

mcf_labs_hajg500

March 17, 2022

THOMPSON SCATTERING LAB

```
[1]: import numpy as np
from IPython import display
import matplotlib.pyplot as plt
from mpl_toolkits import mplot3d
import pandas as pd
from scipy.optimize import curve_fit
import scipy.io
import os
import re
from os import listdir
from os.path import isfile, join
```

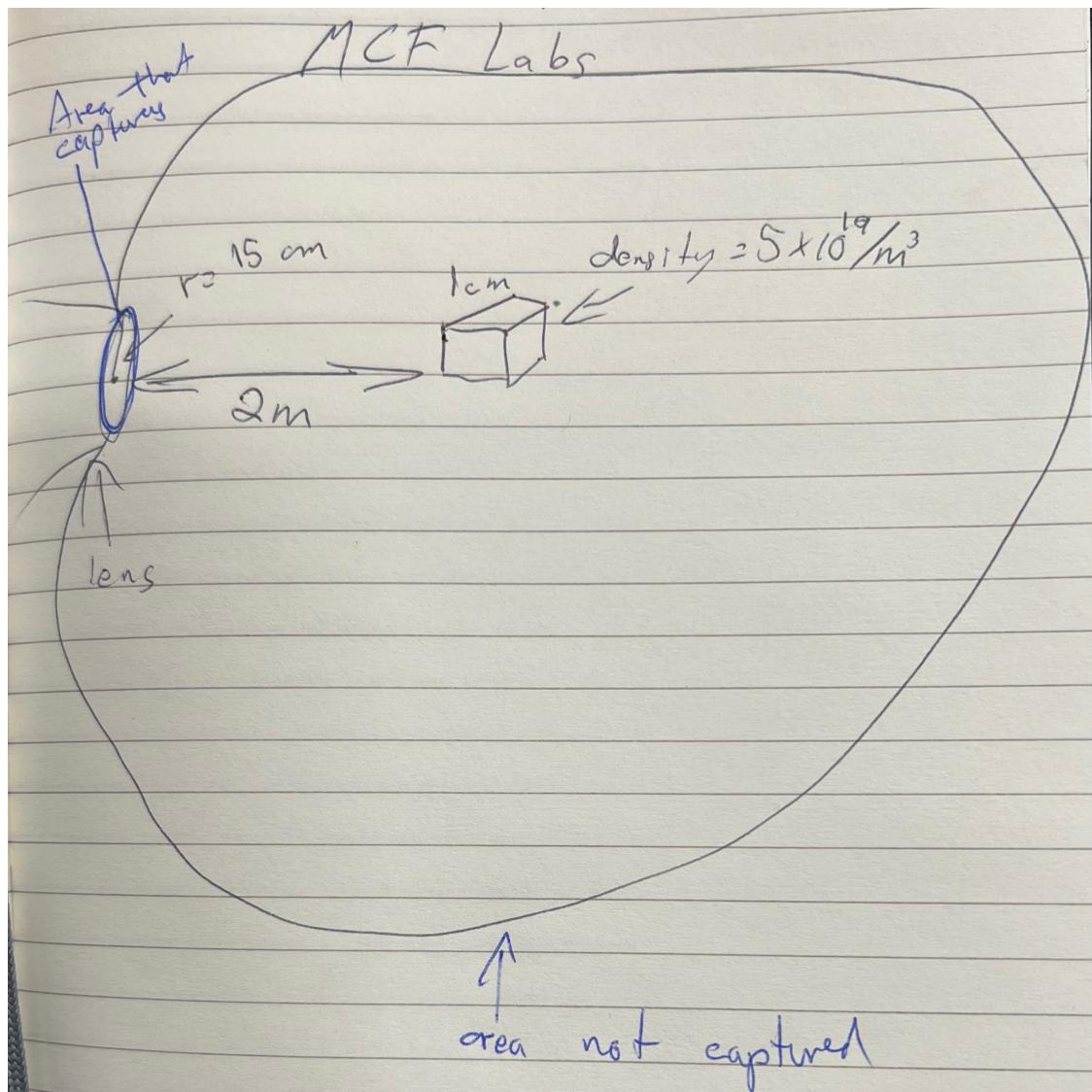
Section 2

Fraction of photons that are collected

To get the fraction of photons collected by the 30 cm diameter lens, I first conceptualised what it meant. If the photons are coming out of a volume, and are scattered uniformly in every direction, we can assume that only the area of the lens collects the photons. Everything else is lost.

```
[2]: display.Image("./supporting_imgs/section_2_img_1.jpg")
```

```
[2]:
```



```
[3]: lens_radius = 15 / 100 # meter
scattering_radius = 2 # meter
```

```
[4]: scattering_area = 4 * np.pi * scattering_radius**2
print ("The scattering area is: {} m^2".format(scattering_area))
```

The scattering area is: 50.26548245743669 m²

```
[5]: lens_area = np.pi * lens_radius**2
print ("The lens area is: {} m^2".format(lens_area))
```

The lens area is: 0.07068583470577035 m²

```
[6]: collected_photons_fraction = lens_area / scattering_area
      print ("The collected photons fractions is: {}".
             format(collected_photons_fraction))
```

The collected photons fractions is: 0.00140625

Photons collected by the lens

```
[7]: planck_constant = 6.626e-34 # J*s
      speed_of_light = 3e8 # meter / s
      laser_wavelength = 694.3e-9 # meter
      laser_energy_per_pulse = 10 # J
```

```
[8]: energy_per_photon = planck_constant * speed_of_light / laser_wavelength
      print ("The energy per photon is: {}".format(energy_per_photon))#
```

The energy per photon is: 2.8630275097220224e-19

Now that we have the energy per photon, we can get the total number of photons

```
[9]: total_number_of_photons = laser_energy_per_pulse / energy_per_photon
      print ("The total number of photons is: {}".format(total_number_of_photons))
```

The total number of photons is: 3.492806117315625e+19

Those are the photons that go through the plasma volume. Now, we have to find out how many of those photons interact with the plasma volume using the TS cross section, the plasma density, and the length of the plasma volume.

```
[10]: TS_cross_section = 6.65e-29 # meter^2
       plasma_density = 5e19 # meter^-3
       length = 0.01 # meter
```

```
[11]: photons_scattered = TS_cross_section * plasma_density * length * total_number_of_photons
      print ("The amount of photons scattered are: {}".format(photons_scattered))
```

The amount of photons scattered are: 1161358034.0074453

```
[12]: photons_collected = collected_photons_fraction * photons_scattered
      print ("The number of photons collected by the lens is: {}".
             format(photons_collected))
```

The number of photons collected by the lens is: 1633159.73532297

Section 3

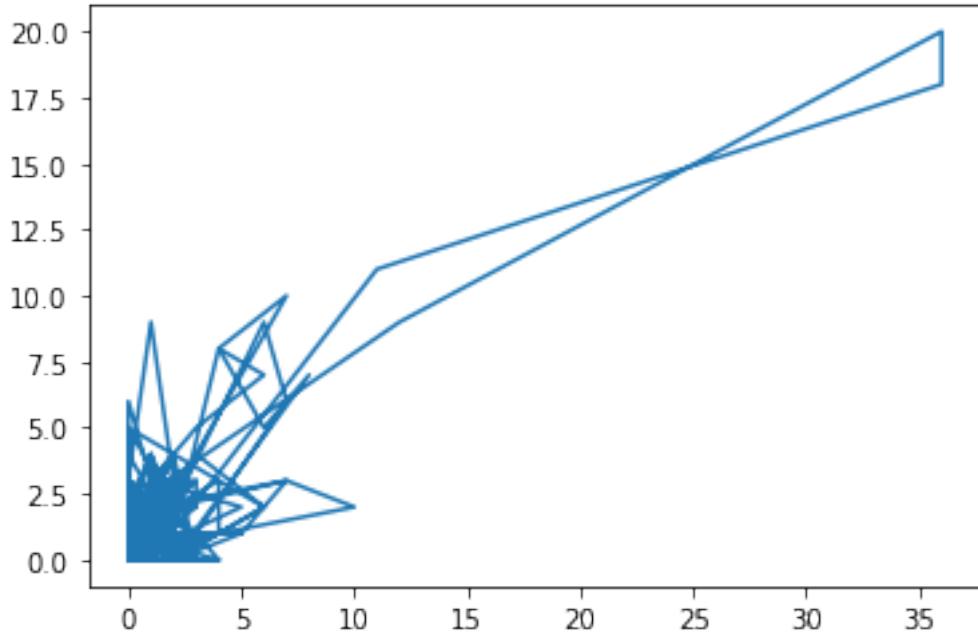
```
[13]: intensity = np.loadtxt('../TS_data_files/intensity.dat')           # 2D array of
       ↪CCD counts data
```

```
[14]: print ("So, this data file is a 2D array with shape {}. How can we make sense  
        ↵of this data?".format(intensity.shape))
```

So, this data file is a 2D array with shape (284, 302). How can we make sense of this data?

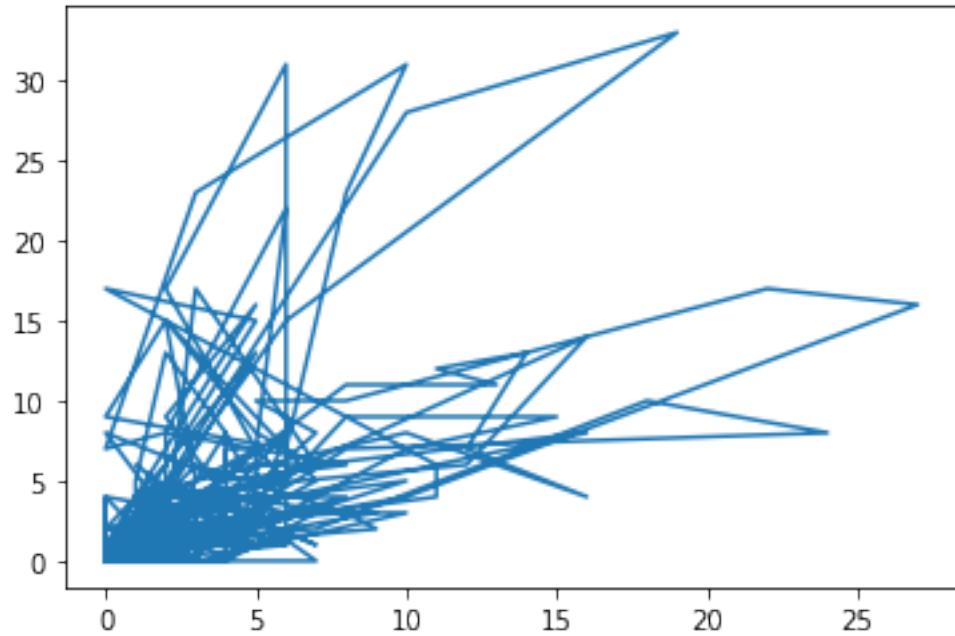
```
[15]: plt.plot(intensity[:, 0], intensity[:, 1])
```

```
[15]: [<matplotlib.lines.Line2D at 0x7fa4aded4850>]
```



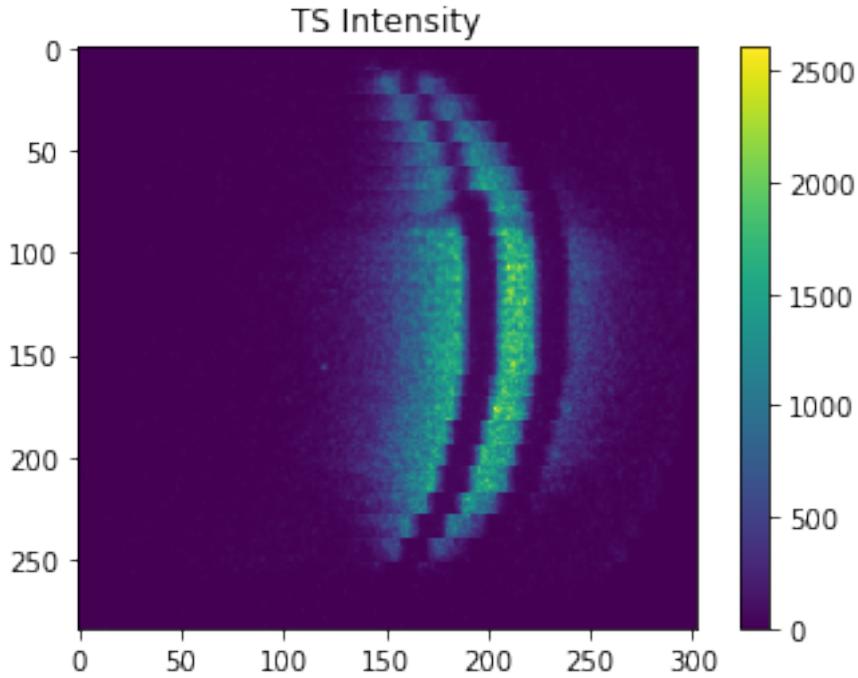
```
[16]: plt.plot(intensity[0, :], intensity[1, :])
```

```
[16]: [<matplotlib.lines.Line2D at 0x7fa4add72370>]
```



Those looked pretty strange, so I will plot it as a colorplot.

```
[17]: fig = plt.figure()
ax = fig.add_subplot(111)
ax.set_title("TS Intensity")
plt.imshow(intensity)
plt.colorbar(orientation="vertical")
plt.show()
```



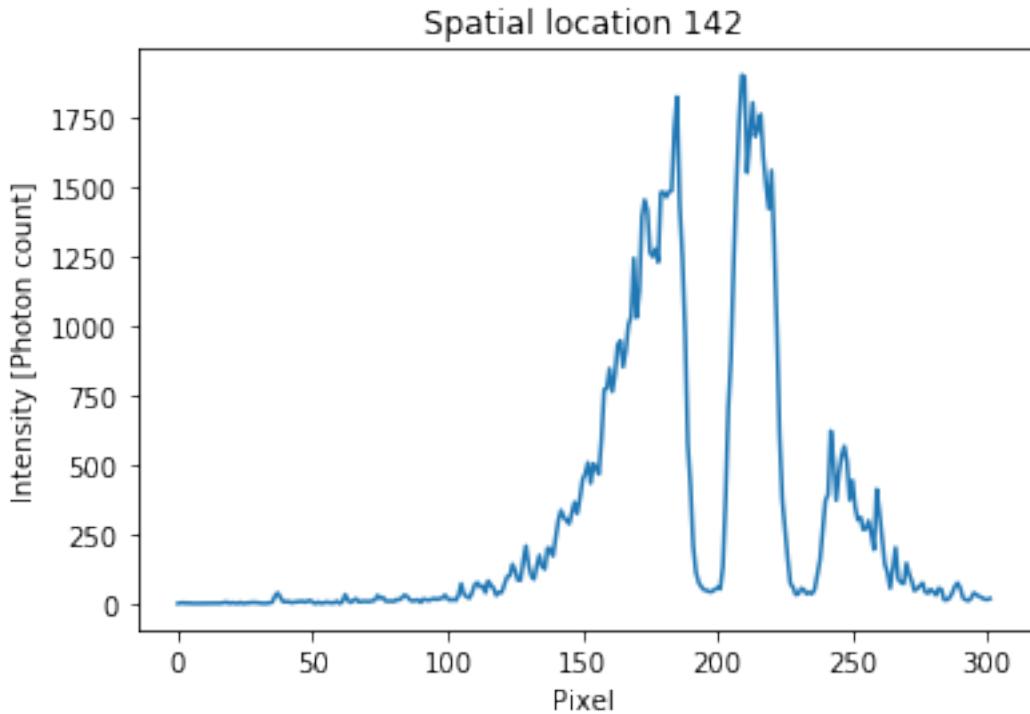
This looked closer to what it is intended to represent. But, which axis is the spatial position and which one is the wavelength?

```
[18]: # rad_mesh = ""
# plt.pcolor(wavelength, rad_mesh, intensity)
```

After some thinking, I believe that this is not the wavelength, but the pixel location.

```
[19]: spatial_location_idx_center = int(intensity.shape[0] / 2)
spatial_location_idx = spatial_location_idx_center
plt.plot(intensity[spatial_location_idx])
plt.xlabel("Pixel")
plt.ylabel("Intensity [Photon count]")
plt.title("Spatial location {}".format(spatial_location_idx))
```

```
[19]: Text(0.5, 1.0, 'Spatial location 142')
```

