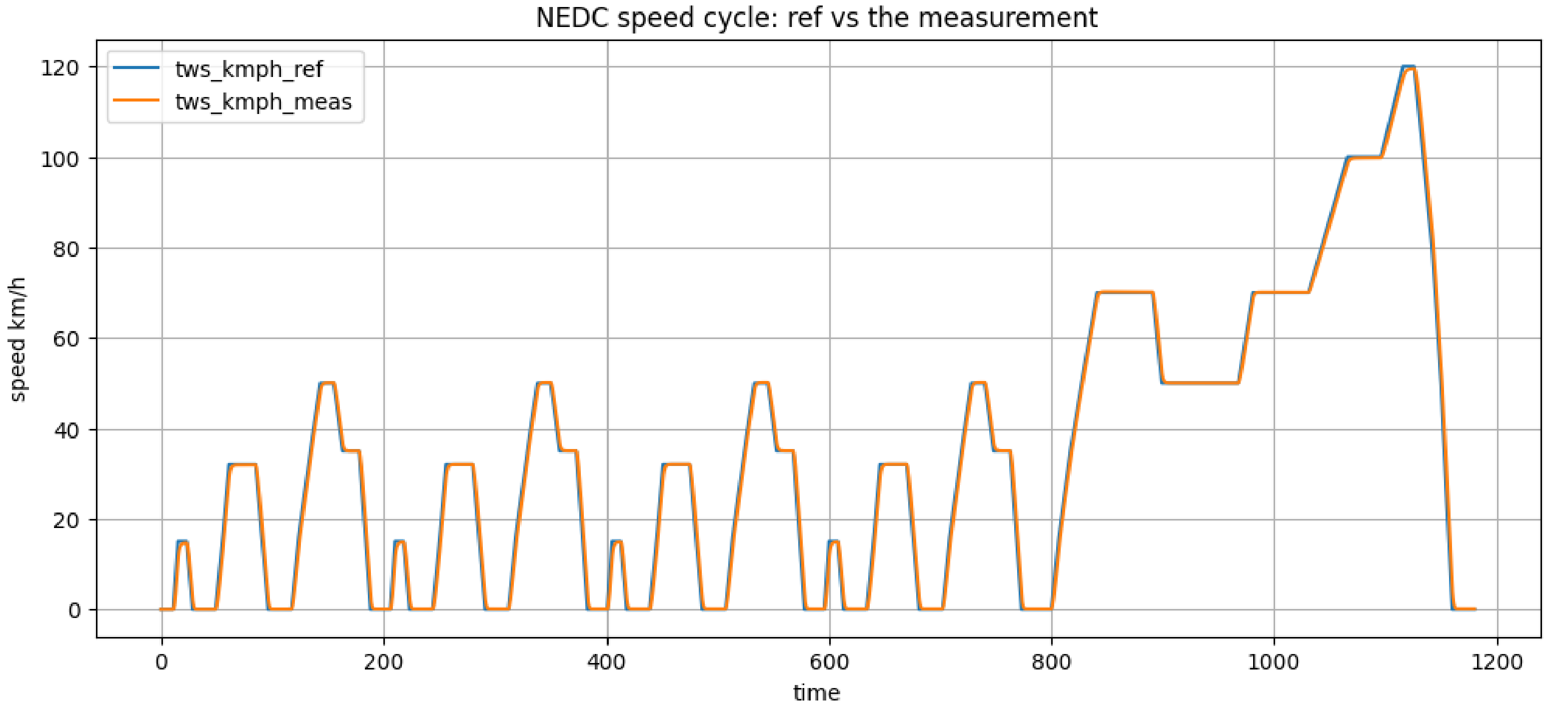
In [243]:
```
# Convert the selectionned variables to a dataFrame
c=cols[0]
# the time
time  = mat[c][0][0][0].flatten()
dfNEDC=pd.DataFrame(time,columns=['time'])
# the other variables
for c in cols:
    value = mat[c][0][0][1][0][0][0].flatten()
    dfNEDC[c]=value

# Display the head of the DF
dfNEDC.head(2)
```

Out[243]:

	time	tws_I_bat_ev	tws_Power_AC_ev	tws_Power_DC_ev	tws_Power_meca_ev	tws_Power_wheel_ev	tws_Ubat_ev	tws_acceleration_break	tws_a
0	0.0	0.0	0.0	0.0	0.0	0.0	403.2	0.0	
1	0.5	0.0	0.0	0.0	0.0	0.0	403.2	0.0	

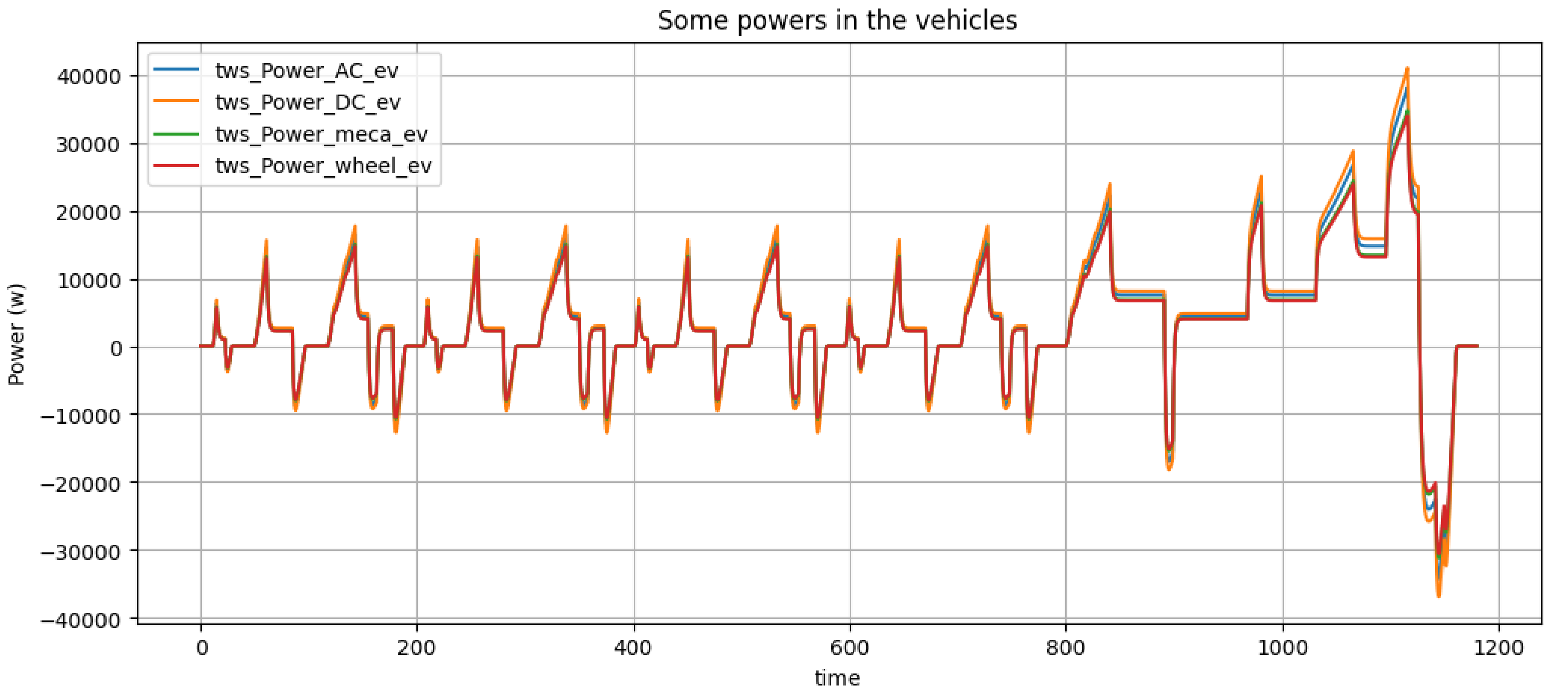
Plot the speed: ref and measurement

In [244]:
```
dfNEDC.plot(x='time', y=['tws_kmph_ref','tws_kmph_meas'],figsize=(12, 5))
plt.grid()
plt.ylabel('speed km/h')
plt.title('NEDC speed cycle: ref vs the measurement')
plt.show()
```



Plot the different powers

In [245]:
```
dfNEDC.plot(x='time', y=['tws_Power_AC_ev', 'tws_Power_DC_ev',
            'tws_Power_meca_ev', 'tws_Power_wheel_ev'],figsize=(12, 5))
plt.grid()
plt.ylabel('Power (w)')
plt.title('Some powers in the vehicles')
plt.show()
```



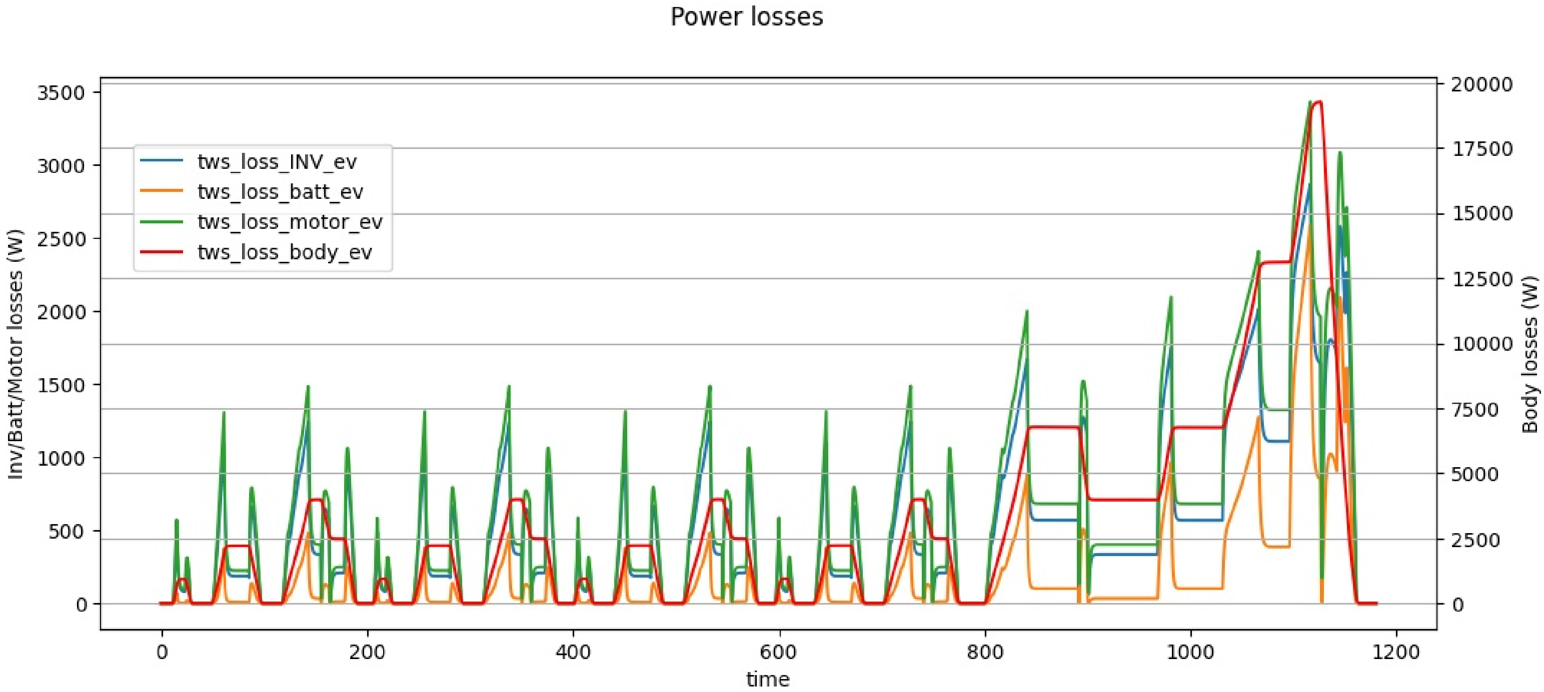
Change some errors in the nomination of the columns

In [246]:
```
dfNEDC.rename({'tws_battery_power': 'tws_battery_energy_j',
               'rmp_2_kmph':'rpm_2_kmph'},axis=1,inplace=True)
```