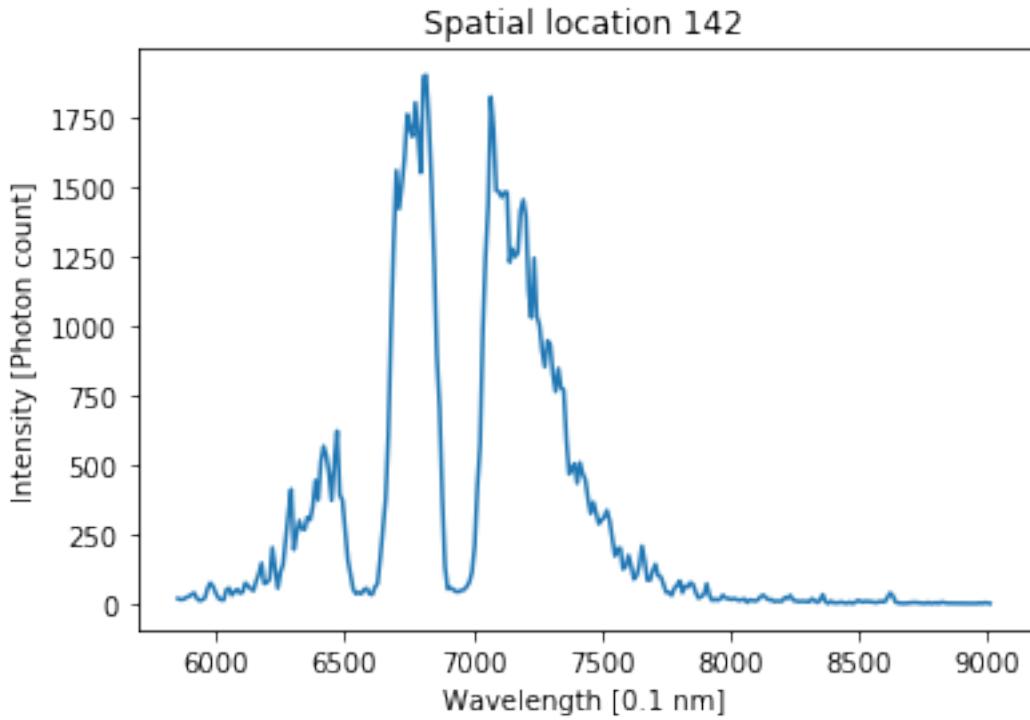


To change from pixels to wavelength. I'll use the lambda.dat file to get that information.

```
[20]: wavelength = np.loadtxt('../TS_data_files/lambda.dat')           # 2D array of CCD
      ↪counts data
```

```
[21]: plt.plot(wavelength[spatial_location_idx], intensity[spatial_location_idx])
plt.xlabel("Wavelength [0.1 nm]")
plt.ylabel("Intensity [Photon count]")
plt.title("Spatial location {}".format(spatial_location_idx))
```

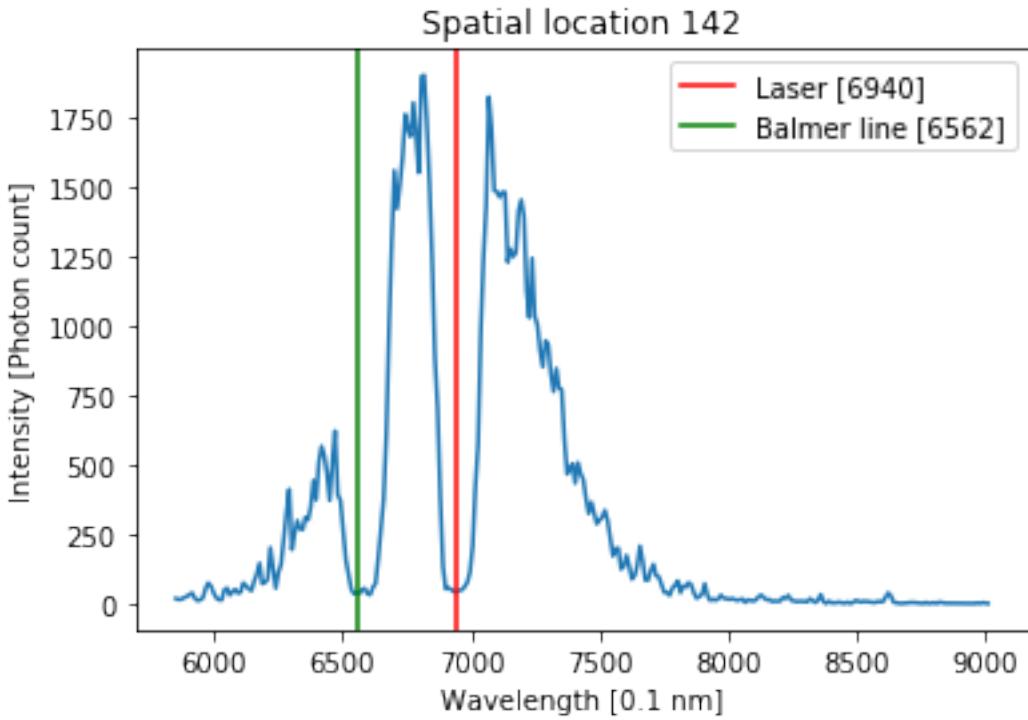
```
[21]: Text(0.5, 1.0, 'Spatial location 142')
```



There are 2 wavelengths that are filtered out. These two wavelengths are the Balmer line and the laser. The Balmer line is one of the spectral line emissions from the hydrogen atom, and since the plasma species is made out of hydrogen, we have to account for that. The wavelengths for the Balmer line and the laser are going to be much higher than what we are measuring, so to avoid skewing the data, they were removed. This poses a new challenge since we have cropped data. This will be addressed later on.

```
[22]: plt.plot(wavelength[spatial_location_idx], intensity[spatial_location_idx])
plt.axvline(6940, label="Laser [6940]", color="r")
plt.axvline(6562, label="Balmer line [6562]", color="g")
plt.legend(loc="best")
plt.xlabel("Wavelength [0.1 nm]")
plt.ylabel("Intensity [Photon count]")
plt.title("Spatial location {}".format(spatial_location_idx))
```

```
[22]: Text(0.5, 1.0, 'Spatial location 142')
```



Section 4

To get the electron temperature, T_e , we first have to fit a Gaussian.

```
[23]: def gaussian(x, *params):
    A = params[0]
    x0 = params[1]
    c = params[2]
    # y0 = params[3]
    return A*np.exp(-(x-x0)**2 / (2*c**2))
```

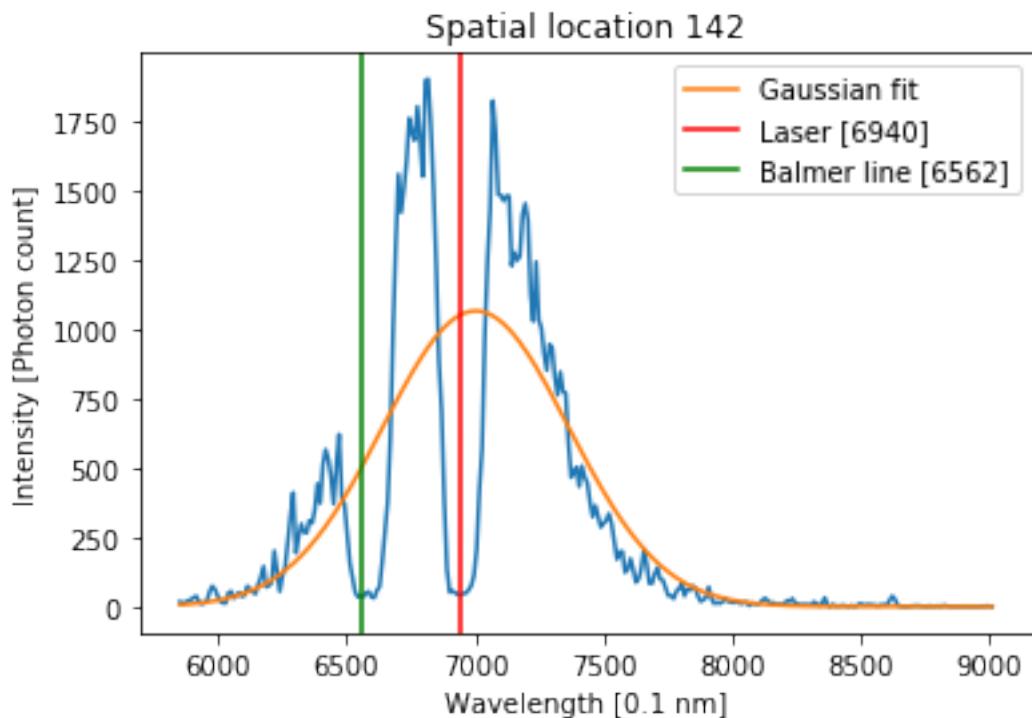
```
[24]: xdata, ydata = wavelength[spatial_location_idx], intensity[spatial_location_idx]
guess = [1000,7000,100]
print("Our initial guess is: {}".format(guess))
popt, pcov = curve_fit(gaussian, xdata, ydata, p0=guess)
yfit = gaussian(xdata, *popt)
for i in range(len(popt)):
    print ("Parameter",i,":",popt[i]," +/- ",np.sqrt(pcov[i][i]))
print("Fit parameters : ", popt)
print("Fit standard deviations : ", np.sqrt(np.diag(pcov)))
```

Our initial guess is: [1000, 7000, 100]
 Parameter 0 : 1066.335981865511 +/- 49.736674119270916
 Parameter 1 : 7002.229673522936 +/- 19.499872229800808
 Parameter 2 : 362.0664781462552 +/- 19.50619439181259

```
Fit parameters : [1066.33598187 7002.22967352 362.06647815]
Fit standard deviations : [49.73667412 19.49987223 19.50619439]
```

```
[25]: plt.plot(xdata, ydata)
plt.plot(xdata, yfit, label="Gaussian fit")
plt.axvline(6940, label="Laser [6940]", color="r")
plt.axvline(6562, label="Balmer line [6562]", color="g")
plt.legend(loc="best")
plt.xlabel("Wavelength [0.1 nm]")
plt.ylabel("Intensity [Photon count]")
plt.title("Spatial location {}".format(spatial_location_idx))
```

```
[25]: Text(0.5, 1.0, 'Spatial location 142')
```



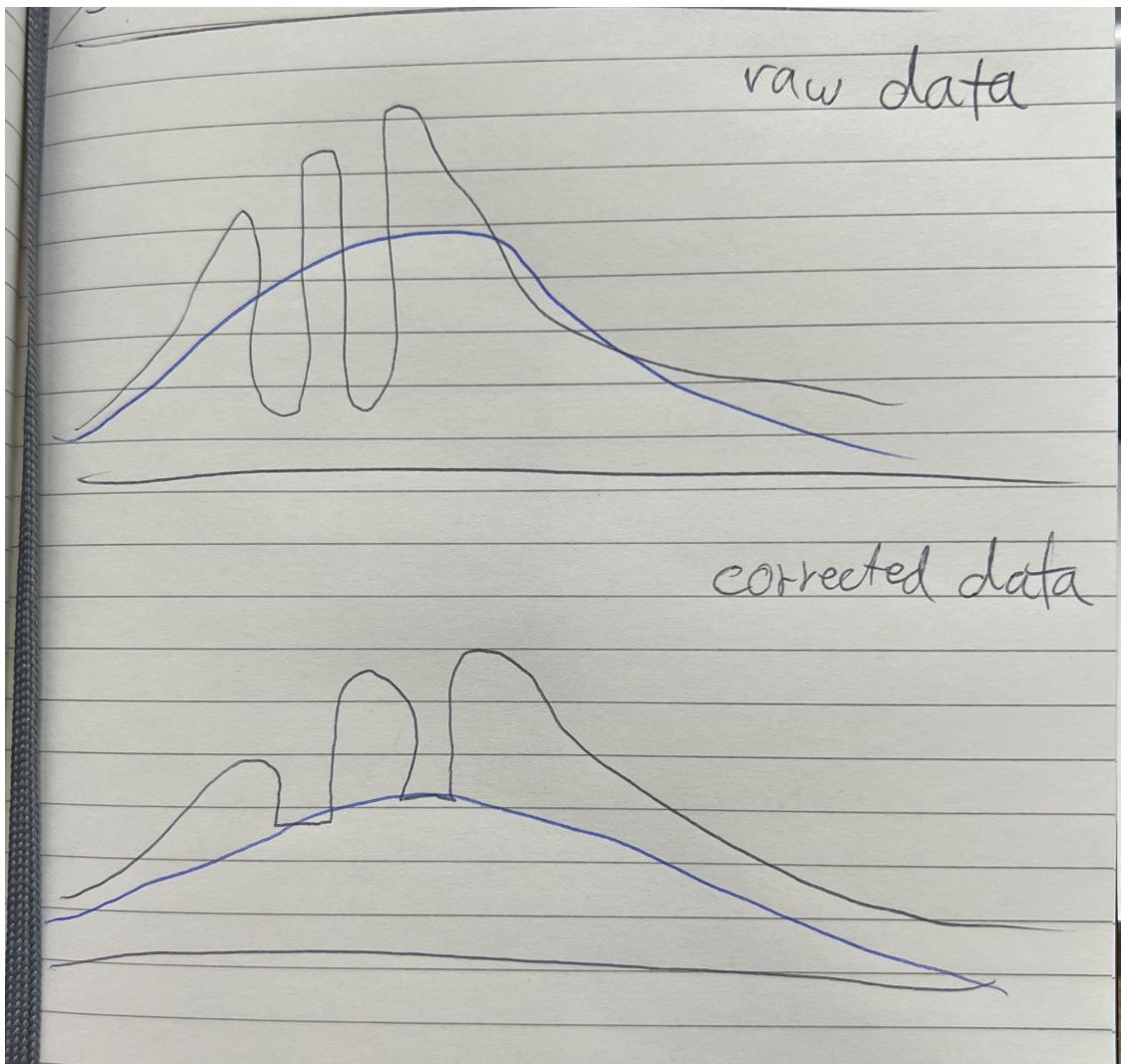
The Gaussian is at least following the trend, but the problem is that I'm fitting data that is not real (the 2 omitted wavelengths). Now, I have to figure out how to manage this.

I'm going to try to fit a Gaussian, and then crop the data below the Gaussian. Then, I'll fit another Gaussian with the corrected data, and do the same process of cropping the data below the new Gaussian line. I'm not sure if it'll work, but it's worth the try. I'll stop the process by looking at the difference between the previous and current Gaussian, and if the difference is below a threshold, I'll stop the process.

The idea behind is that, since we have cropped data, the Gaussian fit will always be below what we need. So, if for every data point, we get the maximum between the raw data and the Gaussian fitted data, we will get data that is closer to the truth.

```
[26]: display.Image("./supporting_imgs/section_4_img_1.jpg")
```

[26]:



```
[27]: data_before_correction = np.stack([yfit, ydata], axis=1)
y_corrected_data = np.amax(data_before_correction, axis=1)
```

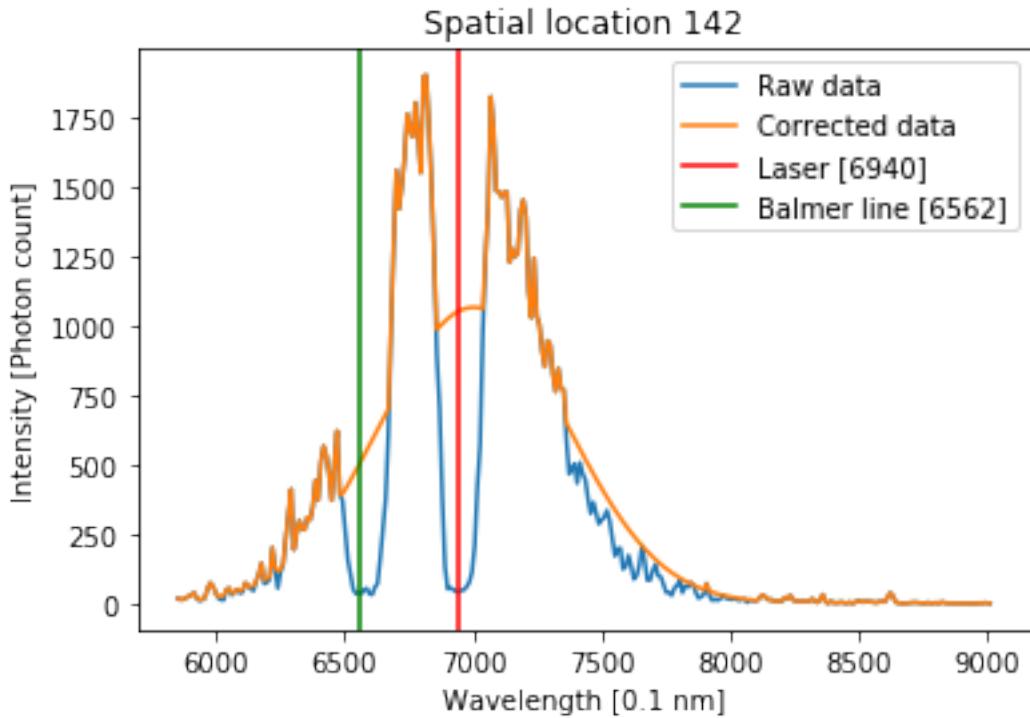
```
[28]: plt.plot(xdata, ydata, label="Raw data")
# plt.plot(xdata, yfit, label="Gaussian fit")
plt.plot(xdata, y_corrected_data, label="Corrected data")
plt.axvline(6940, label="Laser [6940]", color="r")
plt.axvline(6562, label="Balmer line [6562]", color="g")
```

```

plt.legend(loc="best")
plt.xlabel("Wavelength [0.1 nm]")
plt.ylabel("Intensity [Photon count]")
plt.title("Spatial location {}".format(spatial_location_idx))