Plot the different losses

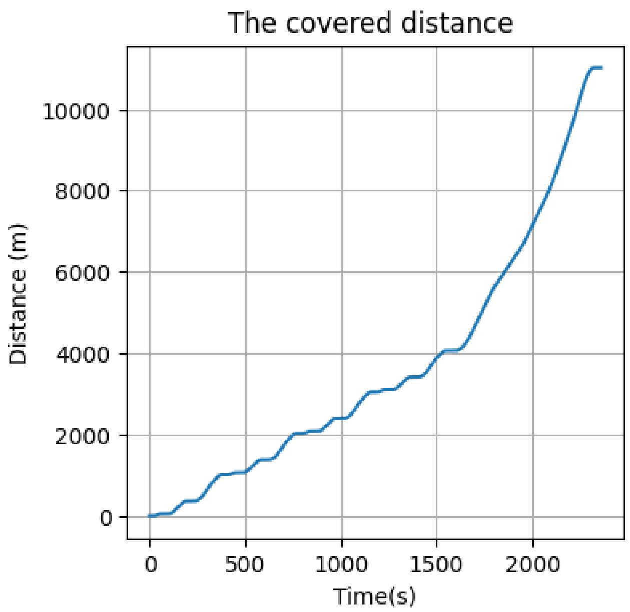
In [247]:
```
# Create a new figure with two y-axes
fig, ax1 = plt.subplots(figsize=(5,3))
ax2 = ax1.twinx()


# AX1
dfNEDC.plot(x='time', y=['tws_loss_INV_ev',
                'tws_loss_batt_ev',
                'tws_loss_motor_ev'],figsize=(12, 5),
       ax=ax1)
ax1.set_ylabel('Inv/Batt/Motor losses (W)')

# AX2
dfNEDC.plot(x='time', y=['tws_loss_body_ev'],
       ax=ax2,c='r')
```

```
ax2.set_ylabel('Body losses (W)')

# GENERAL SETTINGS
plt.suptitle('Power losses' )
ax1.legend().set_visible(False)
ax2.legend().set_visible(False)
fig.legend(loc='upper right', bbox_to_anchor=(0.3, 0.8))
plt.grid()
plt.show()
```



Plot the covered distance

In [248]:
```
dfNEDC[ 'tws_distance_ev'].plot(figsize=(4, 4))
plt.grid()
plt.ylabel('Distance (m)')
plt.xlabel('Time(s)')
plt.title('The covered distance ')
plt.show()
```



The autonomy of this simulation

In [249]:
```
delta_soc=dfNEDC['tws_soc_ev'].iloc[0]-dfNEDC['tws_soc_ev'].iloc[-1]
delta_dist=dfNEDC['tws_distance_ev'].iloc[-1]-dfNEDC[ 'tws_distance_ev'].iloc[0]
autonomy = 100*delta_dist/(delta_soc*1000)
matlab_auto=mat['autonomy'].item()
print('The autonomy of the NEDC cycle is: ','{:.2f}'.format(autonomy),'km')
print('The autonomy calculated by matlab is: ',  '{:.2f}'.format(matlab_auto),'km')
```

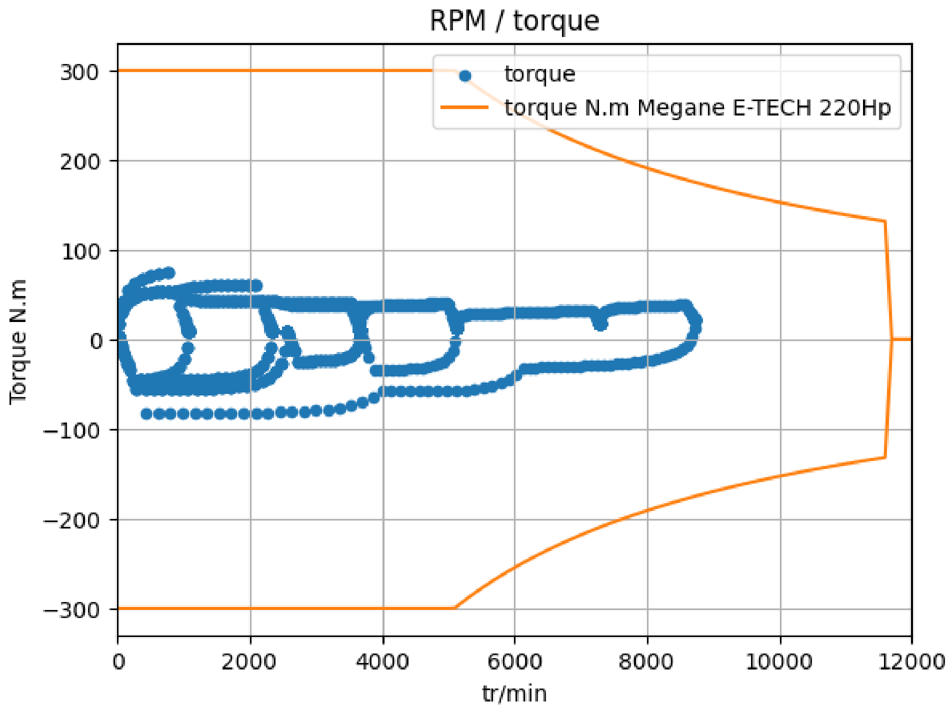
The autonomy of the NEDC cycle is: 525.38 km
The autonomy calculated by matlab is: 525.38 km

In [250]:
```
# Store the autonomy in the dic_auto dictionary
dic_auto['nedc']=autonomy
```

Calculate the RPM

In [251]:rpm_2_kmph=mat['rmp_2_kmph'].item()
```
dfNEDC['tws_rpm']=dfNEDC['tws_kmph_meas']/rpm_2_kmph
```
Plot the RPM / torque

In [252]:
```
dfNEDC.plot(x='tws_rpm',y='tws_torque_motor_ev',kind='scatter',c='C0',label='torque')
plt.plot(motor_speed_rpmPM,motor_torquePM,label='torque N.m Megane E-TECH 220Hp',c='C1')
plt.plot(motor_speed_rpmPM,-motor_torquePM,c='C1')
plt.xlim([0,12000])
plt.grid()
plt.xlabel('tr/min')
plt.ylabel('Torque N.m')
plt.title('RPM / torque')
plt.legend()
plt.show()
```



In [253]:dfNEDC=dfNEDC.astype('float32')

Paris heigh way A5 225km

Read the matlab/simulink results

In [263]:mat = scipy.io.loadmat('../matlabFiles/ParisA5_225km/parisA5_results.mat')

Select only variables that start with 'tws_...'

In [264]:cols=[x for x in mat.keys() if 'tws_' in x]

Convert the selectionned variables to a dataFrame

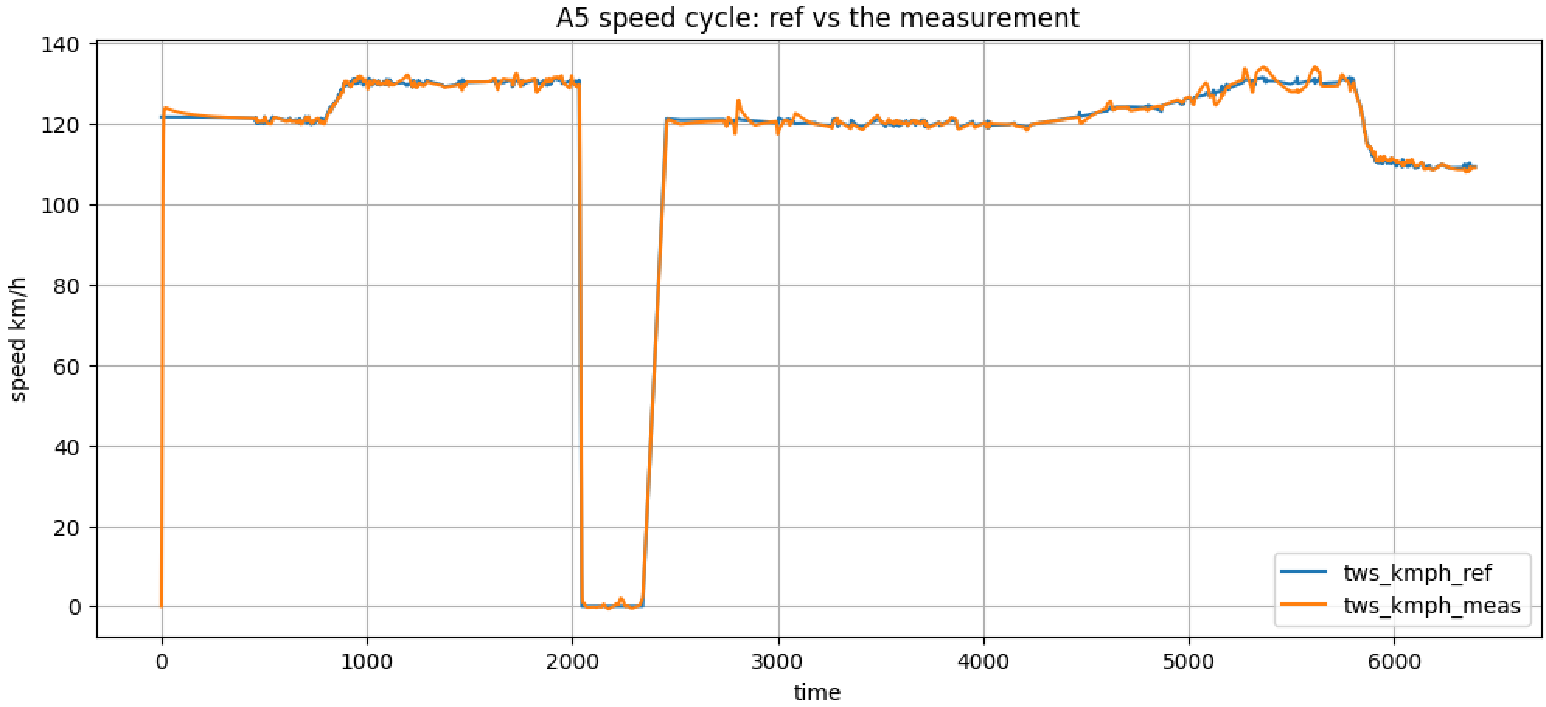
In [265]:
```
# Convert the selectionned variables to a dataFrame
c=cols[0]
# the time
time  = mat[c][0][0][0].flatten()
dfA5=pd.DataFrame(time,columns=['time'])
# the other variables
for c in cols:
    value = mat[c][0][0][1][0][0][0].flatten()
    dfA5[c]=value

# Display the head of the DF
dfA5.head(2)
```

Out[265]:

	time	tws_I_bat_ev	tws_Power_AC_ev	tws_Power_DC_ev	tws_Power_meca_ev	tws_Power_wheel_ev	tws_Ubat_ev	tws_acceleration_break	tws_a
0	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	403.200000	1.0	
1	0.5	54.717315	20517.648701	22061.987851	18671.060318	18297.639112	403.199385	1.0	