```

[28]: Text(0.5, 1.0, 'Spatial location 142')



The corrected data looks better than the raw data. Let's see how the Gaussian fit works.

```

[29]: xdata, ydata = wavelength[spatial_location_idx], intensity[spatial_location_idx]
guess = [1000,7000,100]
print("Our initial guess is: {}".format(guess))
popt, pcov = curve_fit(gaussian, xdata, y_corrected_data, p0=guess)
yfit = gaussian(xdata, *popt)
for i in range(len(popt)):
    print ("Parameter",i,":",popt[i],"+/-",np.sqrt(pcov[i][i]))
print("Fit parameters : ", popt)
print("Fit standard deviations : ", np.sqrt(np.diag(pcov)))
plt.plot(xdata, ydata)
plt.plot(xdata, yfit, label="Gaussian fit")
plt.plot(xdata, y_corrected_data, label="Corrected data")
plt.axvline(6940, label="Laser [6940]", color="r")
plt.axvline(6562, label="Balmer line [6562]", color="g")

```

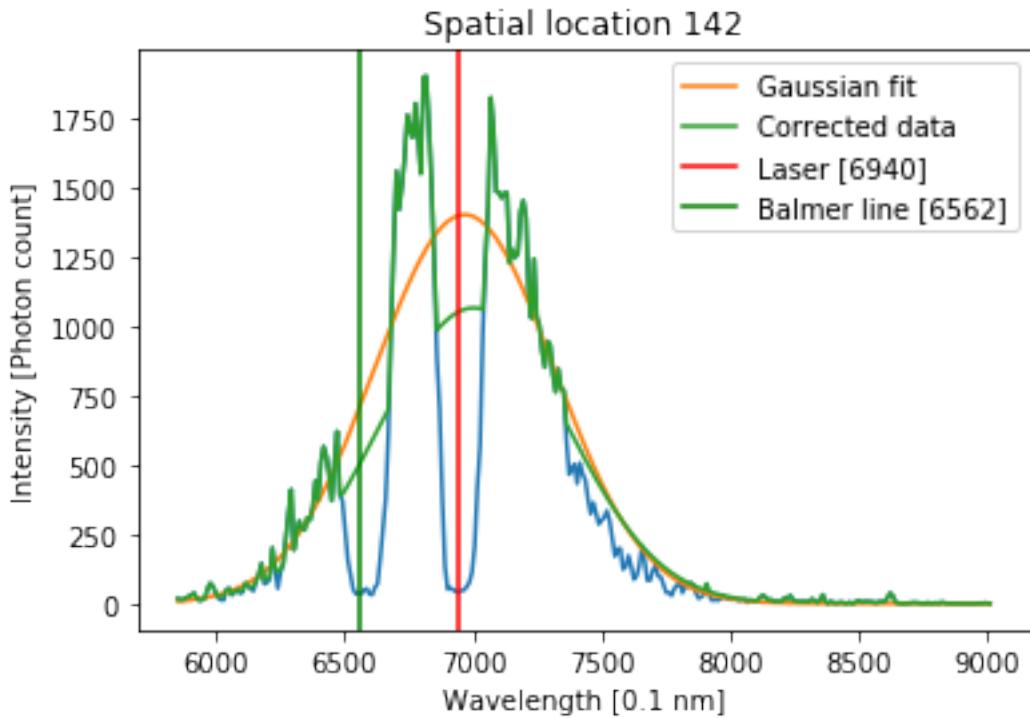
```

plt.legend(loc="best")
plt.xlabel("Wavelength [0.1 nm]")
plt.ylabel("Intensity [Photon count]")
plt.title("Spatial location {}".format(spatial_location_idx))

```

Our initial guess is: [1000, 7000, 100]
Parameter 0 : 1402.443049842505 +/- 25.477317957332332
Parameter 1 : 6966.575704852783 +/- 7.306483044957813
Parameter 2 : 348.3369964804944 +/- 7.308565393023998
Fit parameters : [1402.44304984 6966.57570485 348.33699648]
Fit standard deviations : [25.47731796 7.30648304 7.30856539]

[29]: Text(0.5, 1.0, 'Spatial location 142')



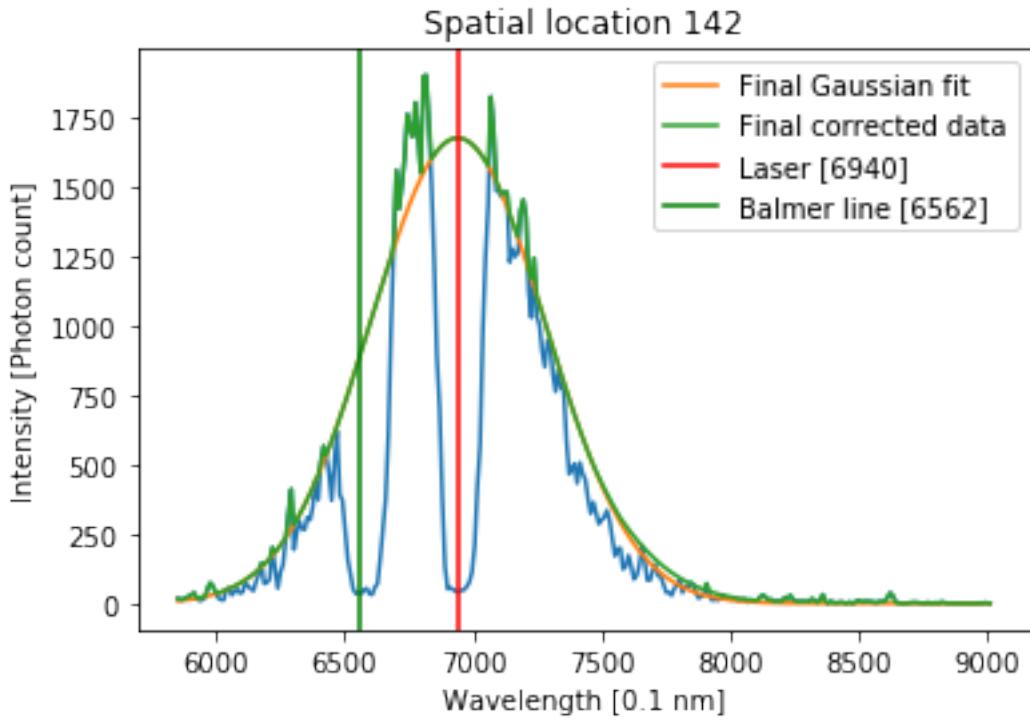
The new Gaussian fit looks much more closer to the truth. I'll put everything in a while loop and do this until the difference is not that big. I'll put it in a function so that I can reuse it later on. For the difference I'll use the parameter A, as that is the one that needs to get as close to the top as possible. That parameter is also easier to see if the Gaussian fit is doing a good job at fitting the data or not. I'll also put a limit of 10 Gaussian fits to avoid overdoing it. I don't think it's necessary, but it's good to have an extra safety limit.

```
[30]: def get_gaussian_fit(spatial_location_idx=spatial_location_idx_center, A_0=10, print_results=True):
    xdata, ydata = wavelength[spatial_location_idx], intensity[spatial_location_idx]
    y_data_for_fit = ydata
    A_previous = 1
    # below 10% difference, or if it runs more than 10 times, the while loop will stop
    i = 1
    while A_previous / A_0 <+ .9 and i < 11:
        i += 1
        guess = [A_0, 7000, 1000]
        popt, pcov = curve_fit(gaussian, xdata, y_data_for_fit, p0=guess)
        yfit = gaussian(xdata, *popt)
        data_before_correction = np.stack([yfit, y_data_for_fit], axis=1)
        y_data_for_fit = np.amax(data_before_correction, axis=1)
        A_previous = A_0
        A_0 = popt[0]
    if print_results:
        print("The final parameters are: {}".format(popt))
        plt.plot(xdata, ydata)
        plt.plot(xdata, yfit, label="Final Gaussian fit")
        plt.plot(xdata, y_data_for_fit, label="Final corrected data")
        plt.axvline(6940, label="Laser [6940]", color="r")
        plt.axvline(6562, label="Balmer line [6562]", color="g")
        plt.legend(loc="best")
        plt.xlabel("Wavelength [0.1 nm]")
        plt.ylabel("Intensity [Photon count]")
        plt.title("Spatial location {}".format(spatial_location_idx))

    return popt, pcov
```

```
[31]: popt, pcov = get_gaussian_fit(spatial_location_idx)
```

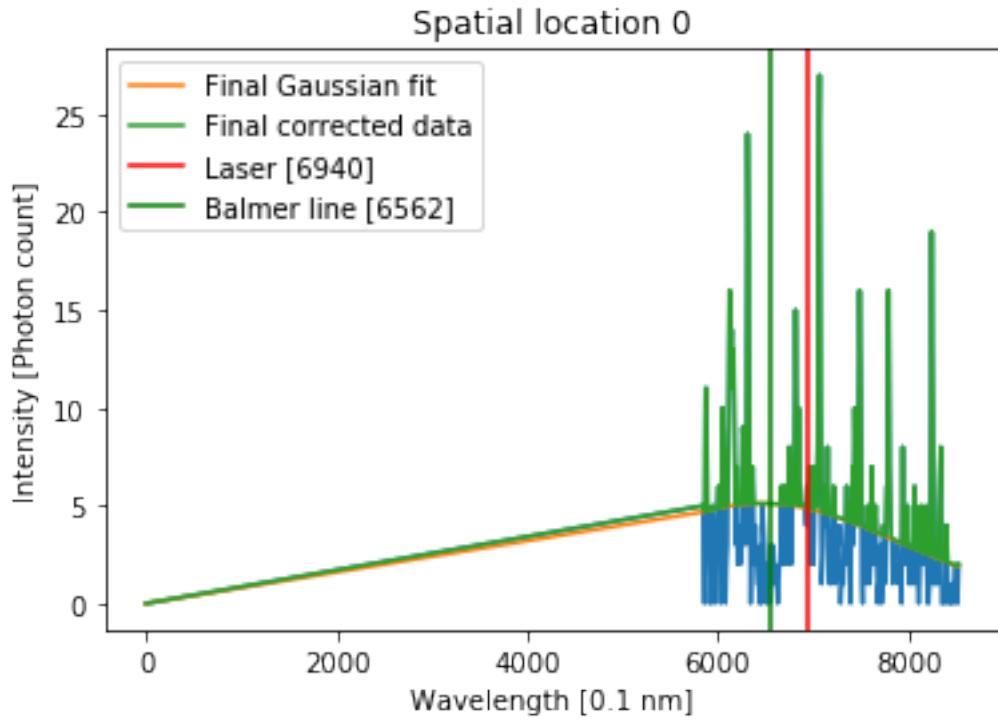
The final parameters are: [1675.94546979 6940.08260542 338.24543083]



This looks nice! I'll try with several other spatial locations to see how it looks like.

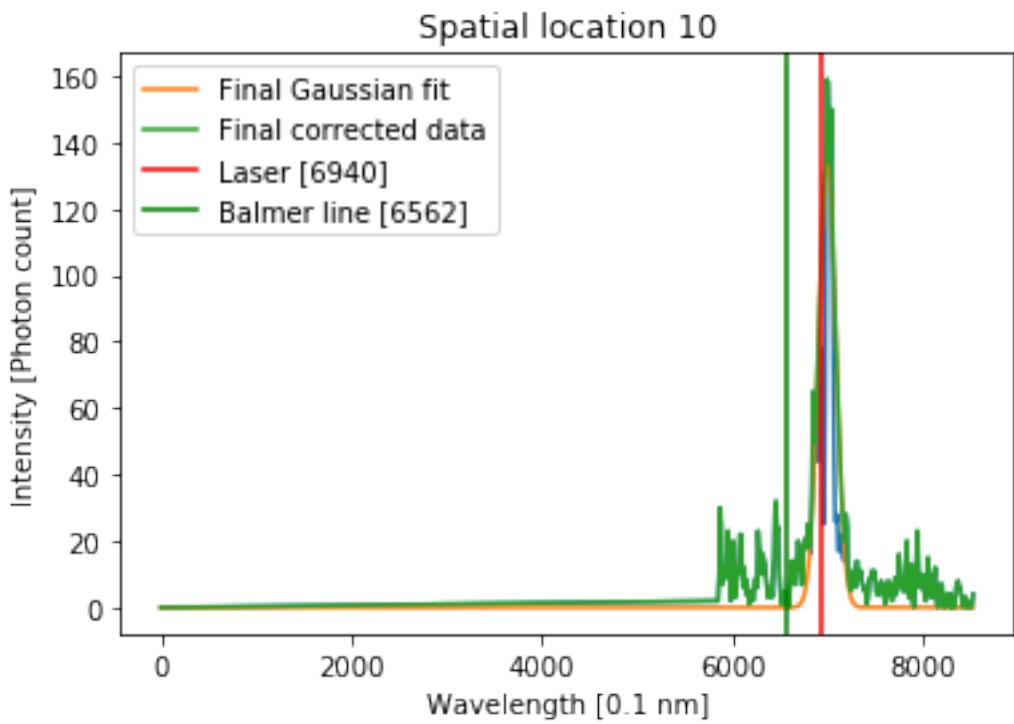
```
[32]: popt, pcov = get_gaussian_fit(0)
```

The final parameters are: [5.11757044e+00 6.46456628e+03 1.46053558e+03]



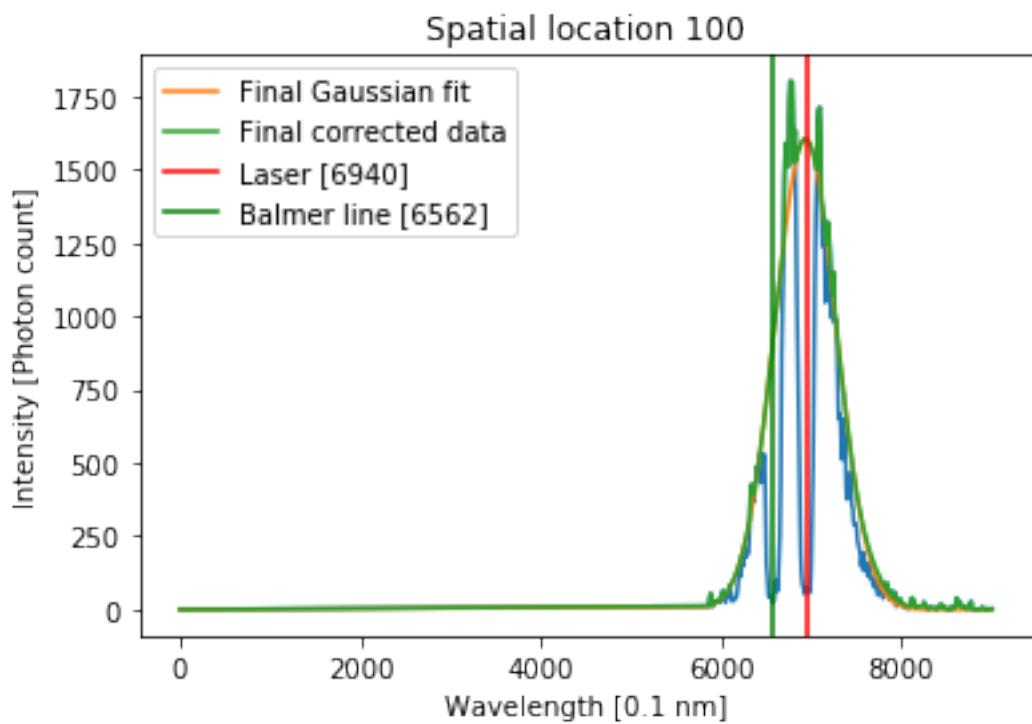
```
[33]: popt, pcov = get_gaussian_fit(10)
```

```
The final parameters are: [ 135.0657511  6997.27007365   90.40477438]
```