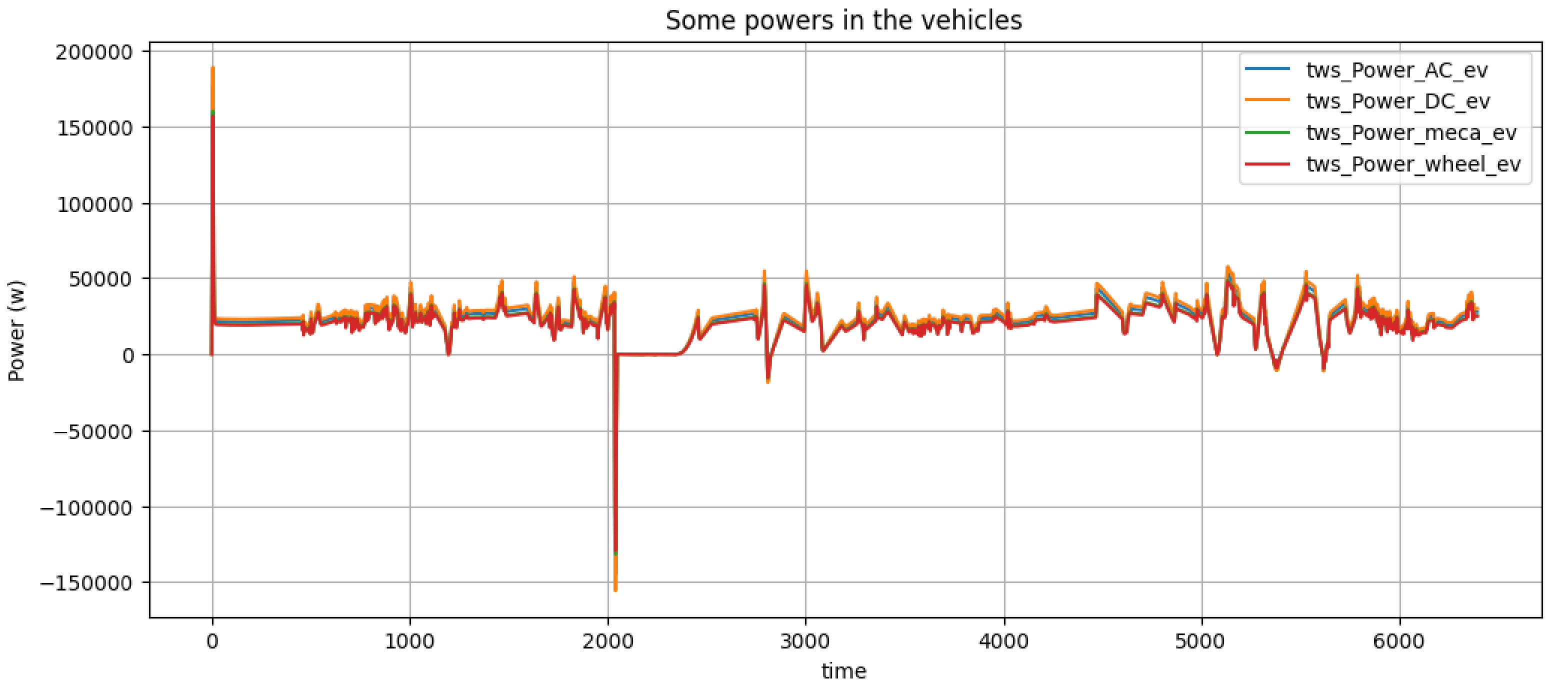
Plot the speed: ref and measurement

In [266]:
```
dfA5.plot(x='time', y=['tws_kmph_ref','tws_kmph_meas'],figsize=(12, 5))
plt.grid()
plt.ylabel('speed km/h')
plt.title('A5 speed cycle: ref vs the measurement')
plt.show()
```



Plot the different powers

```
In [267]:dfA5.plot(x='time', y=['tws_Power_AC_ev', 'tws_Power_DC_ev',
            'tws_Power_meca_ev', 'tws_Power_wheel_ev'],figsize=(12, 5))
        plt.grid()
        plt.ylabel('Power (w)')
        plt.title('Some powers in the vehicles')
        plt.show()
```



Change some errors in the nomination of the columns

```
In [268]:dfA5.rename({'tws_battery_power': 'tws_battery_energy_j',
                'rmp_2_kmph':'rpm_2_kmph'},axis=1,inplace=True)
```

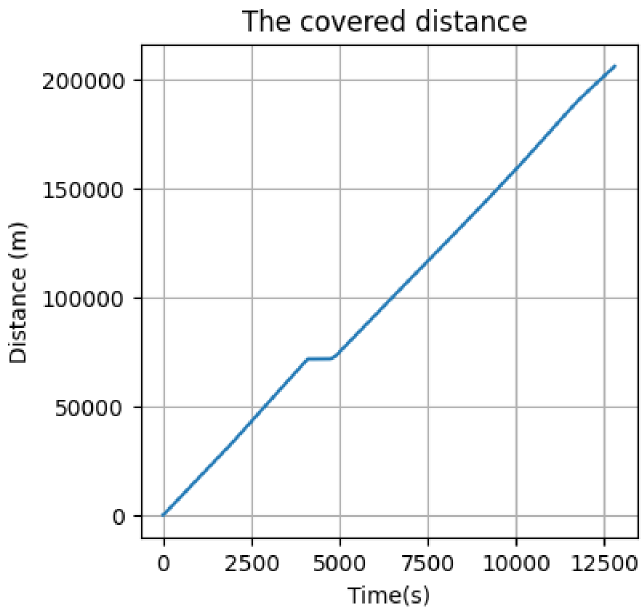
Plot the different losses

```
In [269]:# Create a new figure with two y-axes
        fig, ax1 = plt.subplots(figsize=(5,3))
        ax2 = ax1.twinx()


        # AX1
        dfA5.plot(x='time', y=['tws_loss_INV_ev',
                    'tws_loss_batt_ev',
                    'tws_loss_motor_ev'],figsize=(12, 5),
              ax=ax1)
        ax1.set_ylabel('Inv/Batt/Motor losses (W)')

        # AX2
        dfA5.plot(x='time', y=['tws_loss_body_ev'],
              ax=ax2,c='r')
```

```
ax2.set_ylabel('Body losses (W)')

# GENERAL SETTINGS
plt.suptitle('Power losses' )
ax1.legend().set_visible(False)
ax2.legend().set_visible(False)
fig.legend(loc='upper right', bbox_to_anchor=(0.3, 0.8))
plt.grid()
plt.show()
```

Plot the covered distance

In [270]:
```
dfA5[ 'tws_distance_ev'].plot(figsize=(4, 4))
plt.grid()
plt.ylabel('Distance (m)')
plt.xlabel('Time(s)')
plt.title('The covered distance ')
plt.show()
```



The autonomy of this simulation

In [271]:
```
delta_soc=dfA5['tws_soc_ev'].iloc[0]-dfA5['tws_soc_ev'].iloc[-1]
delta_dist=dfA5['tws_distance_ev'].iloc[-1]-dfA5[ 'tws_distance_ev'].iloc[0]
autonomy = 100*delta_dist/(delta_soc*1000)
matlab_auto=mat['autonomy'].item()
print('The autonomy of the A5 cycle is: ','{:.2f}'.format(autonomy),'km')
print('The autonomy calculated by matlab is: ',  '{:.2f}'.format(matlab_auto),'km')
```

The autonomy of the A5 cycle is: 287.56 km
The autonomy calculated by matlab is: 287.56 km

In [272]:
```
# Store the autonomy in the dic_auto dictionary
dic_auto['highway']=autonomy
```

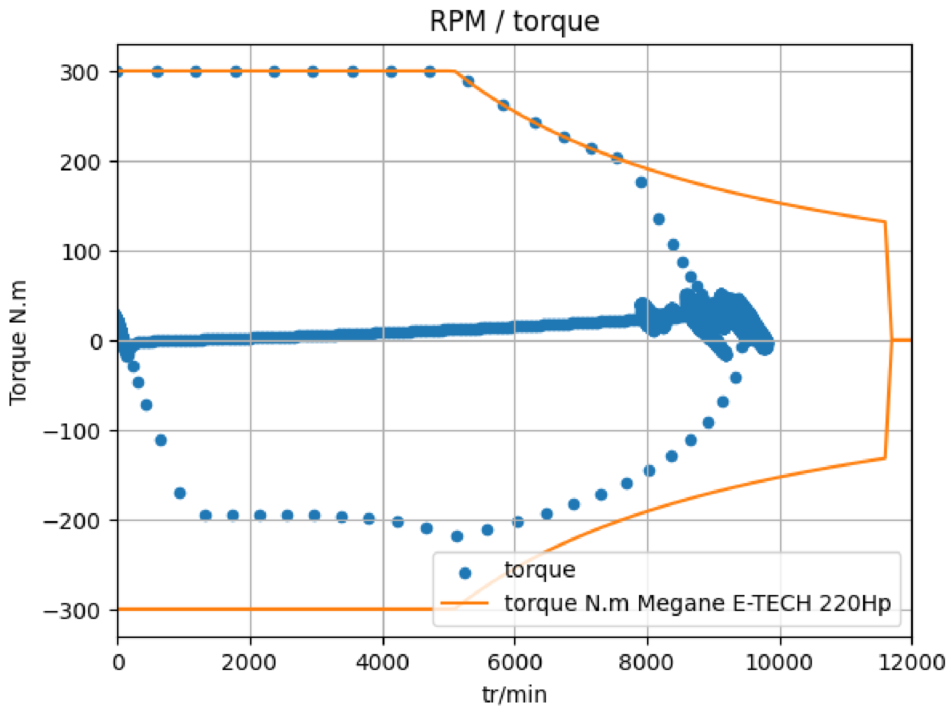
Calculate the RPM

In [273]:
```
rpm_2_kmph=mat['rmp_2_kmph'].item()
```

```
dfA5['tws_rpm']=dfA5['tws_kmph_meas']/rpm_2_kmph
```

Plot the RPM / torque

In [274]:
```
dfA5.plot(x='tws_rpm',y='tws_torque_motor_ev',kind='scatter',c='C0',label='torque')
plt.plot(motor_speed_rpmPM,motor_torquePM,label='torque N.m Megane E-TECH 220Hp',c='C1')
plt.plot(motor_speed_rpmPM,-motor_torquePM,c='C1')
plt.legend()
plt.xlim([0,12000])
plt.grid()
plt.xlabel('tr/min')
plt.ylabel('Torque N.m')
plt.title('RPM / torque')
plt.show()
```



In [275]:
```
dfA5=dfA5.astype('float32')
```

The impact of speed on autonomy

Read the matlab/simulink results

In [276]:
```
mat = scipy.io.loadmat('../matlabFiles/speed_autonomy/speed_auto_results.mat')
```

Select only variables that start with 'tws_...'

In [277]:
```
cols=[x for x in mat.keys() if 'tws_' in x]
```

Convert the selectionned variables to a dataFrame

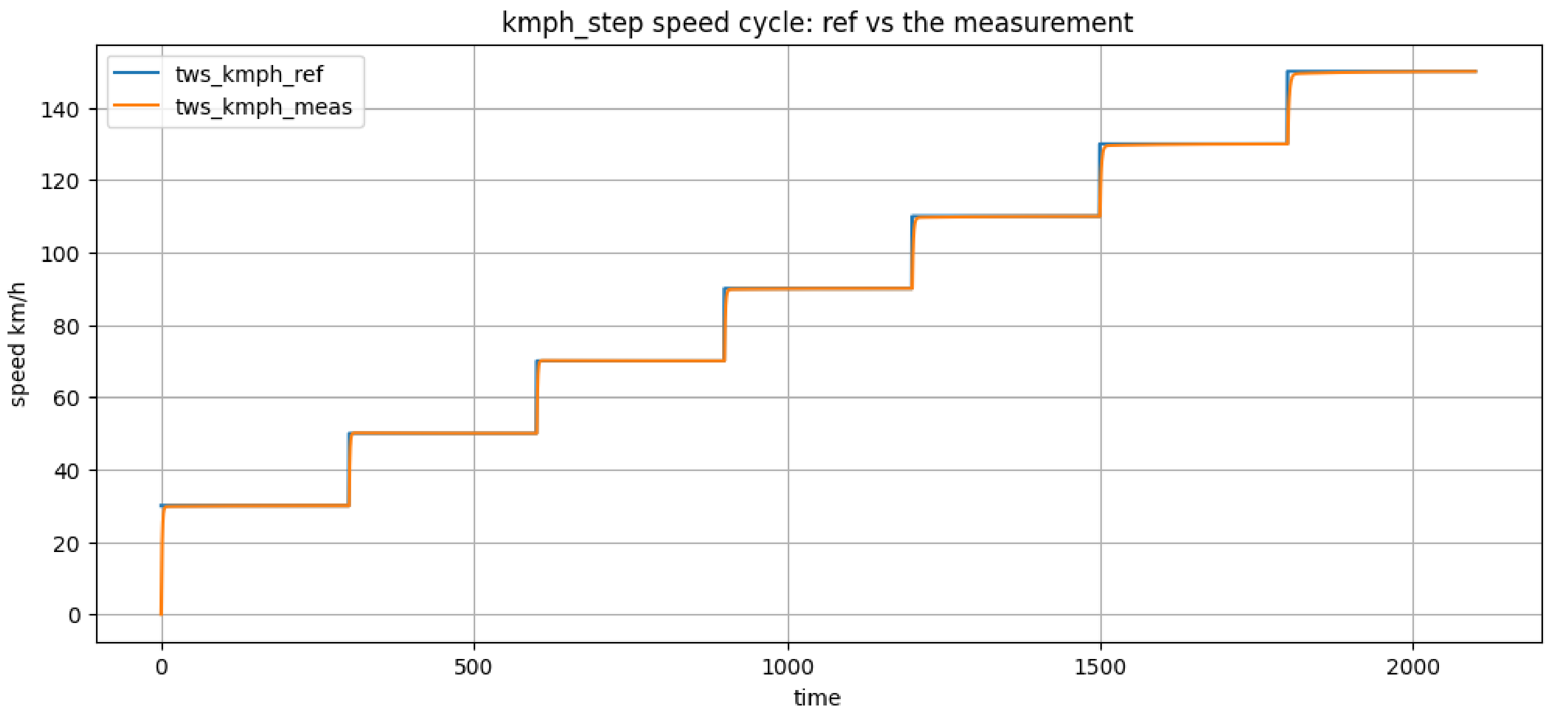
In [278]:
```
# Convert the selectionned variables to a dataFrame
c=cols[0]
# the time
time  = mat[c][0][0][0].flatten()
dfkmph_step=pd.DataFrame(time,columns=['time'])
# the other variables
for c in cols:
    value = mat[c][0][0][1][0][0][0].flatten()
    dfkmph_step[c]=value

# Display the head of the DF
dfkmph_step.head(2)
```