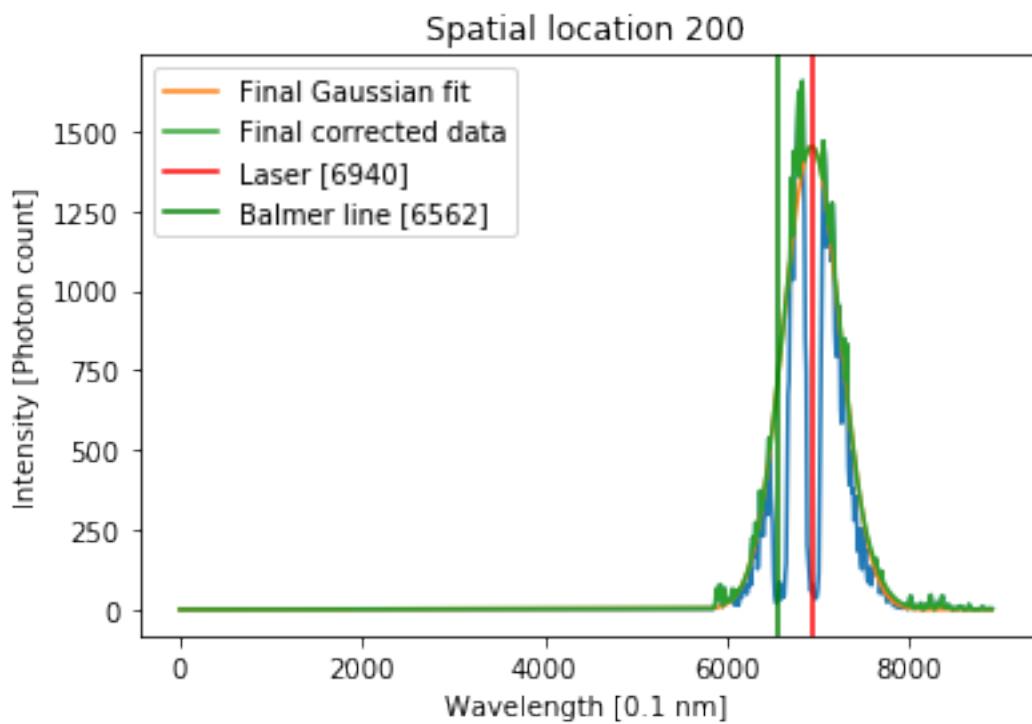
```
[34]: popt, pcov = get_gaussian_fit(100)
```

The final parameters are: [1605.40992411 6932.82201841 339.07166172]



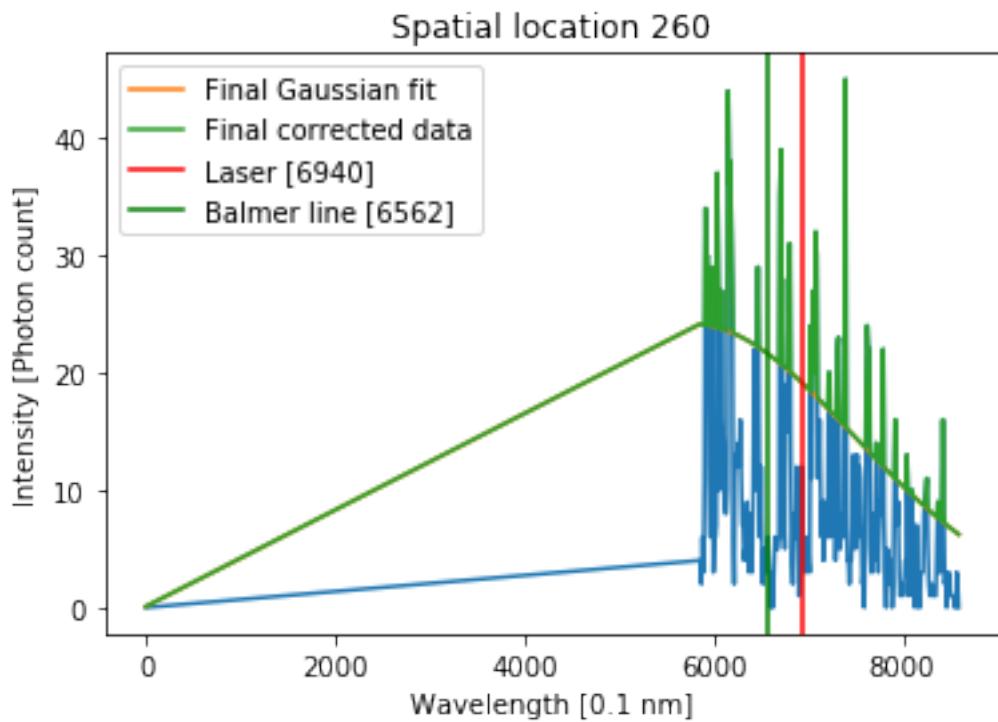
```
[35]: popt, pcov = get_gaussian_fit(200)
```

```
The final parameters are: [1451.40722321 6928.16861725 314.18305066]
```



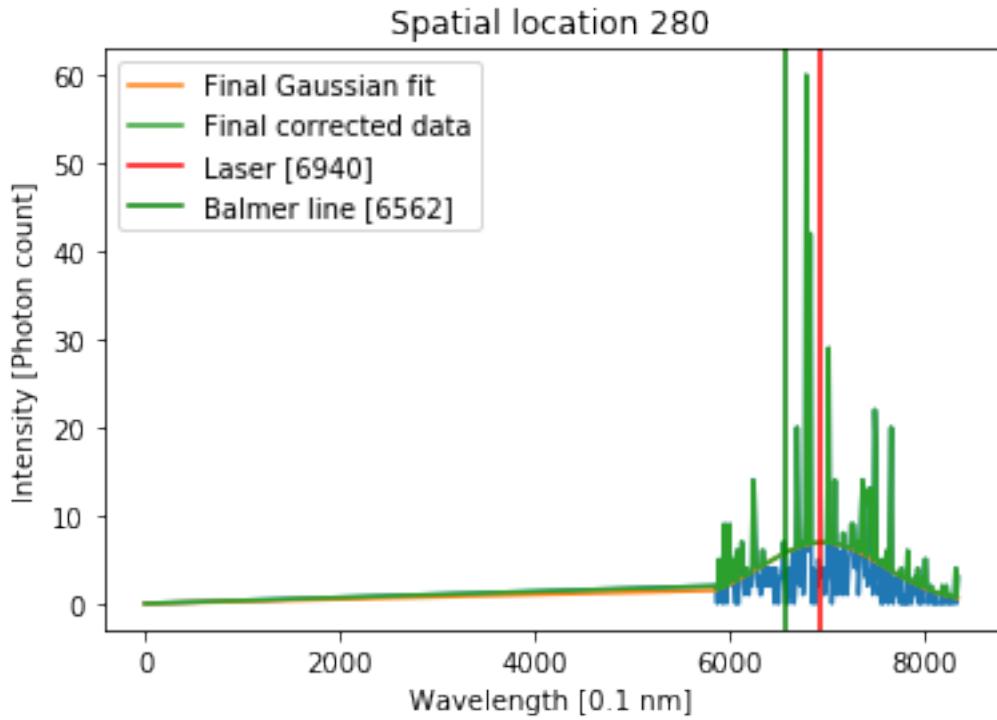
```
[36]: popt, pcov = get_gaussian_fit(260)
```

The final parameters are: [24.15256912 5765.76819851 1716.43085633]



```
[37]: popt, pcov = get_gaussian_fit(280)
```

The final parameters are: [6.92915113e+00 6.95572160e+03 6.30907342e+02]



Looks like the function struggles with the limits (0, 283). I'll probably have to crop the data in those cases, because there's too much noise.

In terms of the initial condition (A_0 parameter), I tried with several values, and what's needed for this to work with edge cases (e.g. spatial index = 10, 250) is to have a small enough A_0 parameter. That will ensure that the function is not stopped before reaching an acceptable fit. This doesn't solve the very extreme values (e.g. spatial index = 0, over 250).

Now, unto the electron temperature T_e .

Section 4

```
[38]: boltzmann_constant = 1.380649e-23 # m2 kg s-2 K-1
lambda_i = 6943 # 0.1 nm
electron_energy = 0.511 * 1000000 # eV
```

```
[39]: angles = np.loadtxt('../TS_data_files/angle.dat') # 1D array of scattering angles
angles.shape
```

```
[39]: (284,)
```

```
[40]: display.Image("./supporting_imgs/section_4_img_2.jpg")
```

```
[40]:
```

The image shows a handwritten derivation of the formula for electron temperature (T_e) from the optical depth equation (σ_λ). The derivation starts with the equation $\sigma_\lambda = C_p \lambda / \beta_\text{H} \sqrt{2} \sin(\frac{\theta}{2})$, where C_p is a parameter. This is followed by the definition of β_H as $\sqrt{\frac{2k_b T_e}{m_e c^2}}$. The next step is $C_p = \lambda / \sqrt{\frac{2k_b T_e}{m_e c^2}} \sqrt{2} \sin(\frac{\theta}{2})$. This is then rearranged to $C_p^2 = \lambda^2 \left(\frac{2k_b T_e}{m_e c^2} \right) 2 \sin^2\left(\frac{\theta}{2}\right)$. Finally, the formula for T_e is derived as $T_e = \frac{C_p^2 m_e c^2}{\lambda^2 4 k_b \sin^2\left(\frac{\theta}{2}\right)}$.

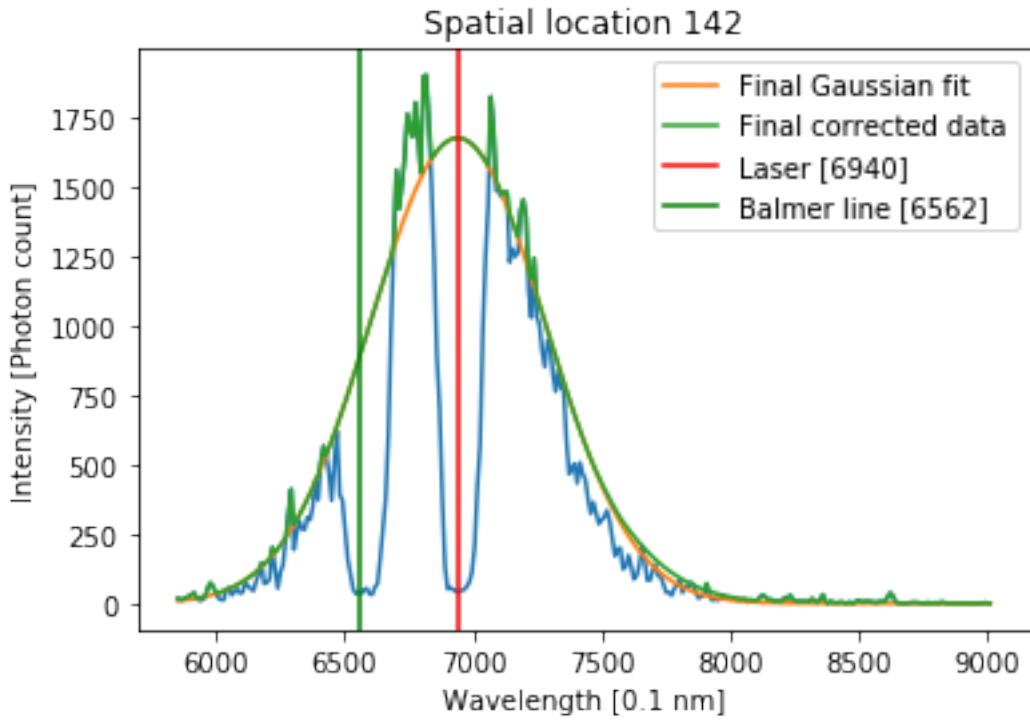
I solved for T_e in the given equation. I'm assuming `sigma_lambda` to be the same as the C parameter that we are getting from the Gaussian fit.

```
[41]: def get_electron_temperature(spatial_location_idx=spatial_location_idx_center,
                                print_results=True):
    popt, pcov = get_gaussian_fit(spatial_location_idx,
                                    print_results=print_results)
    C = popt[2] # what are the units?
    angle = angles[spatial_location_idx]
    T_e = (C**2 * electron_energy) / (lambda_i**2 * 4 * np.sin(angle/2)**2)
    if print_results:
        print ("The electron energy for location {} is: {} ev".
              format(spatial_location_idx, T_e))
    return T_e # eV
```

```
[42]: get_electron_temperature(spatial_location_idx_center)
```

The final parameters are: [1675.94546979 6940.08260542 338.24543083]
The electron energy for location 142 is: 548.5627637512292 ev

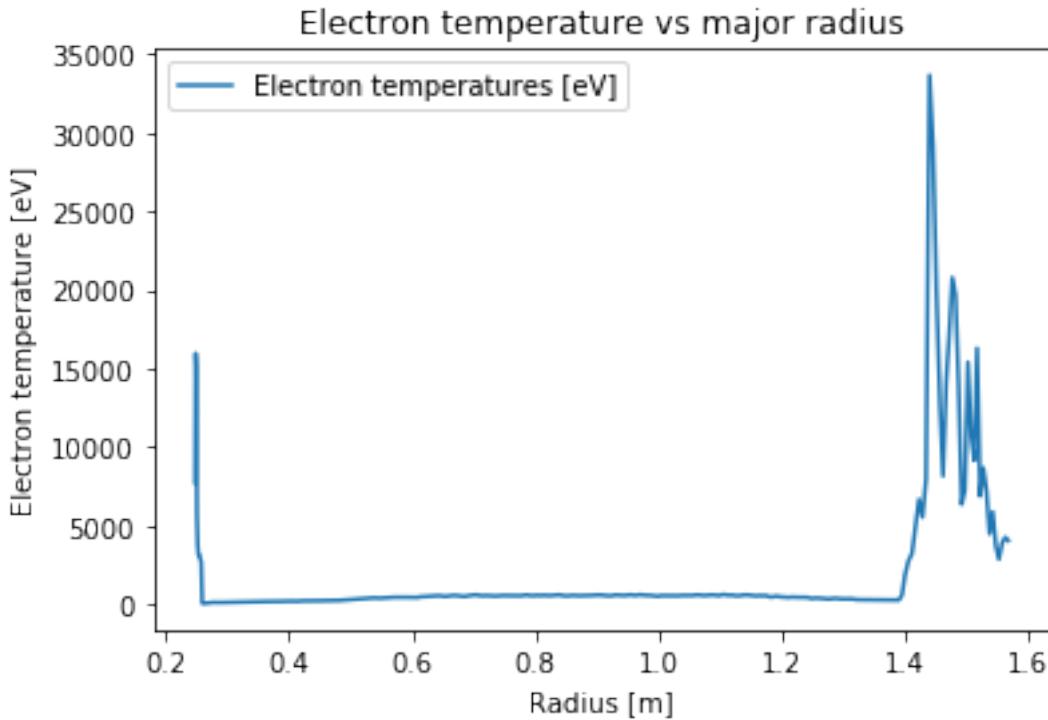
```
[42]: 548.5627637512292
```



Now that we have a function that can get the electron temperature given a spatial location index, I'll look through all of the data to see what I get.