Out[278]:

	time	tws_I_bat_ev	tws_Power_AC_ev	tws_Power_DC_ev	tws_Power_meca_ev	tws_Power_wheel_ev	tws_Ubat_ev	tws_acceleration_break	tws_a
0	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	403.200000	1.0	
1	0.5	54.486782	20431.204693	21969.037305	18592.396271	18220.548345	403.199388	1.0	

Plot the speed: ref and measurement

In [279]:
```
dfkmph_step.plot(x='time', y=['tws_kmph_ref','tws_kmph_meas'],figsize=(12, 5))
plt.grid()
plt.ylabel('speed km/h')
plt.title('kmph_step speed cycle: ref vs the measurement')
plt.show()
```

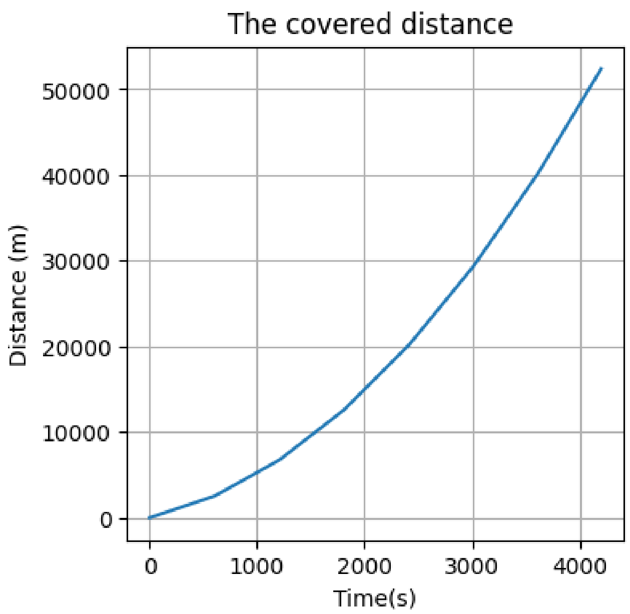


Change some errors in the nomination of the columns

```
In [280]:dfkmph_step.rename({'tws_battery_power': 'tws_battery_energy_j',
                    'rmp_2_kmph':'rpm_2_kmph'},axis=1,inplace=True)
```

Plot the covered distance

```
In [281]:dfkmph_step[ 'tws_distance_ev'].plot(figsize=(4, 4))
         plt.grid()
         plt.ylabel('Distance (m)')
         plt.xlabel('Time(s)')
         plt.title('The covered distance ')
         plt.show()
```

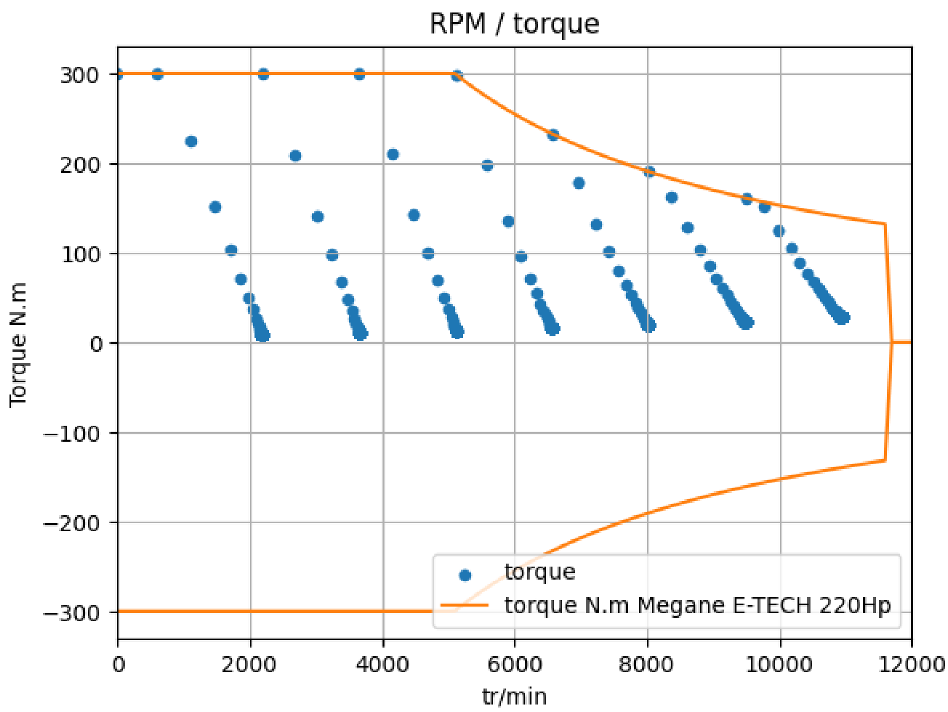


Calculate the RPM

```
In [282]:rpm_2_kmph=mat['rmp_2_kmph'].item()
         dfkmph_step['tws_rpm']=dfkmph_step['tws_kmph_meas']/rpm_2_kmph
```

Plot the RPM / torque

```
In [283]:dfkmph_step.plot(x='tws_rpm',y='tws_torque_motor_ev',kind='scatter',c='C0',label='torque')
         plt.plot(motor_speed_rpmPM,motor_torquePM,label='torque N.m Megane E-TECH 220Hp',c='C1')
         plt.plot(motor_speed_rpmPM,-motor_torquePM,c='C1')
         plt.legend()
         plt.xlim([0,12000])
         plt.grid()
         plt.xlabel('tr/min')
         plt.ylabel('Torque N.m')
         plt.title('RPM / torque')
         plt.show()
```



Calculate autonomy by speed

In [284]:
```
# - speed_step: Step size for speed calculations
speed_step=mat['speed_step'][0][0]
# - sim_time: Total simulation time
sim_time=mat['sim_time'][0][0]
# - Ts: Time step
Ts=mat['Ts'][0][0]
# - n_step: Number of simulation steps
n_step=int(sim_time/(speed_step*Ts))
# - i: Index for iteration
i=int(0.98*speed_step/Ts)
# - di: Index for delta calculations
di=int(0.5*speed_step/Ts)

speed_step, sim_time,Ts, n_step,i,di
auto_list = []

# List to store results
while i < sim_time / Ts:
    # Calculate change in state of charge (delta_soc)
    delta_soc = dfkmph_step.loc[i - di : i, 'tws_soc_ev']
    delta_soc = delta_soc.iloc[0] - delta_soc.iloc[-1]

    # Calculate change in distance (delta_dist)
    delta_dist = dfkmph_step.loc[i - di : i, 'tws_distance_ev']
    delta_dist = delta_dist.iloc[-1] - delta_dist.iloc[0]

    # Calculate autonomy (distance covered per unit SOC)
    autonomy = 100 * delta_dist / (delta_soc * 1000)

    # Calculate average speed (kmph)
    kmph = dfkmph_step.loc[i - di : i, 'tws_kmph_meas'].mean()

    # Append results to the auto_list
    auto_list.append({"kmph": kmph, "autonomy": autonomy})
    i += int(speed_step / Ts)
```

In [285]:
```
dfauto=pd.DataFrame(auto_list)#.plot.bar(x='kmph',y='autonomy')
dfauto.kmph= (dfauto.kmph+0.5).astype(int)
dfauto
```

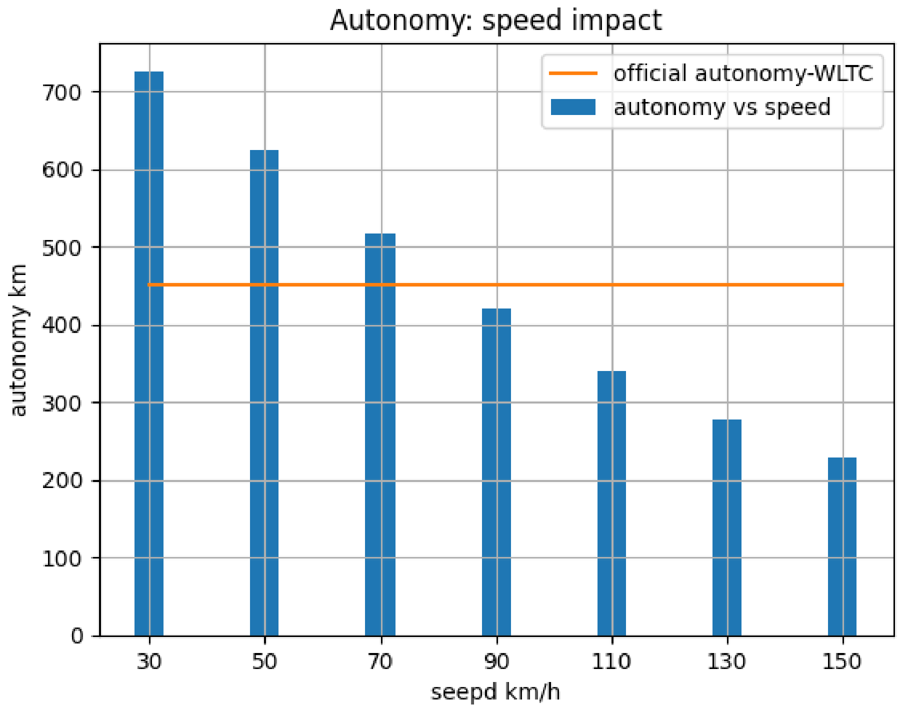
Out[285]:

	kmph	autonomy
0	30	725.536021
1	50	624.870433
2	70	516.899120
3	90	420.116752
4	110	340.486424
5	130	277.409475
6	150	228.123454

In [286]:
```
for i in range(len(dfauto)):
    kmph=dfauto.loc[i,'kmph']
    autonomy=dfauto.loc[i,'autonomy']
    dic_auto[str(kmph)+'km/h']=autonomy
```

Plot the autonomy vs speed

In [287]:
```
plt.bar(dfauto.kmph,dfauto.autonomy,width=5,label='autonomy vs speed')
# AUTO 450 # https://cdn.group.renault.com/ren/fr/product-plans/brochures/megane-e-tech-electrique/brochure-megane-electrique.pdf.asset.pdf/6614
plt.plot([30,150],[450,450],c='C1',label='official autonomy-WLTC')

plt.xticks(range(30,160,20))
plt.legend()
plt.grid()
plt.ylabel('autonomy km')
plt.xlabel('seepd km/h')
plt.title('Autonomy: speed impact')
plt.show()

plt.show()
```