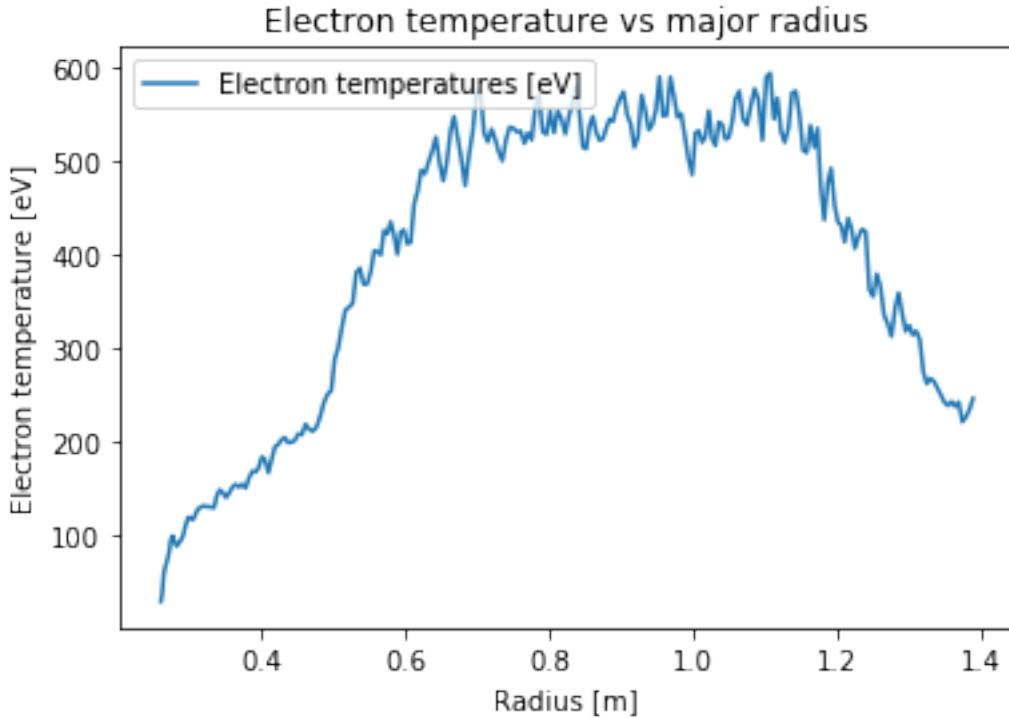
```
[43]: radius = np.loadtxt('../TS_data_files/radius.dat') # 1D array of major radii
```

```
[44]: spatial_locations = range(wavelength.shape[0])
electron_temperatures = [get_electron_temperature(spatial_location,
                                                print_results=False) for spatial_location in spatial_locations]
plt.plot(radius[spatial_locations], electron_temperatures, label="Electron
temperatures [eV]")
plt.legend(loc="upper left")
plt.title("Electron temperature vs major radius")
plt.xlabel("Radius [m]")
plt.ylabel("Electron temperature [eV]")
plt.show()
```



That looks weird. Going back to when we tested multiple locations on the Gaussian fit, we could see that for the extreme values of `spatial_location_idx = 0` and over 250, the Gaussian fit didn't work very well. So, it makes sense that in this graph, the results don't make a lot of sense. I'll crop the data to remove the noise present in the extreme values.

```
[45]: # New range without the peaks
spatial_locations = range(10, 250)
electron_temperatures = [get_electron_temperature(spatial_location, ↴
    ↪print_results=False) for spatial_location in spatial_locations]
plt.plot(radius[spatial_locations], electron_temperatures, label="Electron ↴
    ↪temperatures [eV]")
plt.legend(loc="upper left")
plt.title("Electron temperature vs major radius")
plt.xlabel("Radius [m]")
plt.ylabel("Electron temperature [eV]")
plt.show()
```



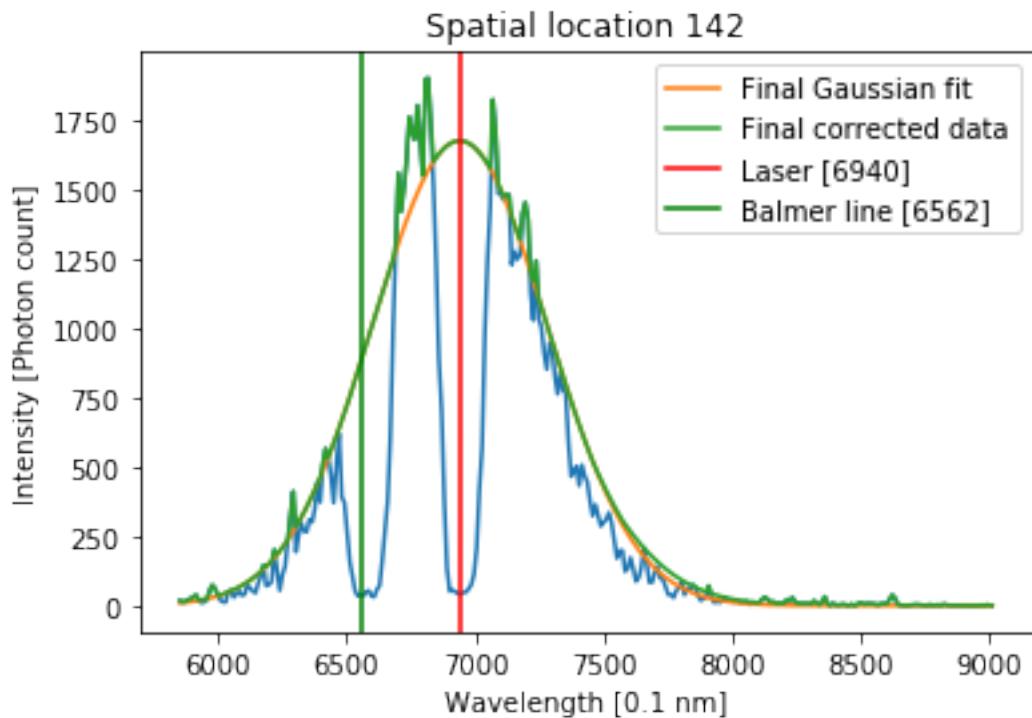
This makes a lot more sense. Now, I need to add the uncertainties. So far, we only have the uncertainties from the Gaussian fit. I'll start with those.

```
[46]: def get_electron_temperature_with_uncertainty(spatial_location_idx=spatial_location_idx_center,
                                                print_results=True):
    popt, pcov = get_gaussian_fit(spatial_location_idx, print_results)
    C = popt[2]
    C_error = np.sqrt(pcov[2][2])
    C_error_pct = C_error / C
    # print ("C_error_pct: {}".format(C_error_pct))
    angle = angles[spatial_location_idx]
    T_e = (C**2 * electron_energy) / (lambda_i**2 * 4 * np.sin(angle/2)**2)
    # add the radius significant figures to the error bars
    # times 2 because of the C**2.
    T_e_error = T_e * C_error_pct * 2
    if print_results:
        print ("The electron energy for location {} is: {} += {} ev".
              format(spatial_location_idx, T_e, T_e_error))
    return T_e, T_e_error # eV
```

```
[47]: get_electron_temperature_with_uncertainty()
```

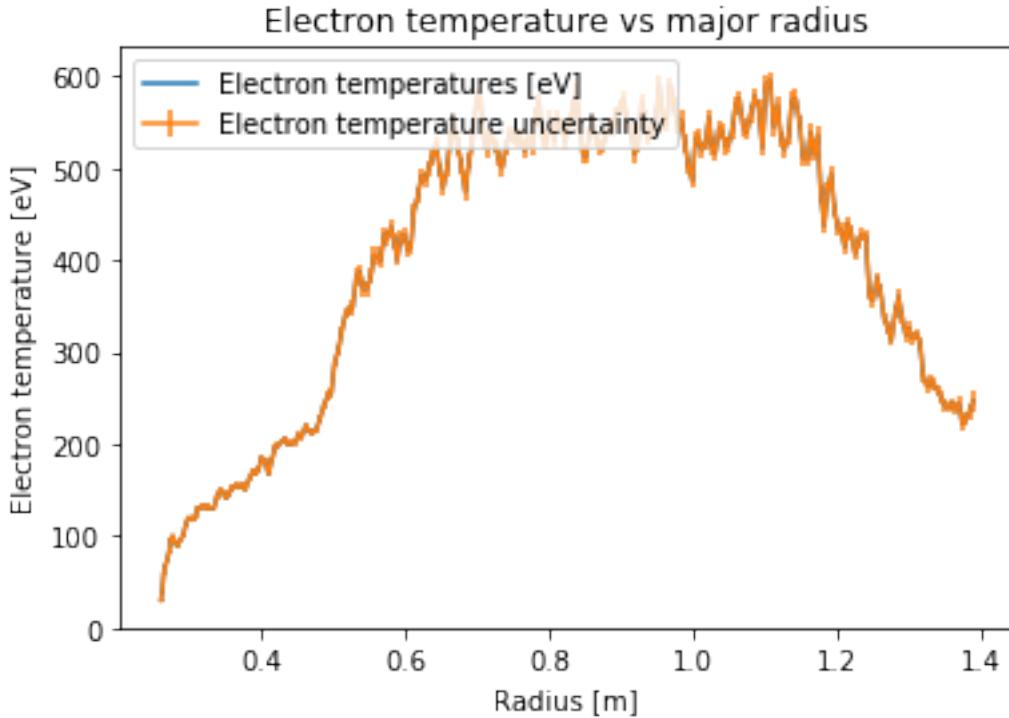
```
The final parameters are: [1675.94546979 6940.08260542 338.24543083]
The electron energy for location 142 is: 548.5627637512292 += 8.359963398938485
ev
```

[47]: (548.5627637512292, 8.359963398938485)



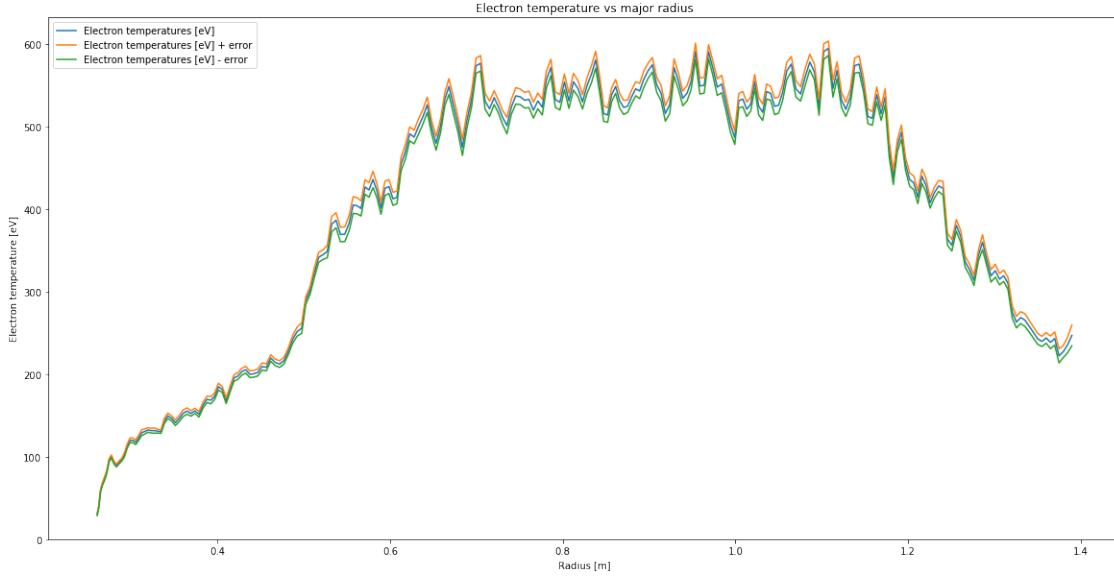
```
[48]: electron_temperature_obj = np.array([get_electron_temperature_with_uncertainty(spatial_location, print_results=False) for spatial_location in spatial_locations])
```

```
[49]: plt.plot(radius[spatial_locations], electron_temperature_obj[:,0], label="Electron temperatures [eV]")
plt.errorbar(radius[spatial_locations], electron_temperature_obj[:,0], yerr=electron_temperature_obj[:,1], label="Electron temperature uncertainty")
plt.legend(loc="upper left")
plt.title("Electron temperature vs major radius")
plt.xlabel("Radius [m]")
plt.ylabel("Electron temperature [eV]")
plt.show()
```



We have too many data points, so it looks like a new graph on top of it. I'll try with plotting another 2 plots, the first one with the $T_e + \text{error}$, and the other one with $T_e - \text{error}$.

```
[50]: # To have a bigger graph
plt.rcParams['figure.figsize'] = [20, 10]
plt.plot(radius[spatial_locations], electron_temperature_obj[:,0],
         label="Electron temperatures [eV]")
plt.plot(radius[spatial_locations], electron_temperature_obj[:,0] +
         electron_temperature_obj[:,1], label="Electron temperatures [eV] + error")
plt.plot(radius[spatial_locations], electron_temperature_obj[:,0] -
         electron_temperature_obj[:,1], label="Electron temperatures [eV] - error")
plt.legend(loc="upper left")
plt.title("Electron temperature vs major radius")
plt.xlabel("Radius [m]")
plt.ylabel("Electron temperature [eV]")
plt.show()
```



Conclusions

- Looking at the data and at the results from this whole analysis, it makes sense that the electron temperature is higher the closer it gets to the center of the plasma. It should also go close to 0 at the end of the tokamak (Outside of the graph, radius > 1.4), but there's too much noise in those measurements to make a proper analysis.
- Another interesting thing is that the slope when the radius is big is steeper than the slope when the radius is small. This is because of the density gradient. The density gradient is going to be bigger at the outward edge of the plasma than at the inward edge of the plasma.
- The uncertainties get bigger in the higher temperatures. That's probably because it gets harder to measure high temperatures. Probably there are other effects (such as the relativistic effects suggested in the extension section). I haven't analysed that, so I can't say that relativistic effects have anything to do right now at < 1 kev, but it is worth considering.
- So far, we are only considering the uncertainty that comes from the Gaussian fit. We are still missing the uncertainties associated with the instrument and the angles at which the photon reach the lens.

TOKAMAK FLIGHT SIMULATOR LAB

In this lab, we will use the METIS tokamak flight simulator to see how different input parameters affect the confinement time and triple product of the system. First, we will run the simulation for DD on the JET tokamak with different NBI power values. These NBI powers can fluctuate from 0 to 40 MW, so I'll try different values within this range.

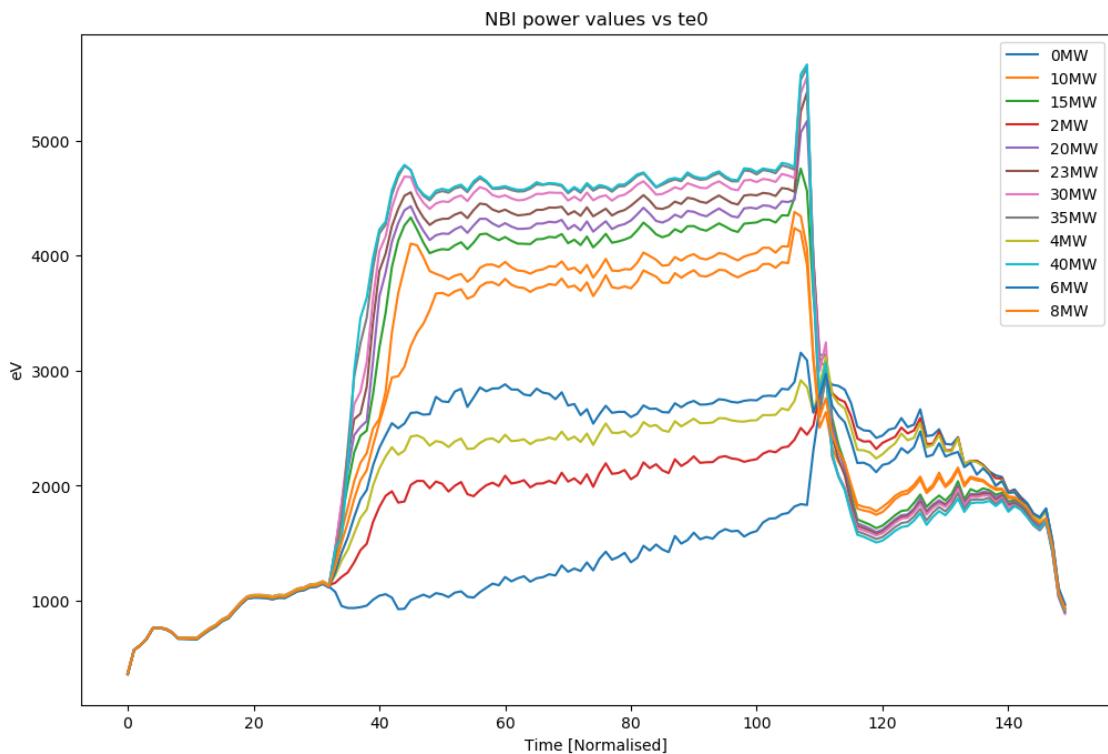
```
[51]: NBI_data_path = os.path.dirname(os.path.abspath("__file__")) + "/../
       ↳tokamak_data/NBI/"
NBI_data_files = [f for f in os.listdir(NBI_data_path) if os.path.isfile(os.
       ↳path.join(NBI_data_path, f))]
try:
    NBI_data_files.remove('defaultjet_0.mat') # This is the same as the nbi 15
       ↳file
    NBI_data_files.remove("defaultjet.mat") # This is the same as the nbi 15
       ↳file
except:
    pass
NBI_data_files.sort()
# NBI_data_files
```

```
[52]: def get_variable_data(variable, file_name, subsection='zerod'):
    full_dataset = scipy.io.loadmat("../tokamak_data/{}".format(file_name))
    data = full_dataset['post'][subsection][0][0][variable][0][0]
    return data
```