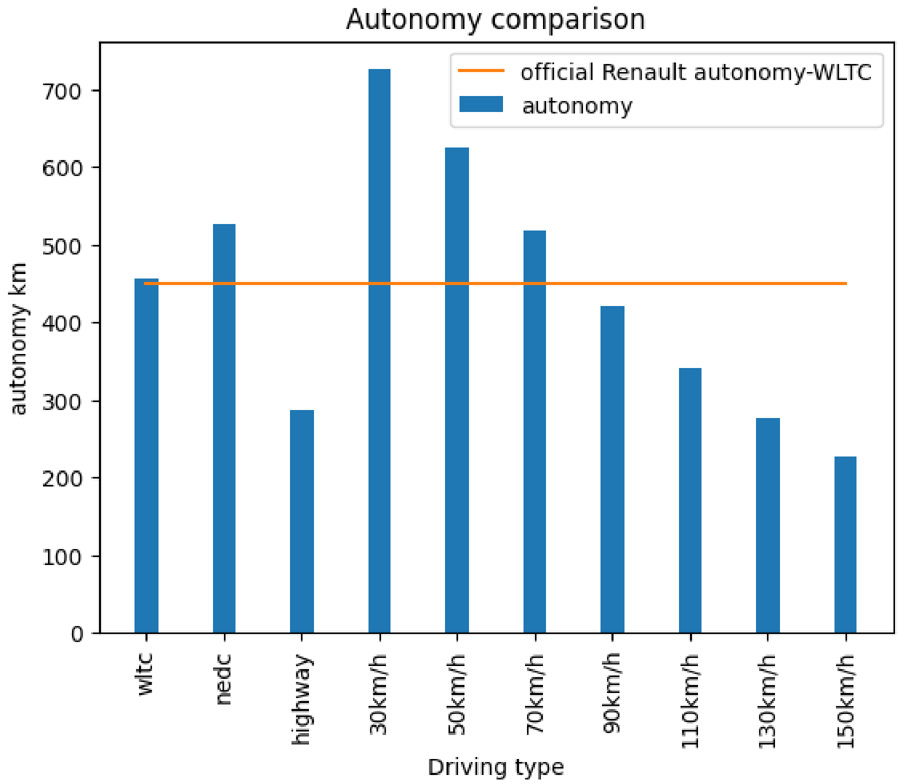


In [288]:
```
dfkmph_step=dfkmph_step.astype('float32')
```

Comparaison

In [289]:
```
# Dcitonary to dataFrame
dic_auto_s=pd.Series(dic_auto)
```

In [290]:
```
# Bar plot

plt.bar(dic_auto_s.index,dic_auto_s.values,width=0.3,label='autonomy')

# AUTO 450 # https://cdn.group.renault.com/ren/fr/product-plans/brochures/megane-e-tech-electrique/brochure-megane-electrique.pdf.asset.pdf/6614
n=len(dic_auto_s.index)
plt.plot([450]*n,c='C1',label='official Renault autonomy-WLTC')

plt.xticks(dic_auto_s.index)
plt.legend()
#plt.grid()
plt.ylabel('autonomy km')
plt.xlabel('Driving type')
plt.title('Autonomy comparison')
plt.xticks(rotation=90)
plt.show()
```



We can see that the autonomy depend a lot of the speed of the vehicle, in general a high speed reduce the autonomy of an electric car.

This can be explained by the fact of the cubic relation between the drag loss and car speed.
In general, an electrical car is good for the city uses, but not in the highway uses

Save the data

drop the duplicated columns

In [291]:
```
listdf=[dfwltc, dfNEDC, dfA5 ,dfkmph_step]

for df in listdf:
    #the time column is duplicated: 'time' and 'tws_time'
    df.drop('time',axis=1,inplace=True)
```

Rename columns

In [292]:
```
dfwltc.columns
```

Out[292]:
```
Index(['tws_I_bat_ev', 'tws_Power_AC_ev', 'tws_Power_DC_ev',
       'tws_Power_meca_ev', 'tws_Power_wheel_ev', 'tws_Ubat_ev',
       'tws_acceleration_break', 'tws_acceleration_ev', 'tws_battery_energy_j',
       'tws_distance_ev', 'tws_kmph_meas', 'tws_kmph_ref', 'tws_loss_INV_ev',
       'tws_loss_batt_ev', 'tws_loss_body_ev', 'tws_loss_motor_ev',
       'tws_road_grad', 'tws_soc_ev', 'tws_time', 'tws_torque_motor_ev',
       'tws_rpm'],
      dtype='object')
```

In [293]:
```
cols=dfwltc.columns
newcols=[x.replace('tws_','') for x in cols]
dic_cols={x:y for (x,y) in zip(cols, newcols)}
print(dic_cols)
```

```
{'tws_I_bat_ev': 'I_bat_ev', 'tws_Power_AC_ev': 'Power_AC_ev', 'tws_Power_DC_ev': 'Power_DC_ev', 'tws_Power_meca_ev': 'Power_meca_ev', 'tws_Power_wheel_ev': 'Power_wheel_ev', 'tws_Ubat_ev': 'Ubat_ev', 'tws_acceleration_break': 'acceleration_break', 'tws_acceleration_ev': 'acceleration_ev', 'tws_battery_energy_j': 'battery_energy_j', 'tws_distance_ev': 'distance_ev', 'tws_kmph_meas': 'kmph_meas', 'tws_kmph_ref': 'kmph_ref', 'tws_loss_INV_ev': 'loss_INV_ev', 'tws_loss_batt_ev': 'loss_batt_ev', 'tws_loss_body_ev': 'loss_body_ev', 'tws_loss_motor_ev': 'loss_motor_ev', 'tws_road_grad': 'road_grad', 'tws_soc_ev': 'soc_ev', 'tws_time': 'time', 'tws_torque_motor_ev': 'torque_motor_ev', 'tws_rpm': 'rpm'}
```

In [294]:
```
for df in listdf:
    df.rename(dic_cols,axis=1,inplace=True)
```

In [295]:
```
dfwltc.columns
```

Out[295]:
```
Index(['I_bat_ev', 'Power_AC_ev', 'Power_DC_ev', 'Power_meca_ev',
       'Power_wheel_ev', 'Ubat_ev', 'acceleration_break', 'acceleration_ev',
       'battery_energy_j', 'distance_ev', 'kmph_meas', 'kmph_ref',
       'loss_INV_ev', 'loss_batt_ev', 'loss_body_ev', 'loss_motor_ev',
       'road_grad', 'soc_ev', 'time', 'torque_motor_ev', 'rpm'],
      dtype='object')
```

add session ID

In [296]:
```
sessions=['WLTC', 'NEDC','Highway' ,'speed_steps']
for (df,s) in zip(listdf,sessions):
    df['session']=s
```

Concatenate the 4 dataFrame

In [297]:
```
df=pd.concat(listdf,axis=0).reset_index(drop=True)
df.head(2)
```

Out[297]:

	I_bat_ev	Power_AC_ev	Power_DC_ev	Power_meca_ev	Power_wheel_ev	Ubat_ev	acceleration_break	acceleration_ev	battery_energy_j	dista
0	0.0	0.0	0.0	0.0	0.0	403.200012	0.0	0.0	216000000.0	
1	0.0	0.0	0.0	0.0	0.0	403.200012	0.0	0.0	216000000.0	

In [298]:
```
df.shape
```

Out[298]:(22954, 23)

Correct the battery energy

In [299]:
```
df.drop(['tws_battery_energy', 'battery_energy_j'],axis=1,inplace=True)
```

In [300]:
```
bat_energy_kwh=mat['bat_energy_kwh'].item()
df['bat_energy_kwh']=df.soc_ev*bat_energy_kwh/100
```

Verifay the dataFrame

In [301]:
```
df.isna().sum()
```

Out[301]:
```
I_bat_ev              0
Power_AC_ev           0
Power_DC_ev           0
Power_meca_ev         0
Power_wheel_ev        0
Ubat_ev               0
acceleration_break    0
acceleration_ev       0
distance_ev           0
kmph_meas             0
kmph_ref              0
loss_INV_ev           0
loss_batt_ev          0
loss_body_ev          0
loss_motor_ev         0
road_grad             0
soc_ev                0
time                  0
torque_motor_ev       0
rpm                   0
session               0
bat_energy_kwh        0
dtype: int64
```

In [302]:
```
df.shape
```

Out[302]:(22954, 22)

In [303]:
```
df.columns
```

Out[303]:
```
Index(['I_bat_ev', 'Power_AC_ev', 'Power_DC_ev', 'Power_meca_ev',
       'Power_wheel_ev', 'Ubat_ev', 'acceleration_break', 'acceleration_ev',
       'distance_ev', 'kmph_meas', 'kmph_ref', 'loss_INV_ev', 'loss_batt_ev',
       'loss_body_ev', 'loss_motor_ev', 'road_grad', 'soc_ev', 'time',
       'torque_motor_ev', 'rpm', 'session', 'bat_energy_kwh'],
      dtype='object')
```

Save the dataFrame

In [304]:
```
df.to_csv('../data/output/MEGANE_E_TECH_EV60_220_driv_data.csv',index=False)
```

Download dataset

Download the dataset asDirectly by pandas csv reading as a csv file from the link

Directly by pandas csv reading as

In [308]:
```
# read raw data
url='https://raw.githubusercontent.com/bouz1/EV_Matlab_Simulink_Megane_E_TECH_to_generate_data/main/data/output/MEGANE_E_TECH_EV6(
df_read=pd.read_csv(url)
# display the head
df_read.head(2)
```

Out[308]:

	I_bat_ev	Power_AC_ev	Power_DC_ev	Power_meca_ev	Power_wheel_ev	Ubat_ev	acceleration_break	acceleration_ev	distance_ev	kmph_meas
0	0.0	0.0	0.0	0.0	0.0	403.2	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	403.2	0.0	0.0	0.0	0.0

From kaggle

See the below link

https://www.kaggle.com/datasets/bozzabb/ev-matlabsimulink-megane-e-tech-time-series-data/data

Dataset exploration

Columns description

- I_bat_ev : The HV battery current [A]
- Power_AC_ev : The AC power, transferred from the inverter to the motor [W]
- Power_DC_ev : The DC power, transferred from the battery to the inverter [W]
- Power_meca_ev : The mechanical power, the output of the motor [W]
- Power_wheel_ev : The mechanical power, in the output of the motor reductor [W]
- Ubat_ev : The battery DC voltage [V]
- acceleration_break : The acceleration/break command, range [-1,1], [-1,0] : break, [0,1] : acceleration
- acceleration_ev : The acceleration the EV [m/s2]
- distance_ev : The distance of the EV [m]
- kmph_meas : The speed of the EV [km/h]
- kmph_ref : The speed reference of the EV [km/h]
- loss_INV_ev : The power loss of the inverter [W]
- loss_batt_ev : The power loss of the battery [W]
- loss_body_ev : The power loss of the vehicle body (drag, rolling, ...) [W]
- loss_motor_ev : The power loss of the motor [W]
- road_grad : The road gradient [°]
- soc_ev : The battery state of charge (soc) [%]
- time : The time [s]
- torque_motor_ev : The motor torque [N.m]
- rpm : The motor speed [tr/min]
- session : The simulation session, NEDC cyle, WLTC cyle, Highway driving, the step speed driving
- bat_energy_kwh : the battery energy [kWh]

The dataset description: min / max / mean ...

In [310]:df_read.describe([0.05,0.5,0.95])

Out[310]:

	I_bat_ev	Power_AC_ev	Power_DC_ev	Power_meca_ev	Power_wheel_ev	Ubat_ev	acceleration_break	acceleration_ev	distance_
count	13156.000000	13156.000000	13156.000000	13156.000000	13156.000000	13156.000000	13156.000000	13156.000000	13156.0000
mean	32.442944	12064.418988	12972.493545	10978.621286	10759.048849	401.516020	0.074985	0.007270	14002.5778
std	46.709617	17348.127051	18653.900148	15786.795739	15471.059799	2.677987	0.117583	0.417998	13209.4240
min	-481.082670	-175824.170000	-189058.250000	-160000.000000	-156800.000000	392.318050	-1.000000	-4.911469	0.0000
5%	-19.296253	-7231.250100	-7775.538075	-6580.437750	-6448.829175	394.473950	-0.111309	-0.649117	573.4587
50%	24.074572	8988.260250	9664.795500	8179.316650	8015.730500	402.709650	0.067963	0.000142	9433.4450
95%	100.116999	36667.457000	39427.375000	33367.387000	32700.038500	403.175178	0.212428	0.594538	41956.6975
max	475.829380	175824.170000	189058.250000	160000.000000	156800.000000	403.200000	1.000000	4.600298	52385.2400

Annexes

Convert a route from google maps to GPS coordinates

Get the data

Step1: chose a route that we will use

Highway arounb Paris: A5, 225 km derection Belfort
[Google Maps LINK of the route]
(https://www.google.com/maps/dir/48.6151004,2.5530508/47.9639166,+5.1467886/@47.9211937,5.190454,9.25z/data=!4m12!4m11!1m5!3m4!1m2!1d2.556
entry=ttu)

Convert the google maps route link to json with GPS cordinate:

You can use the free online service below:
https://mapstogpx.com/
You can **download** the json file of the route from the repository path "data/raw/route.json

or directely by the link:
https://raw.githubusercontent.com/bouz1/EV_Matlab_Simulink_Megane_E_TECH_to_generate_data/main/data/raw/route.json

Post-processing of data

Read json and convert it to a DataFrame

In [311]:
```
with open('../data/raw/route.json') as f:
    txt=f.read()
    f.close()
    del(f)
```

```
gps = json.loads(txt)
points = gps['points']

dfgps=pd.DataFrame(points)
dfgps=dfgps[['lng','lat']]
dfgps.head(2)
```

Out[311]:

	lng	lat
0	2.553051	48.61510
1	2.553110	48.61519

Plot the route int the MAP

In [312]:
```
fig = px.scatter_mapbox(dfgps, lat='lat', lon='lng', zoom=7)

fig.update_layout(
    mapbox_style="open-street-map",
    margin={'r':0,'t':0,'l':0,'b':0},
    height=500,width=800
)

fig.show()
```

API to get the elevation of each (longitude, latitude) GPS point

Example of API use:

https://wxs.ign.fr/calcul/alti/rest/elevation.json?lon=0.2367|2.1570&lat=48.0551|46.6077&zonly=true
Getting the elevation for each point

In [313]:
```
# Use an API to find the elevation of each time juste in the first time, if we run the Notebook again, we will avoid this step
First_time= False

if First_time:

    # Initialize an empty list to store elevation values
    elev_list = []

    # Iterate through the data in steps of 20
    for i in range(0, len(dfgps), 20):
        # Extract longitude and latitude values for the current chunk
        lons = dfgps.iloc[i:i+20, :].lng.values
        lats = dfgps.iloc[i:i+20, :].lat.values

        # Convert the lists of longitude and latitude values to pipe-separated strings
        lons = '|'.join([str(x) for x in lons])
        lats = '|'.join([str(x) for x in lats])

        # Construct the URL for elevation data using IGN's API
```

```
        url = 'https://wxs.ign.fr/calcul/alti/rest/elevation.json?lon=' + lons + '&lat=' + lats + '&zonly=true'

        # Make a request to the API and retrieve elevation data
        result = requests.get(url)
        elevations = result.json()['elevations']

        # Append the elevation values to the elev_list
        elev_list += elevations

        # Print progress (overwriting the line)
        print(f'\r{i}', end='', flush=True)

    # Add the elevation column to the DF:
    dfgps['elev']=elev_list
    # The elevation API is very slow, so we will save the DataFrame as parquet format to avoid waiting this API each time
    dfgps.to_parquet(r'../data/processed/dfgps_V0.gzip',compression='gzip')

else:
    # Read the dataFrame with the elevation to avoid waiting this API each time as the Notebook as run again
    dfgps=pd.read_parquet(r'../data/processed/dfgps_V0.gzip')
```

In [314]:

```
dfgps.head(3)
```

Out[314]:

	lng	lat	elev
0	2.553051	48.61510	89.10
1	2.553110	48.61519	89.18
2	2.553130	48.61523	89.10

In [315]:

```
dfgps.dtypes
```

Out[315]:

```
lng     float64
lat     float64
elev    float64
dtype: object
```

Distance between each two successive points: 2D methode

In [316]:

```
def haversine(lat1, lon1, lat2, lon2):
    """
    Calculates the great-circle distance (haversine) between two points on Earth's surface.

    Args:
        lat1 (float): Latitude of the first point in degrees.
        lon1 (float): Longitude of the first point in degrees.
        lat2 (float): Latitude of the second point in degrees.
        lon2 (float): Longitude of the second point in degrees.

    Returns:
        float: Distance between the two points in meters.
    """
    R = 6371e3  # Radius of the Earth in meters (mean radius)

    # Convert latitude and longitude differences to radians
    dlat = (lat2 - lat1) * np.pi / 180
    dlon = (lon2 - lon1) * np.pi / 180

    # Haversine formula
    a = np.sin(dlat / 2) ** 2 + np.cos(lat1) * np.cos(lat2) * np.sin(dlon / 2) ** 2
    c = 2 * np.arctan2(np.sqrt(a), np.sqrt(1 - a))

    # Calculate the distance
    return R * c
```

In [317]:

```
# Assuming dfgps is your DataFrame and it has columns 'lat' and 'lon'
dfgps['lat_shifted'] = dfgps['lat'].shift(1)
dfgps['lon_shifted'] = dfgps['lng'].shift(1)

# Apply the haversine function to each row
dfgps['distance'] = dfgps.apply(lambda row: haversine(row['lat'], row['lng'],\
                                row['lat_shifted'], row['lon_shifted']), axis=1)

# Initialise the distance with 0
dfgps['distance'].iloc[0]=0
```

In [318]:

```
# Drop the shifted columns
dfgps.drop(['lat_shifted','lon_shifted'],axis=1,inplace=True)
dfgps.head(3)
```

Out[318]:

	lng	lat	elev	distance
0	2.553051	48.61510	89.10	0.000000
1	2.553110	48.61519	89.18	9.976786
2	2.553130	48.61523	89.10	4.451300

The minimum distance between two neighboring points

In [319]:
```
# km/h to m/s
mps=(140/3.6)
# the desired minimum time between two rows
dtmin=1 # seconds
# Calcul of the minimum distance
dist_min=int(mps/dtmin)
print('the min distance between 2 neighboring point to have time min of',dtmin,'seconde is',dist_min,'m')
```

the min distance between 2 neighboring point to have time min of 1 seconde is 38 m

Drop the closest points

In [320]:
```
# Initial length of the dfgps
Ni=len(dfgps)

# Drop the closest point if the distance between each successive points is under the minimum dist
for i in dfgps.index[1:]:
    if dfgps.loc[i,'distance'] < dist_min:
        dfgps.drop(i,axis=0,inplace=True)
```

In [321]:
```
print('Initial length of the dfgps:',Ni,'After droping the closest points:',len(dfgps))
```

Initial length of the dfgps: 11636 After droping the closest points: 538

In [322]:
```
# Calculate the cumulative sum of the distance
dfgps['dist_cum']=dfgps.distance.cumsum()
```

In [323]:
```
# Display the head and tails of the DF
dfgps.iloc[[0,1,3,-3,-2,-1],:]
```

Out[323]:

	lng	lat	elev	distance	dist_cum
0	2.553051	48.61510	89.10	0.000000	0.000000
6	2.553730	48.61622	89.28	40.076285	40.076285
97	2.574020	48.61046	94.63	70.515530	150.328039
11563	5.139970	47.97233	407.16	43.767043	31373.911140
11564	5.140240	47.97201	407.98	40.746223	31414.657363
11578	5.141730	47.97029	410.82	39.798272	31454.455635

the total distance is **166.9km**, and we know from google maps that the distance is close to **225km**, the error is caused by the distance calculation without elevation.

Let's verify this hypothesis by the 3D calculation below:

Distance between each two successive points: 3D methode

In [324]:
```
def haversine3D(lat1, lon1, elev1, lat2, lon2, elev2):
    """
    Calculates the great-circle distance (haversine) between two points on Earth's surface.

    Args:
      lat1 (float): Latitude of the first point in degrees.
      lon1 (float): Longitude of the first point in degrees.
      elev1 (float): Elevation of the first point in meters.
      lat2 (float): Latitude of the second point in degrees.
      lon2 (float): Longitude of the second point in degrees.
      elev2 (float): Elevation of the second point in meters.

    Returns:
      float: Delta distance between the two points in meters.
    """
    R = 6371e3  # Radius of the Earth in meters (mean radius)

    # Convert latitude and longitude differences to radians
    dlat = math.radians(lat2 - lat1)
    dlon = math.radians(lon2 - lon1)

    # Haversine formula
    a = math.sin(dlat / 2) ** 2 + math.cos(math.radians(lat1)) * math.cos(math.radians(lat2)) * math.sin(dlon / 2) ** 2
    c = 2 * math.atan2(math.sqrt(a), math.sqrt(1 - a))

    # Calculate the 2D distance
    dist_2d = R * c

    # Calculate the 3D distance (including elevation)
    delta_elev = abs(elev2 - elev1)
```

```
        dist_3d = math.sqrt(dist_2d ** 2 + delta_elev ** 2)

        return dist_3d
```

In [325]:
```
# conserve only the lat, lng and elev columns
dfgps=dfgps[['lat','lng','elev']].reset_index(drop=True)
```

In [326]:
```
# Assuming dfgps is your DataFrame and it has columns 'lat' and 'lon'
dfgps['lat_shifted'] = dfgps['lat'].shift(1)
dfgps['lon_shifted'] = dfgps['lng'].shift(1)
dfgps['elev_shifted'] = dfgps['elev'].shift(1)

# Apply the haversine function to each row
dfgps['distance'] = dfgps.apply(lambda row: haversine3D(row['lat'], row['lng'],\
          row['elev'],row['lat_shifted'], row['lon_shifted'], \
                        row['elev_shifted']), axis=1)

# Initialise the distance with 0
dfgps['distance'].iloc[0]=0

# Drop the shifted columns
dfgps.drop(['lat_shifted','lon_shifted','elev_shifted'],axis=1,inplace=True)

# Calculate the cumulative sum of the distance
dfgps['dist_cum']=dfgps.distance.cumsum()

# Display the head and tails of the DF
dfgps.iloc[[0,1,3,-3,-2,-1],:]
```

Out[326]:

	lat	lng	elev	distance	dist_cum
0	48.61510	2.553051	89.10	0.000000	0.000000
1	48.61622	2.553730	89.28	134.133031	134.133031
3	48.61046	2.574020	94.63	635.524981	1766.041049
535	47.97233	5.139970	407.16	55.188408	220479.167345
536	47.97201	5.140240	407.98	40.875221	220520.042566
537	47.97029	5.141730	410.82	221.112512	220741.155078

Now the total distance is **225 km**, the same as the google maps, so our first hypothesis is verified

In [327]:
```
dfgps.distance.iloc[1:].min()
```

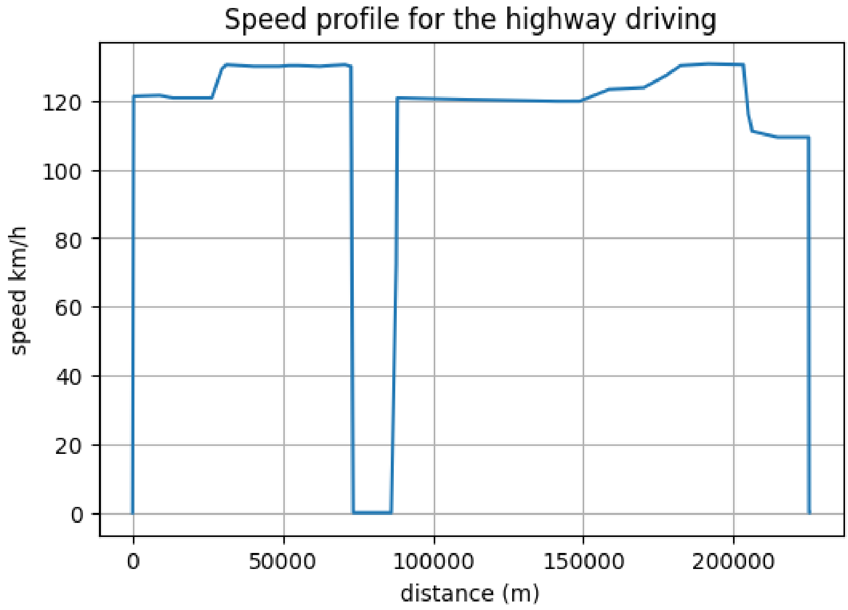
Out[327]:38.21631956319751

Speed profile

In [328]:
```
# The speed profile in the file "highway_A5_speed.csv" is maded manually
df_speed_A5=pd.read_csv('../data/raw/highway_A5_speed.csv')
dis=df_speed_A5.distance.values
speed=df_speed_A5.kmph.values

display(df_speed_A5.tail(3))
```

	distance	kmph
35	225053.179491	109.413854
36	225186.651795	0.000000
37	225189.000000	0.000000