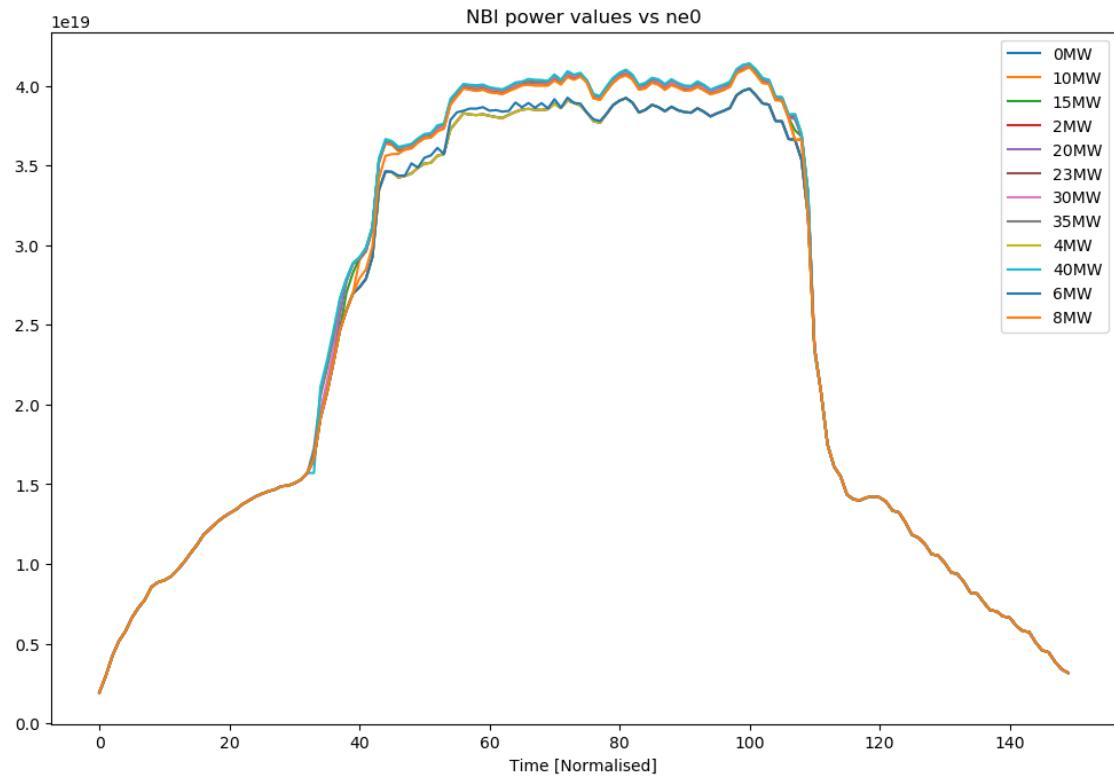
```
[53]: def get_nbi_from_file(file_name):
    nbi_pattern = "NBI_(.*?)\.mat"
    nbi_string = re.search(nbi_pattern, file_name).group(1)
    nbi_value = nbi_string + "MW"
    return nbi_value
```

```
[54]: def plot_variable_vs_nbi(variable, ylabel, xlabel="Time [Normalised]"):
    title = "NBI power values vs {}".format(variable)
    fig=plt.figure(figsize=(12,8), dpi= 100, facecolor='w', edgecolor='k')
    for file in NBI_data_files:
        nbi_value = get_nbi_from_file(file)
        # variable = "te0"
        data = get_variable_data(variable, "NBI/{}".format(file))
        plt.plot(data, label=nbi_value)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.title(title)
    plt.legend(loc="best")
```

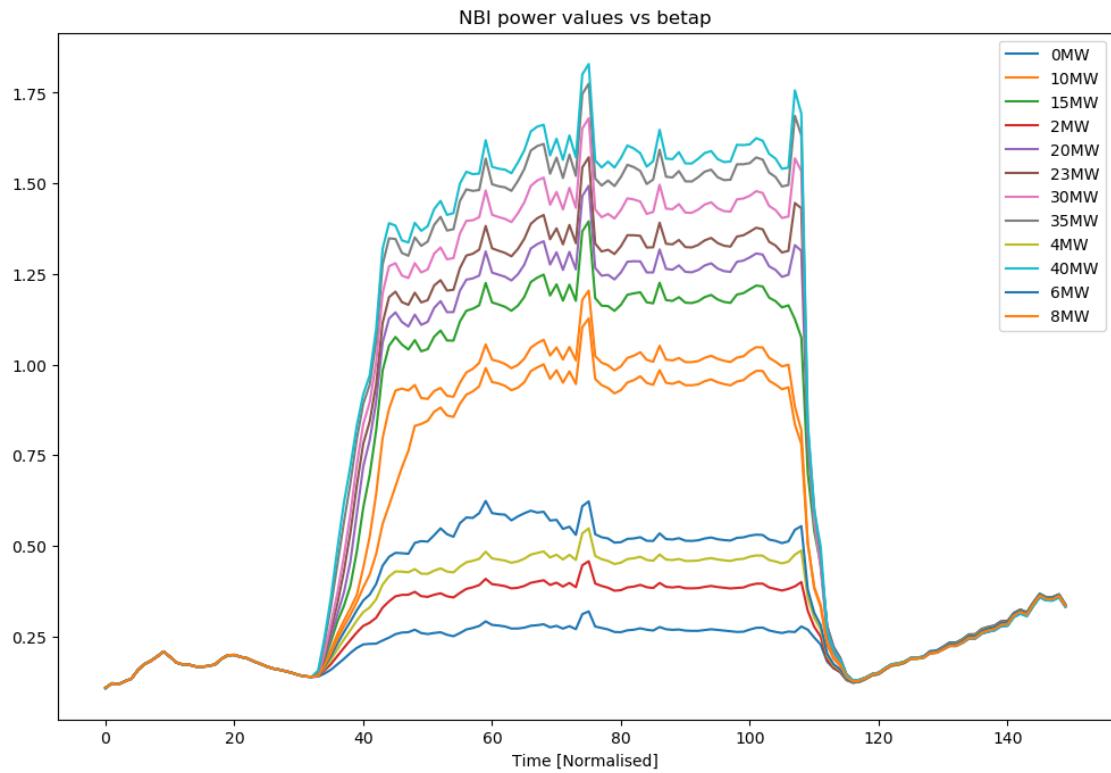
```
[55]: plot_variable_vs_nbi("te0", "eV")
```



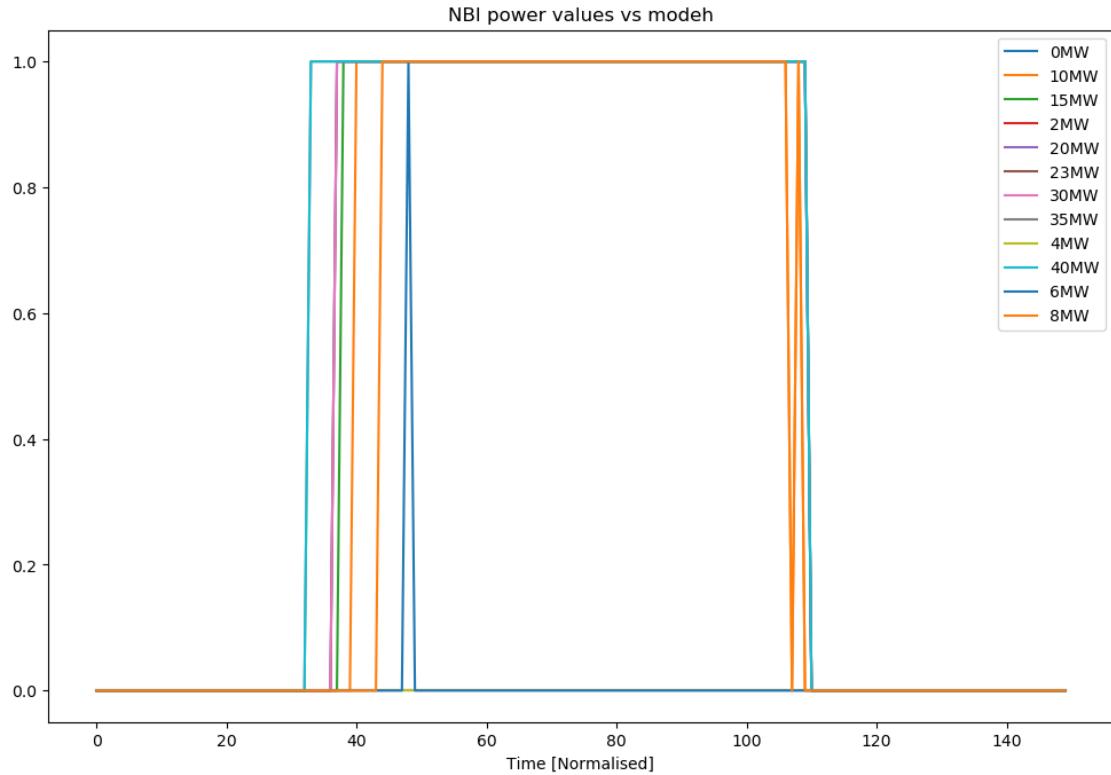
```
[56]: plot_variable_vs_nbi("ne0", "")
```



```
[57]: plot_variable_vs_nbi("betap", "")
```

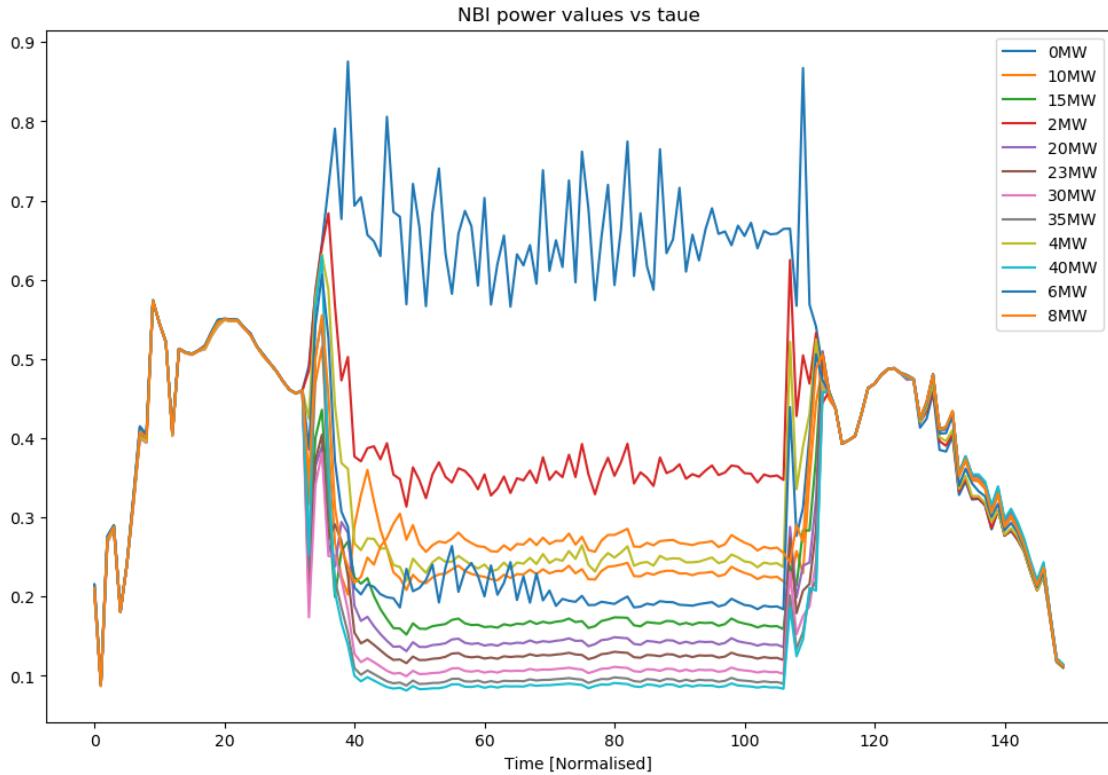


```
[58]: plot_variable_vs_nbi("modeh", "")
```



After plotting the electron temperature, number density, and beta with respect to NBI, we can see several things. The first one is that there's a clearly a threshold that, once it is passed, the plasma gets into H-mode. This threshold is between 6 and 8 MW, so we can assume it is about 7MW. We can see more clearly when the plasma is in H-mode with the modeh plot. The magnitude of how different the values are depending on whether the plasma is or isn't in H-mode differs in the different parameters. For example, the number density doesn't vary that much, but if we see the comparison in the electron temperature or in beta, we can see that the values change significantly.

```
[59]: plot_variable_vs_nbi("taue", "")
```



We know that $\tau_{ae} = \text{stored energy} / \text{power loss}$. So, more than a time measurement, it is the inverse rate at which energy is lost. Looking at it in this way makes more sense. However, it is strange that the confinement time goes down when the NBI power is increased, but when we think about it, it makes sense because with more power, the temperature rises significantly. If the temperature rises, but we are still applying the same magnetic field, the magnetic field won't be able to confine the plasma effectively, so the plasma will escape. Thus, the confinement time will decrease when the NBI power is increased.

Triple product calculation (Density, temperature, and confinement time)

```
[60]: def get_triple_product(file, file_folder):
    te0 = get_variable_data("te0", "{}_{}".format(file_folder, file))
    ne0 = get_variable_data("ne0", "{}_{}".format(file_folder, file))
    taue = get_variable_data("taue", "{}_{}".format(file_folder, file))
    triple_product = te0 * ne0 * taue
    all_data = np.stack([te0, ne0, taue, triple_product], axis=1)
    return all_data
```

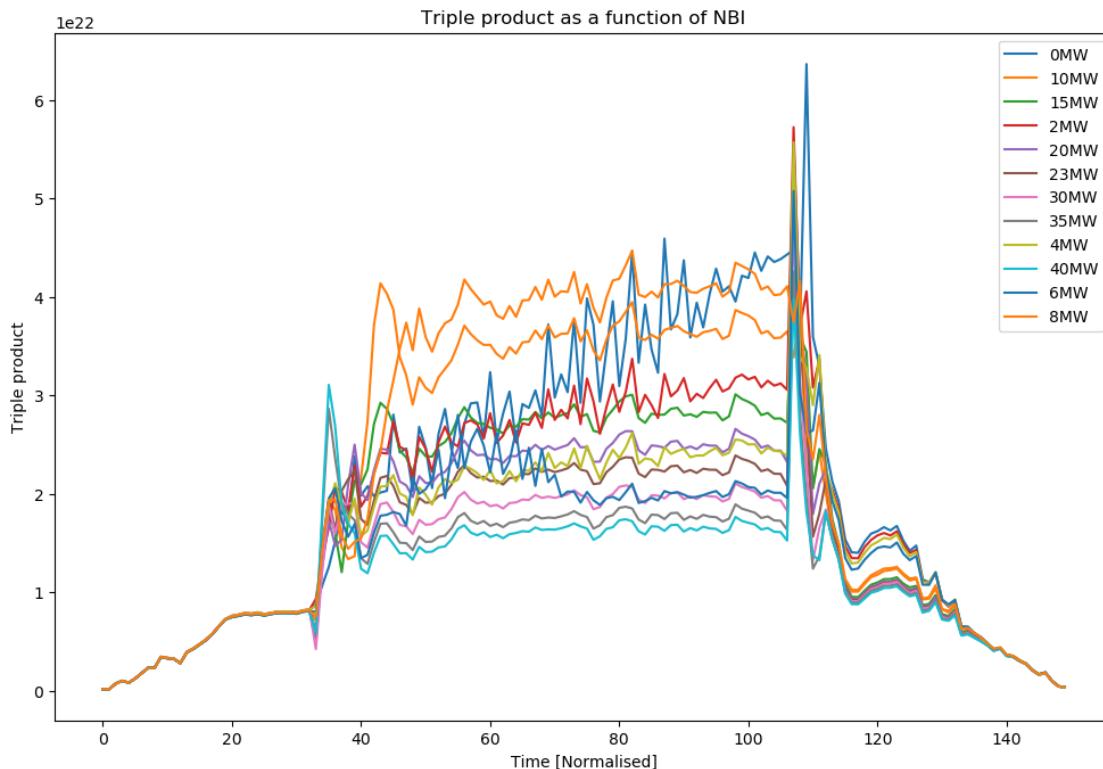
```
[61]: fig = plt.figure(figsize=(12,8), dpi=100, facecolor="w", edgecolor="k")
for file in NBI_data_files:
    nbi_value = get_nbi_from_file(file)
    tp_array = get_triple_product(file, "NBI")
```

```

tp = tp_array[:, -1]
plt.plot(tp, label=nbi_value)
plt.xlabel("Time [Normalised]")
plt.ylabel("Triple product")
plt.legend(loc="best")
plt.title("Triple product as a function of NBI")

```

[61]: Text(0.5, 1.0, 'Triple product as a function of NBI')



The magnitude of the triple product decreases when NBI power increases.