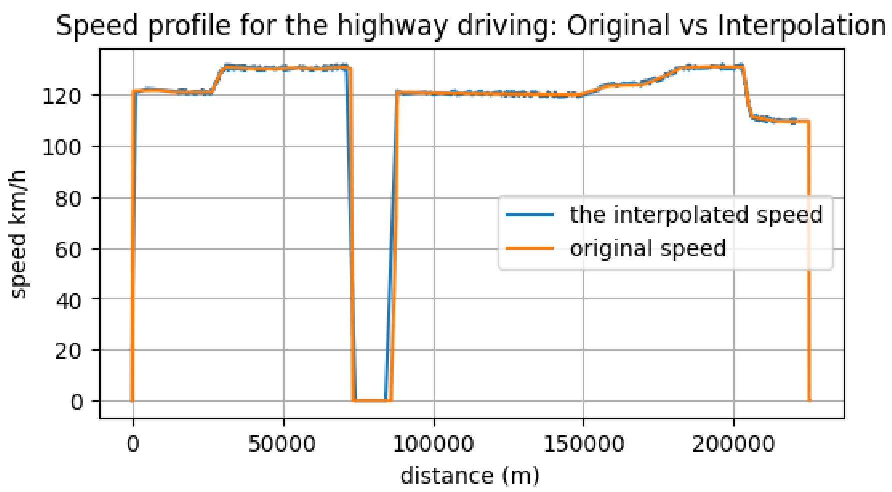
In [329]:
```
#Plot

figure(figsize=(6,4))
plt.plot(dis,speed)
plt.xlabel('distance (m)')
plt.ylabel('speed km/h')
plt.grid()
plt.title('Speed profile for the highway driving')
plt.show()
```



In [330]:print('length of df_speed_A5 is:',len(df_speed_A5),', and the length of dfgps is:',len(dfgps))

length of df_speed_A5 is: 38 , and the length of dfgps is: 538
As we can see above, the length of the gps DataFrame is more than the length of the speed curve profile, so we will use interpolation to generate new speed with the same length as the "dfgps"

In [331]:
```
# x , y of interpolation
dis=np.array(dis)
speed=np.array(speed)

# The interpolation function
f = interpolate.interp1d(dis, speed)

# The ne x "distances"
new_dis = dfgps.dist_cum.values

# Interpolation of the speed
new_speed = f(new_dis)

# add a random noise with +/-1km/h to the new speed
new_speed =new_speed + np.random.uniform(-1,1,len(new_dis))

# Avoid negative speed
new_speed[new_speed<2]=0

# check the original speed and the interpolated speed
# Plot
figure(figsize=(6,3))
plt.plot(new_dis,new_speed, label='the interpolated speed')
plt.plot(dis,speed, label='original speed')

plt.xlabel('distance (m)')
plt.ylabel('speed km/h')
plt.grid()
plt.legend()
plt.title('Speed profile for the highway driving: Original vs Interpolation')
plt.show()
```



Add the speed to the dfgps

In [332]:dfgps['kmph']=new_speed
dfgps.head(2)

Out[332]:

	lat	lng	elev	distance	dist_cum	kmph
0	48.61510	2.553051	89.10	0.000000	0.000000	0.000000
1	48.61622	2.553730	89.28	134.133031	134.133031	44.667525

Time row

Get the time from the distance and the speed

```
In [333]:dt=dfgps.distance/(dfgps.kmph/3.6)
         dt.iloc[0]=dt.mean()
         print('The minimum delta time is',format(dt.min(),'.2f'),'s > 1s')
```

The minimum delta time is 1.17 s > 1s

```
In [334]:# whene the speed is 0 the calculated time is inf
         dt.replace([np.inf, -np.inf], np.nan,inplace=True)
         # replace inf by the mean time
         dt[dt.isna()]=dt.mean()
         # Initialise the beginning with 1s
         dt.iloc[0]=1
```

Check the delta Time variable

```
In [335]:dt.describe()
```

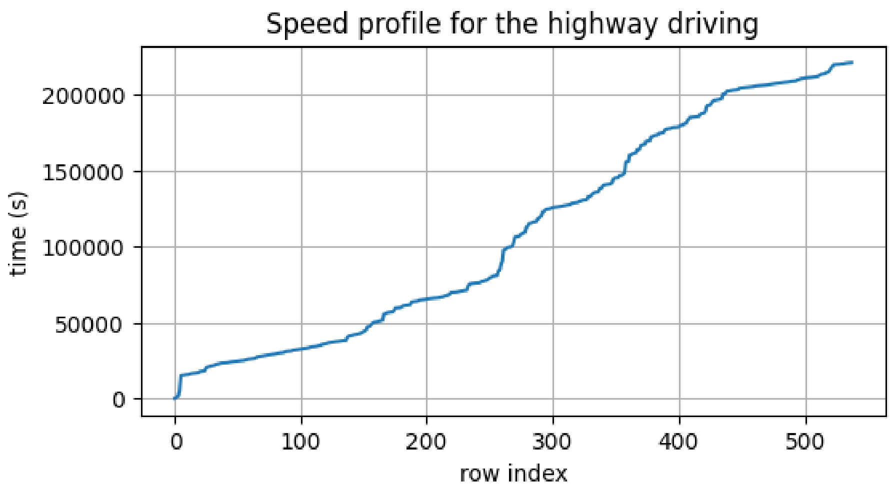
```
Out[335]:count    538.000000
         mean      11.872247
         std       24.518984
         min        1.000000
         25%        2.535842
         50%        4.246091
         75%       11.537547
         max      302.574019
         dtype: float64
```

Add the delta time to the dataframe

```
In [336]:dfgps['dt']=dt
```

Calculate the time by the cumulative sum of delta time

```
In [337]:dfgps['time']=dfgps['dt'].cumsum()
In [338]:figure(figsize=(6,3))
         plt.plot(dfgps.dist_cum)
         plt.xlabel('row index')
         plt.ylabel('time (s)')
         plt.grid()
         plt.title('Speed profile for the highway driving')
         plt.show()
```



Save the df with the time

```
In [339]:dfgps.to_parquet(r'../data/processed/dfgps_V1.gzip',compression='gzip')
```

The road gradient

read the dataframe

```
In [340]:dfgps=pd.read_parquet(r'../data/processed/dfgps_V1.gzip')
In [341]:dfgps.head(2)
```

Out[341]:

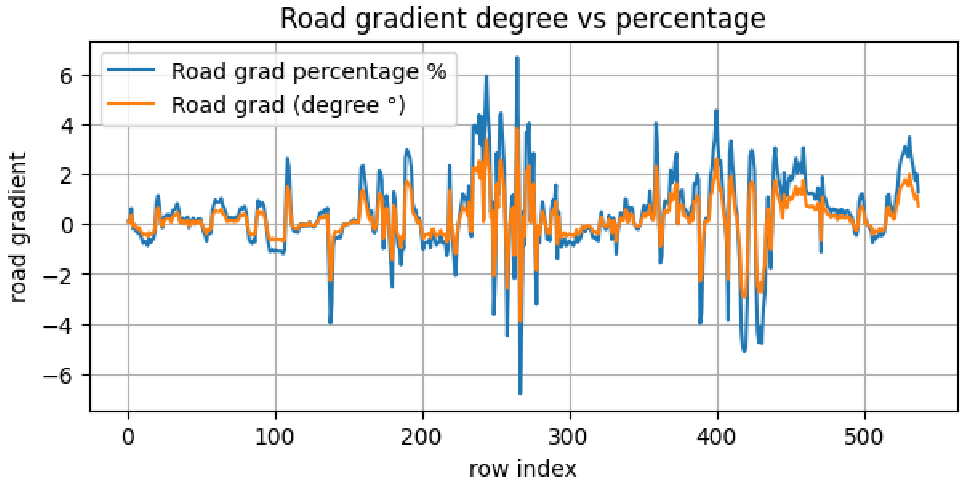
	lat	lng	elev	distance	dist_cum	kmph	dt	time
0	48.61510	2.553051	89.10	0.000000	0.000000	0.000000	1.000000	1.000000
1	48.61622	2.553730	89.28	134.133031	134.133031	44.667525	10.810514	11.810514

Road gradient in % and degree

In [342]:
```
# delta distance
dx=dfgps.dist_cum-dfgps.dist_cum.shift(1)
# delta elevation
dz=dfgps.elev-dfgps.elev.shift(1)
# road gradient in percentage
rouad_grad_100=100*dz/dx
# road gradient in degree with arctan formula
rouad_grad_deg=(180/np.pi)*np.arctan(rouad_grad_100/100) # "(180/np.pi)" convert the gradient to degree
```

Plot the road grad

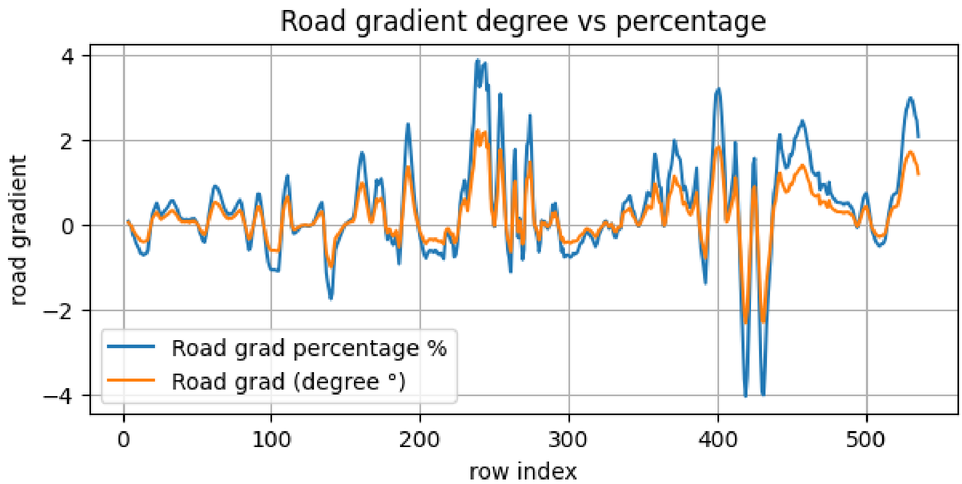
In [343]:
```
figure(figsize=(7,3))
plt.plot(rouad_grad_100,label='Road grad percentage %')
plt.plot(rouad_grad_deg,label='Road grad (degree °)')
plt.xlabel('row index')
plt.ylabel('road gradient')
plt.grid()
plt.legend()
plt.title('Road gradient degree vs percentage')
plt.show()
```



The max of road gradient % is around 7,this is because the no accuracy elevation, but we know that the max value in this highway is around 3.5 - 4% (see the link below), so we propose to use the rolling mean to filter the road grad

https://routes.fandom.com/wiki/Sections_autorouti%C3%A8res_%C3%A0_fortes_pentes

In [344]:
```
rouad_grad_100_f=rouad_grad_100.rolling(6,center=True).mean()
rouad_grad_deg_f=rouad_grad_deg.rolling(6,center=True).mean()

# Plot
figure(figsize=(7,3))
plt.plot(rouad_grad_100_f,label='Road grad percentage %')
plt.plot(rouad_grad_deg_f,label='Road grad (degree °)')
plt.xlabel('row index')
plt.ylabel('road gradient')
plt.grid()
plt.legend()
plt.title('Road gradient degree vs percentage')
plt.show()
```



Plmot the road gradient and elevation

In [345]:
```
from plotly.subplots import make_subplots
import plotly.graph_objects as go
```

In [346]:
```
dfplot=dfgps.copy()
dfplot['rouad_grad_100_f']=rouad_grad_100_f
dfplot['rouad_grad_deg_f']=rouad_grad_deg
```

```
        dfplot.dropna(inplace=True)
In [347]:fig = make_subplots(rows=2, cols=1,  shared_xaxes=True,
                    vertical_spacing=0.02,
                    horizontal_spacing=0.0)

        fig.append_trace(go.Scatter(
                    x=dfplot.dist_cum,
                    y=dfplot.rouad_grad_100_f,name='Rouad Grad' ,
                    text=dfplot[['rouad_grad_100_f', 'elev' ]]
                    ,hovertemplate=' %{y:.2f} , Elevation= %{text[1]}' # :.2f, 2 decimal digits
                    ),
                        row=1, col=1)

        fig.append_trace(go.Scatter(
                    x=dfplot.dist_cum,
                    y=dfplot.elev,
                    name='Elevqtion',
                    text=dfplot[['rouad_grad_100_f', 'elev' ]]
                    ,hovertemplate='%{y} , Rouad Grad= %{text[0]:.2f}' ,
                    stackgroup='one'),
                        row=2, col=1)

        fig.update_traces(xaxis="x2")

        # Update y/xaxis properties
        fig.update_yaxes(title_text='road gradient [%]', row=1, col=1)
        fig.update_yaxes(title_text='Route elevation [m]', row=2, col=1)
        fig.update_xaxes(title_text="Distance [m]", row=2, col=1)

        fig.update_layout(height=500, width=800, title_text="Stacked Subplots",
                          hovermode="x unified",  # Set hovermode to 'x unified'
                          showlegend=False)
        fig.show()
```

Head and tails of the final dataFrame

```
In [348]:dfplot[['time','lng', 'lat', 'elev','dist_cum', 'kmph','rouad_grad_deg_f']].iloc[[0,1,-2,-1],:]
```

Out[348]:

	time	lng	lat	elev	dist_cum	kmph	rouad_grad_deg_f
4	154.260247	2.61141	48.59605	88.45	4948.178223	122.099765	-0.111273
5	456.834266	2.74626	48.57555	87.08	15125.653608	121.090738	-0.007713
534	6376.856405	5.13960	47.97276	406.20	220423.978937	109.741362	1.212880
535	6378.668726	5.13997	47.97233	407.16	220479.167345	109.626453	0.996557

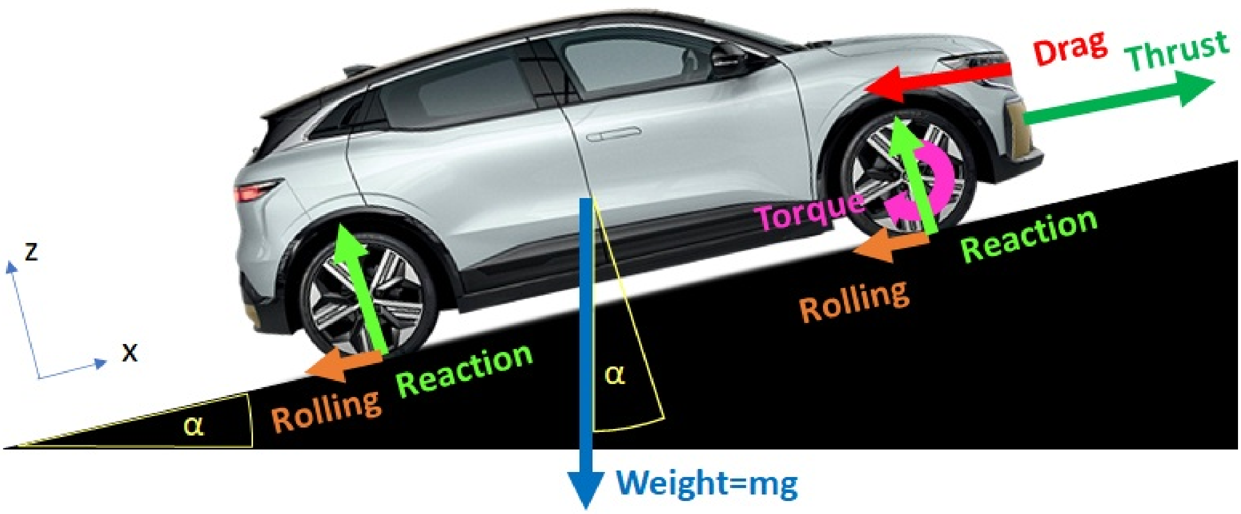
Save the final DataFrame as csv file

```
In [350]:dfplot[['time','lng', 'lat', 'elev','dist_cum', 'kmph','rouad_grad_deg_f']].to_csv('../data/processed/dfgps_fin.csv')
```

Matlab / Simulink

Newton's second law

The figure below show the forces applied to the vehicle



The Newton's second law applied to the vehicle: see above (X-axis projection)

$$\begin{align*} F_x &= m \frac{dv}{dt}= Thrust - (Drag + m.g.sin(\alpha) + Rolling)\\ & with: Thrust = Torque . wheelRadius \end{align*}$$

Simulation hypotheses

For this project, the simulation will be simplified with the below hypothesis:

- All information about the vehicle specification will be gathered from internet: see the links below
- The only inertia of the vehicle is its weight, so we negligee all rotated parte inertias, the inertia of electronic components like the motor winding inductances...
- The motor is controlled with a sample low: max torque utile the power = power max, after that we will adapt max power until the max speed
- The inverter, mechanical reductor, are modeled with a sample efficient confession
- The Coriolis force is negligee
- The gravitational acceleration "g" and earth's radius are constants
- battery cells are assumed to be perfectly balanced
- The drag coefficient will be tuned to find a WLTC autonomy close to Renault official specification
- the wheels are supposed to roll without slipping

Simulink

Initialisation

Below the simulation file used fot the highway driving Init_ParisA5_225km.m

You can find the explanation and the source of the information in the comment of each parameter

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%% Clear all variables %%
clear all;
%% %%%

%% General variables %%
torque_max=300; %% N.m %% https://www.autodauphine.fr/uploads/vehicules_neufs/44/1641221181_ddc90a41141d81d0c5f3.pdf
power_max = 160e3; %% W %% https://www.autodauphine.fr/uploads/vehicules_neufs/44/1641221181_ddc90a41141d81d0c5f3.pdf
m = 1600+80*2; %% %% weight of the vehicle + 2 average persones [kg] https://www.renault.fr/vehicules-electriques/megane-e-tech-electrique/comparateur-specifications.html*
m0= 1600; %% Vehicle without passangers
g = 9.80665 ; %% %% standard gravitational acceleration for the surface of the Earth [m/s2]
mps_to_kmph= 3.6; %% V[km/h] = V[m/s] mps_to_kmph

%% Drag %%
air_density=1.293 ; %% kg m?3 %% air density
SCx= 0.674 ; %% [m²] %% https://www.lesnumeriques.com/voiture/renault-megane-e-tech-electric-la-nouvelle-compacte-electrique-aux-faux-airs-de-suv-n167917.html
%%%The above measurement give a SCx of 0.674
%%%But the idea is to tune the SCx to find an WLTC autonomy between 450 and 470km
SCx= 0.5; %% with this value the autonomy is 457km => OK
k_drag= (1/2)*air_density*SCx; %% N/(m/s)^2 %% drag total coefficient: Drag = k_drag * velocity ^2 https://en.wikipedia.org/wiki/Drag_equation

%% Rolling %%%
% formula Rolling = f · m · g · cos(?) https://x-engineer.org/rolling-resistance/
% f : rolling resistance coefficient = 0.013 https://x-engineer.org/rolling-resistance/
% ? : road with the gradient [rad]
% m: weight of the vehicle [kg] : see above
% k_rolling = f · m · g
k_rolling = 0.013*mg*; %% total rolling coefficient : Rolling = k_rolling· cos(?) see above

%% Reduction ratio %%%
kmph_max=160; %% [km/h] %% max speed: https://fr.wikipedia.org/wiki/Renault_Megane_E-Tech_Electric
rpm_max=11688;%% [tr/min]%% max rpm: https://fr.wikipedia.org/wiki/Renault_Megane_E-Tech_Electric
rmp_2_kmph=(kmph_max/rpm_max);%% V[km/h]= rmp_2_kmph* N[tr/min]
tourque_2_thrust = (2*pi*3.6/60)/rmp_2_kmph; %% Thrust [N] = tourque_2_thrust * Torque[N.m]

%% Efficiency
motor_eff=0.91 ; %% https://renault.com.mt/driveelectric/engine-e-tech-electric.html#:~:text=Our%20externally%20excited%20synchronous%20motor,a%20high%20performance%20of%2091%25.
inverter_eff = 0.93 ; %% example of inverter efficiency : https://www.powersystemsdesign.com/articles/efficient-dc-ac-inverter-for-high-voltage-electric-vehicles/95/15405
reduction_eff=0.98; %% I don't find any value in the web, but a chose this value because reductor will be effcient

%% Inverter %%
U_uvp = 330 ; %% V %% the under voltage protaction

%% Battery %%%
Nb_modules= 12; %% https://www.renaultgroup.com/wp-content/uploads/2023/03/renault_deu_20230316.pdf
Nb_cells_by_modules= 24;%% https://www.renaultgroup.com/wp-content/uploads/2023/03/renault_deu_20230316.pdf
Nb_cells= Nb_modules*Nb_cells_by_modules;*
*Nb_cells_paralles = floor(Nb_cells*4.2/400); % voltage of cell = 4.2V <===> 400v of the batterie
Nb_serial= Nb_cells/Nb_cells_paralles; % Nb of serial cells
soc = [0, 2, 6, 9, 20, 37, 42, 57, 66, 77, 85, 91, 95, 98, 100]; %% State of charge :
https://www.richtek.com/Design%20Support/Technical%20Document/AN024
U_cell=[3.41, 3.61, 3.78, 3.86, 3.89, 3.90, 3.92, 3.97, 4.00, 4.04, 4.10, 4.16, 4.19, 4.195, 4.20]; %% cell voltage :
https://www.richtek.com/Design%20Support/Technical%20Document/AN024
U_bat= U_cell*Nb_serial; %% the battery voltage*
bat_energy_kwh= 60 ; %% kWh %% the battery capacity 60kWh: https://fr.wikipedia.org/wiki/Renault_Megane_E-Tech_Electric
*bat_energy=bat_energy_kwh*1000*3600 ;%% W.s = j %%*
R_dc=0.25 ; %% Ohm %% internal batterie resistnace

%% Speed controlor (PI) %%
K_p= 0.05;%% 0.03
w_I= 0.01; %% 0.01 0.005
P_coef= K_p;
*I_coef = K_p*w_I;

%% WLTC Data %%%
% you can find the pdf in this link https://en.wikipedia.org/wiki/Worldwide_Harmonised_Light_Vehicles_Test_Procedure
data= readtable('../../data/processed/dfgps_fin.csv');
time= data.time;
kmph= data.kmph;
sim_time=max(time); %%% sim time
rouad_grad=data.rouad_grad_deg_f %% Road gradient
Ts= 0.5; %% Simulation step
PWr= power_max/m0; %% = 100 W/kg > 34 ==> class 3 of WLTC ; The power-to-mass ratio (PWr) Pwr = Power[w]/masse[kg]

%% Plot WLTC time/kmph
plot(time,kmph);

%% Initial values
x_initial=0 ; %%m%% initial distance
Velocity_0= 0; %% Initial vehicle speed

Simulation blocks

You can find all simulink pdf printing in the link
for example this link is the pdf of the highway driving in the A5

Below an example of the main block sheet, we can check the above link to see the details of all subsystem like "vehicle", "speed control" ...