I'll plot the maximum triple product that we get for each NBI power value so that we can then compare it to the theoretical result.

```

[62]: fig = plt.figure(figsize=(12,8), dpi=100, facecolor="w", edgecolor="k")
df = pd.DataFrame(columns=["NBI", "max_tp"])
for file in NBI_data_files:
    nbi_value = int(re.search("NBI_(.*?)\.mat", file).group(1))
    tp_array = get_triple_product(file, "NBI")
    tp = tp_array[:, -1]
    max_tp = np.max(tp)
    new_row = {"NBI": nbi_value, "max_tp": max_tp}
    df = df.append(new_row, ignore_index=True)

```

```

df.sort_values(by=["NBI"], inplace=True)
plt.plot(df["NBI"], df["max_tp"], label="Simulation data")
plt.xlabel("NBI power [MW]")
plt.ylabel("Triple product")
plt.legend(loc="best")
plt.title("Maximum achieved triple product per NBI")

```

```

/usr/lib/python3/dist-packages/matplotlib/cbook/__init__.py:1402: FutureWarning:
Support for multi-dimensional indexing (e.g. `obj[:, None]`) is deprecated and
will be removed in a future version. Convert to a numpy array before indexing
instead.

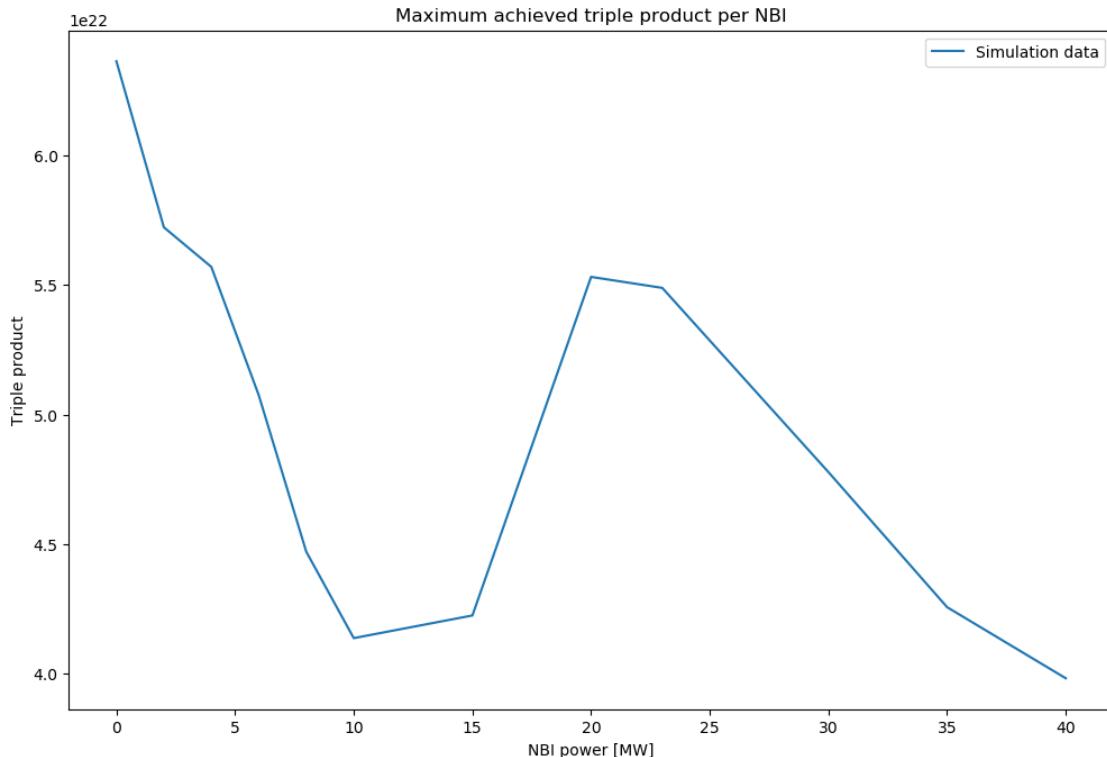
    ndim = x[:, None].ndim
/usr/lib/python3/dist-packages/matplotlib/axes/_base.py:276: FutureWarning:
Support for multi-dimensional indexing (e.g. `obj[:, None]`) is deprecated and
will be removed in a future version. Convert to a numpy array before indexing
instead.

    x = x[:, np.newaxis]
/usr/lib/python3/dist-packages/matplotlib/axes/_base.py:278: FutureWarning:
Support for multi-dimensional indexing (e.g. `obj[:, None]`) is deprecated and
will be removed in a future version. Convert to a numpy array before indexing
instead.

    y = y[:, np.newaxis]

```

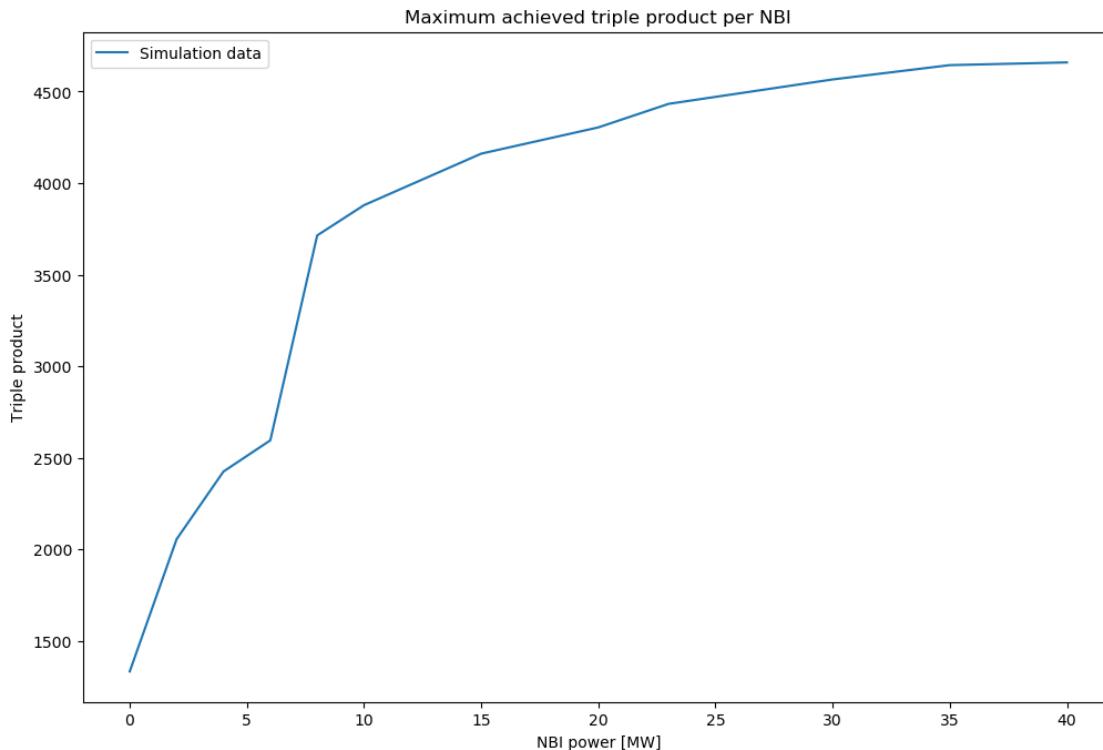
[62]: Text(0.5, 1.0, 'Maximum achieved triple product per NBI')



To know what temperature to use, and what reaction rate to use, I'll plot de temperature at the middle of the simulation (time=80)

```
[63]: fig = plt.figure(figsize=(12,8), dpi=100, facecolor="w", edgecolor="k")
te_df = pd.DataFrame(columns=["NBI", "te0"])
for file in NBI_data_files:
    nbi_value = int(re.search("NBI_(.*?)\.mat", file).group(1))
    te0 = get_variable_data("te0", "{}/{}".format("NBI", file))[80]
    new_row = {"NBI": nbi_value, "te0": te0}
    te_df = te_df.append(new_row, ignore_index=True)
te_df.sort_values(by=["NBI"], inplace=True)
plt.plot(te_df["NBI"], te_df["te0"], label="Simulation data")
plt.xlabel("NBI power [MW]")
plt.ylabel("Triple product")
plt.legend(loc="best")
plt.title("Maximum achieved triple product per NBI")
```

```
[63]: Text(0.5, 1.0, 'Maximum achieved triple product per NBI')
```



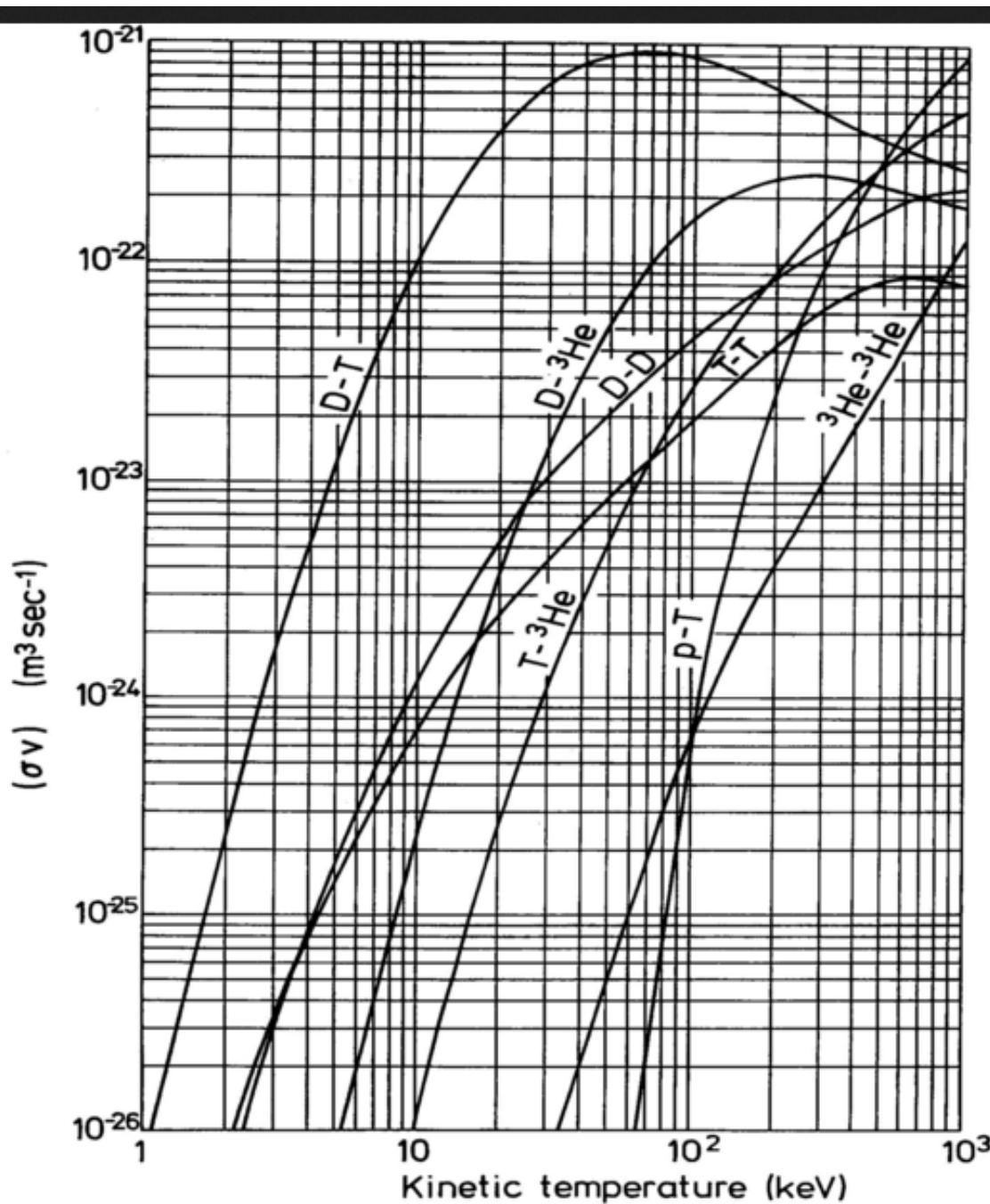
```
[64]: print ("The average temperature for all the simulations is: {}".format(np.
    ↪mean(te_df["te0"])[0]))
```

The average temperature for all the simulations is: 3564.4805168115454

I'll use that value for the reactivity in the following graph

```
[65]: display.Image("./supporting_imgs/reaction_rate.png")
```

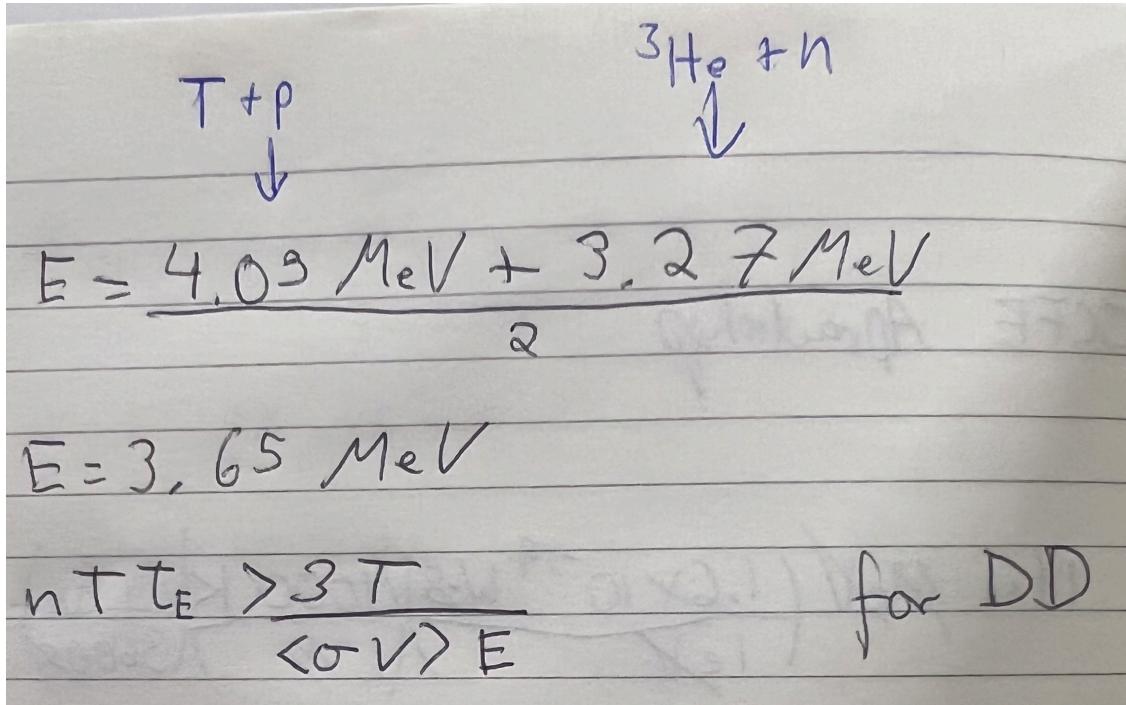
```
[65]:
```



The value that I'll use is 50e-26

```
[66]: display.Image("./supporting_imgs/tp_DD.jpg")
```

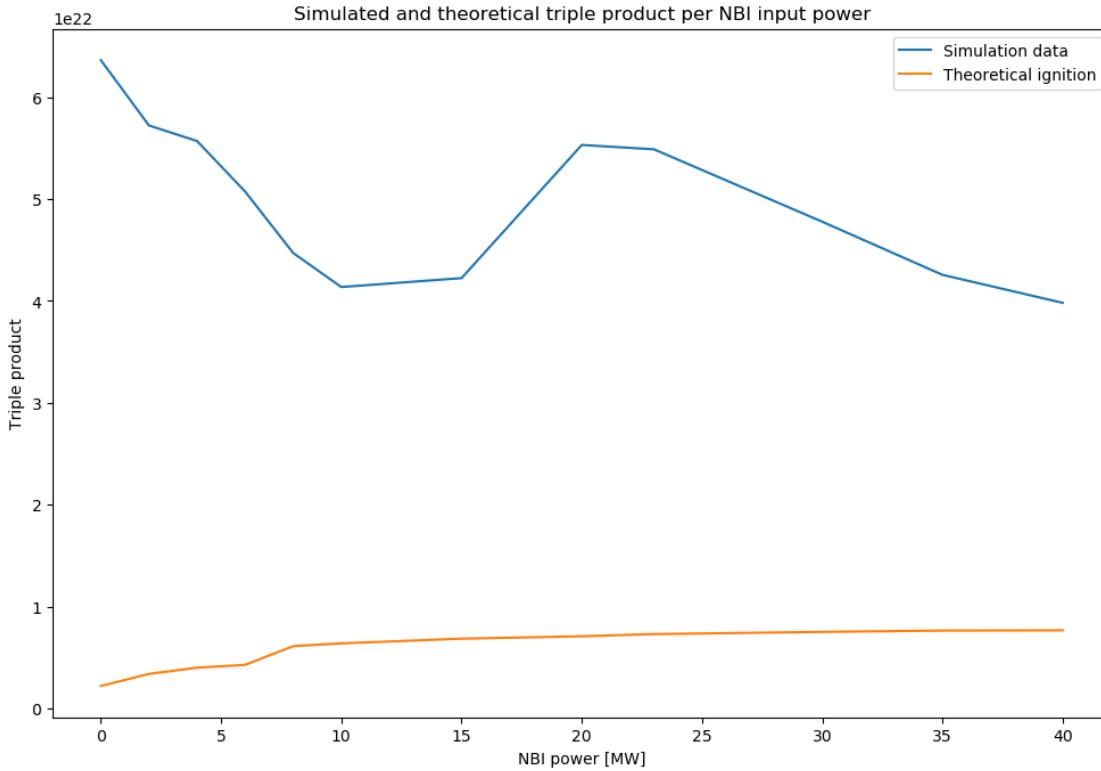
[66]:



I'll use the previous equation and plot it in the triple product vs NBI graph to see how the simulation data compares to the theoretical value.

```
[67]: reactivity_rate = 50e-26
E_DD = 3650000 # eV
ignition_df = pd.merge(df, te_df, left_index=True, right_index=True)
ignition_df["ignition"] = (3*ignition_df["te0"]) / (reactivity_rate * E_DD)
fig = plt.figure(figsize=(12,8), dpi=100, facecolor="w", edgecolor="k")
plt.plot(ignition_df["NBI_x"], ignition_df["max_tp"], label="Simulation data")
plt.plot(ignition_df["NBI_x"], ignition_df["ignition"], label="Theoretical")
plt.xlabel("NBI power [MW]")
plt.ylabel("Triple product")
plt.legend(loc="best")
plt.title("Simulated and theoretical triple product per NBI input power")
```

```
[67]: Text(0.5, 1.0, 'Simulated and theoretical triple product per NBI input power')
```



This is way too optimistic. Ignition is not yet achieved with these parameters. I think that two things are happening here. The first one is that confinement time is not 0 when the NBI power is 0. There are probably some assumptions in Metis that may interfere with the results. They are probably also affecting the results of this analysis. The second thing is that we are taking the maximum triple product of the simulation data. The average could show more realistic results.

Varying nbar, B0, and Ip

To get an idea on how the average density, nbar, the toroidal magnetic field, B0, and the plasma current, Ip, behave, I'll plot how the triple product varies when I change those values. I'll half and double the default values for each of these parameters while keeping everything else constant. The NBI power will be 15MW for all cases.

```
[68]: B0_Ip_nbar_data_path = os.path.dirname(os.path.abspath("__file__")) + "/../
       tokamak_data/B0_Ip_nbar/"
B0_Ip_nbar_data_files = [f for f in os.listdir(B0_Ip_nbar_data_path) if os.path.
       isfile(os.path.join(B0_Ip_nbar_data_path, f))]
try:
    B0_Ip_nbar_data_files.remove('defaultjet_0.mat') # This is the same as the
       nbi 15 file
```

```

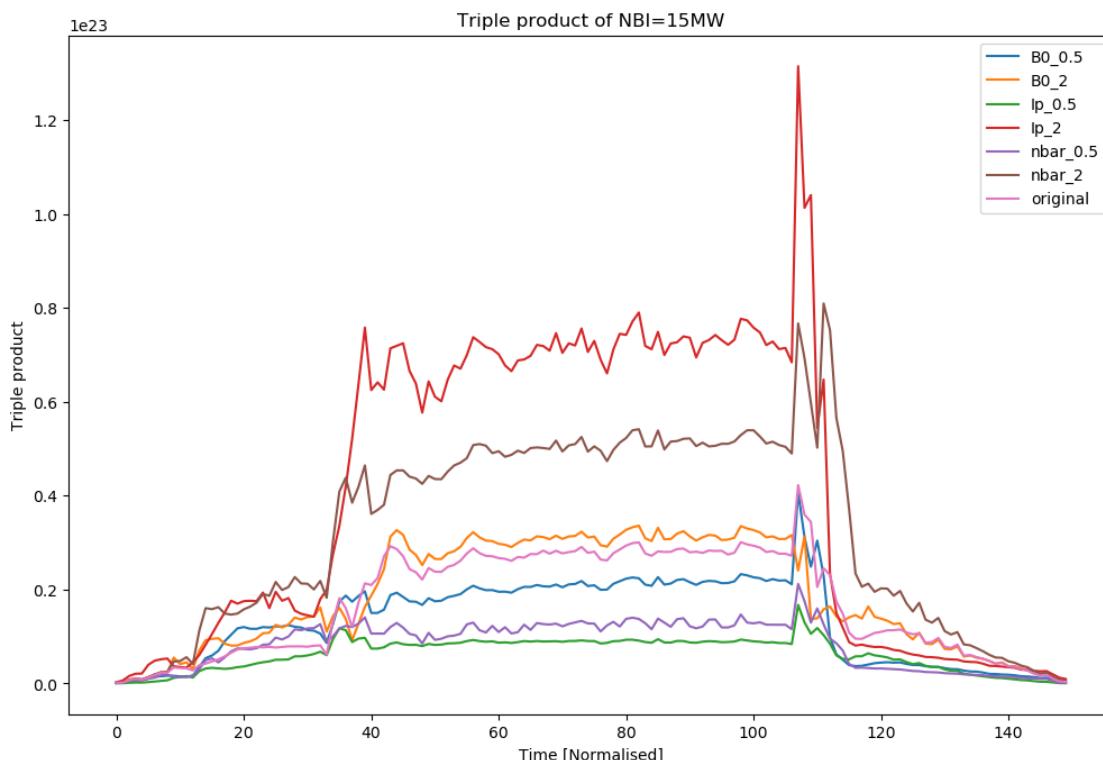
B0_Ip_nbar_data_files.remove("defaultjet.mat") # This is the same as the
→nbi 15 file
except:
    pass
B0_Ip_nbar_data_files.sort()
#B0_Ip_nbar_data_files

```

```
[69]: def get_value_from_file(file_name):
    value_pattern = "defaultjet_(.*?)\.mat"
    value_string = re.search(value_pattern, file_name).group(1)
    return value_string
```

```
[70]: fig = plt.figure(figsize=(12,8), dpi=100, facecolor="w", edgecolor="k")
for file in B0_Ip_nbar_data_files:
    nbi_value = get_value_from_file(file)
    tp_array = get_triple_product(file, "B0_Ip_nbar")
    tp = tp_array[:, -1]
    plt.plot(tp, label=nbi_value)
plt.xlabel("Time [Normalised]")
plt.ylabel("Triple product")
plt.legend(loc="best")
plt.title("Triple product of NBI=15MW")
```

```
[70]: Text(0.5, 1.0, 'Triple product of NBI=15MW')
```

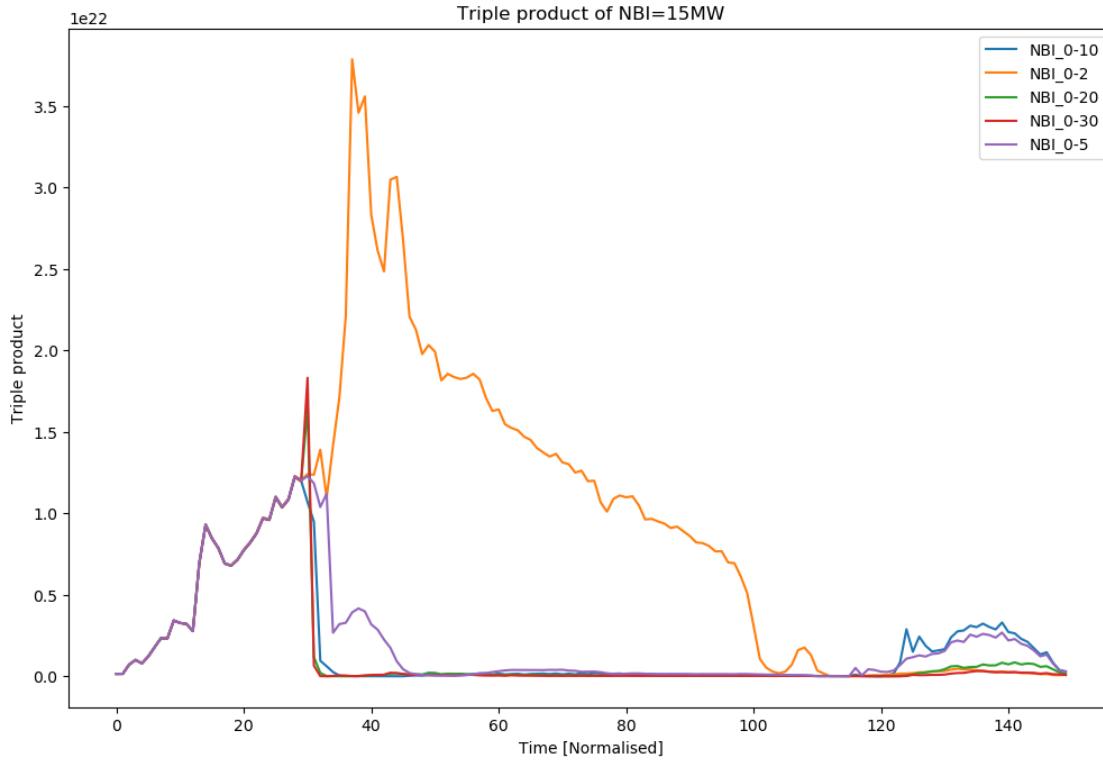


Looks like the plasma current, I_p , is the parameter that influences the triple product the most. When doubling the plasma current, we can see that the triple product is more than doubled from the original value. When the plasma current is halved, the triple product decreases drastically. After the plasma current, the parameter that influences the triple product the most is the average density. Finally, the toroidal field is the parameter that influences the triple product the least, out of these 3 parameters.

```
[71]: power_ramping_data_path = os.path.dirname(os.path.abspath("__file__")) + "/../  
      ↳tokamak_data/power_ramping/"  
power_ramping_data_files = [f for f in os.listdir(power_ramping_data_path) if  
      ↳os.path.isfile(os.path.join(power_ramping_data_path, f))]  
  
try:  
    power_ramping_data_files.remove('defaultjet_0.mat') # This is the same as  
    ↳the nbi 15 file  
    power_ramping_data_files.remove("defaultjet.mat") # This is the same as  
    ↳the nbi 15 file  
except:  
    pass  
power_ramping_data_files.sort()  
# power_ramping_data_files
```

```
[72]: fig = plt.figure(figsize=(12,8), dpi=100, facecolor="w", edgecolor="k")  
for file in power_ramping_data_files:  
    nbi_value = get_value_from_file(file)  
    tp_array = get_triple_product(file, "power_ramping")  
    tp = tp_array[:, -1]  
    plt.plot(tp, label=nbi_value)  
plt.xlabel("Time [Normalised]")  
plt.ylabel("Triple product")  
plt.legend(loc="best")  
plt.title("Triple product of NBI=15MW")
```

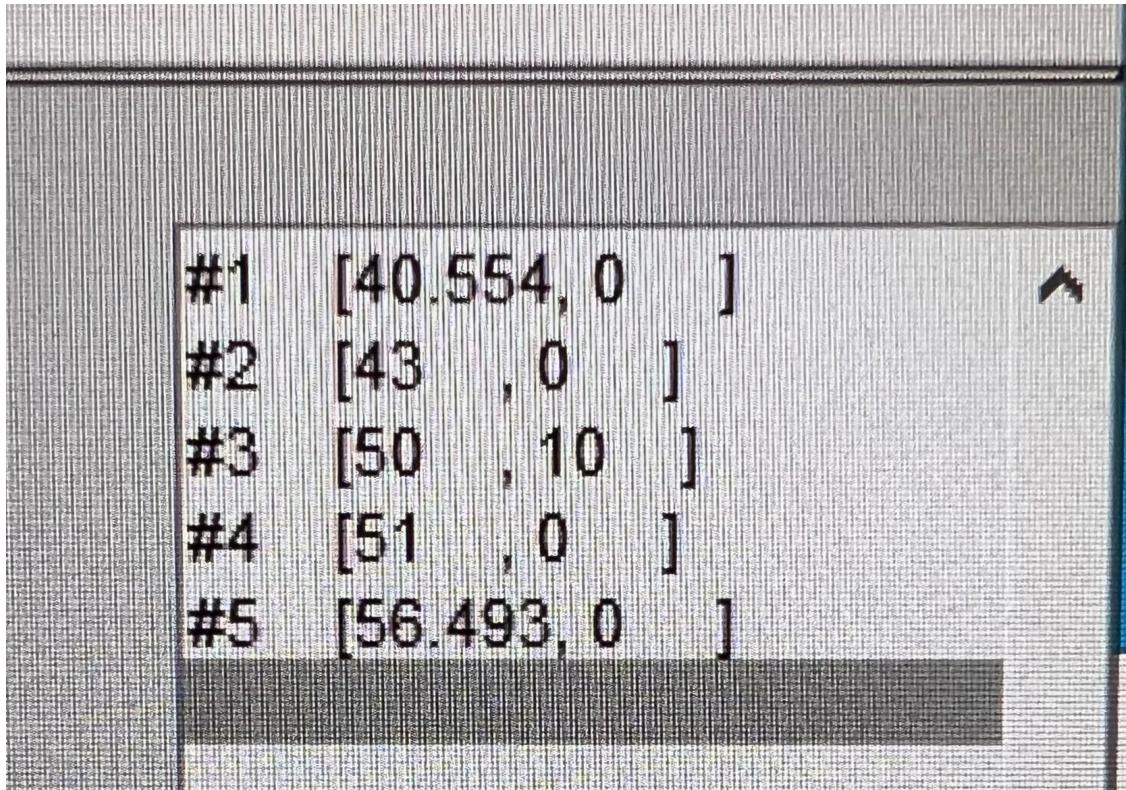
```
[72]: Text(0.5, 1.0, 'Triple product of NBI=15MW')
```



I ramped the NBI power with different rates. I always started at 0 MW and went up to 2, 5, 10, 20, and 30 MW. The points that I used are shown in the following picture. Apparently, the ramping rate does affect the results of the triple product significantly. It is probably due to the fact that the plasma doesn't have enough time to change its properties, so it can't catch up with the changes. This uncertainty is not efficient for what we want to achieve, increase the triple product. From this, we can conclude that the NBI power has to be more constant than what I expected. This is a problem for the experimental method of increasing the power in the same pulse to get more data out of the experiment.

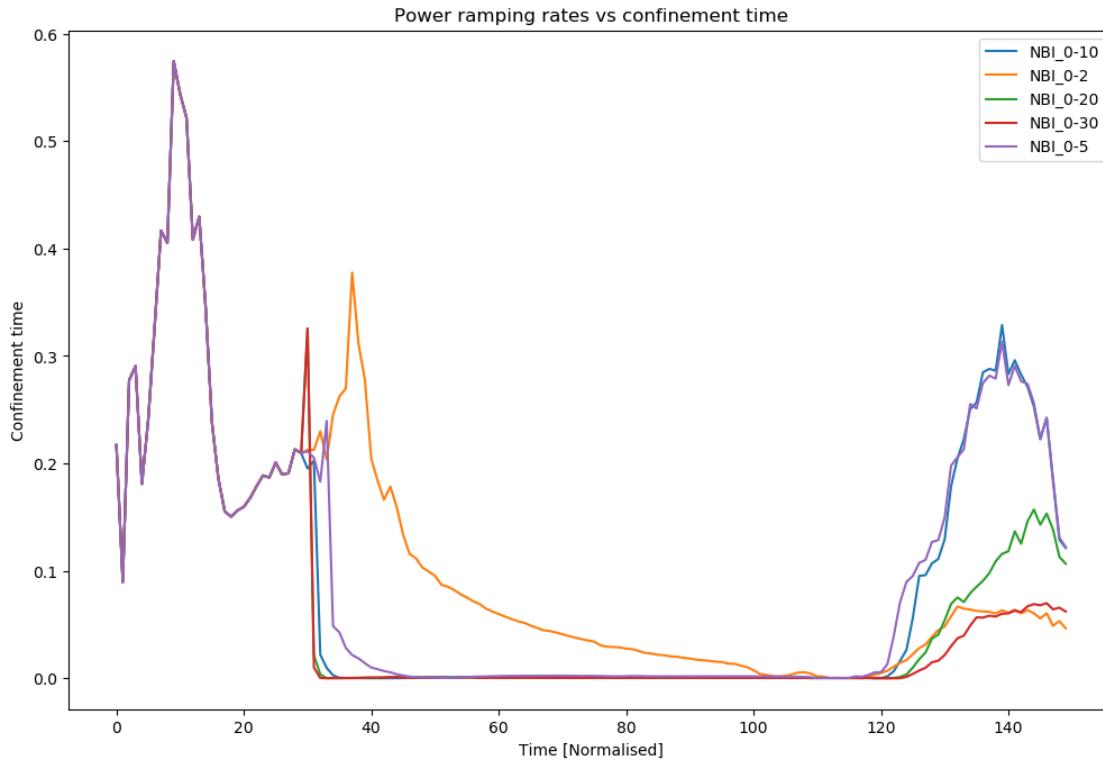
```
[73]: display.Image("./supporting_imgs/metis_input_power_ramping.jpg")
```

```
[73]:
```



```
[74]: fig=plt.figure(figsize=(12,8), dpi= 100, facecolor='w', edgecolor='k')
variable = "taue"
for file in power_ramping_data_files:
    nbi_value = get_value_from_file(file)
    data = get_variable_data(variable, "power_ramping/{}".format(file))
    plt.plot(data, label=nbi_value)
plt.xlabel("Time [Normalised]")
plt.ylabel("Confinement time")
plt.title("Power ramping rates vs confinement time")
plt.legend(loc="best")
```

```
[74]: <matplotlib.legend.Legend at 0x7fa4ace55b50>
```



Confinement time is also going down when the ramping rate increases.

Conclusions

- Confinement time surprisingly decreases when the input NBI power increases.
- The plasma current has a big influence on the triple product. More than the toroidal magnetic field and the average density.
- Ramping the power steeply in the same pulse is not a good idea. At least, it cannot be done without proper knowledge on how this might skew the results.
- The transition from L mode to H mode starts around when the NBI input power is 7 MW. After the transition, things might start behaving unexpectedly.
- Even though Metis has it's limitations and bugs, it can give us a good idea on how the input parameters affect the plasma properties and results.

[]: