BM20BTECH11001-Lab2

September 29, 2021

0.0.1 Model

[1]:
```python
#Creating the model for I=g*V
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
import numpy as np
def ohm_law_model(voltage, specific_conductance, temperature_variance, length, cross_sectional_area, time, usage_intensity, handling_carelessness, storage_location, electron_mobility, density):
    cross_sectional_area = (cross_sectional_area)*(1-((0.03*time)+(0.56*usage_intensity)+(0.1*handling_carelessness)+(0.01*storage_location)))
    length = (length)*(1+((0.002*time)+(-0.21*usage_intensity)+(0.32*handling_carelessness)+(0.12*storage_location)))
    specific_conductance = specific_conductance*(1+((-0.62)*(temperature_variance**2))+(0.26*(electron_mobility))+(-0.42*(density)))
    current = (voltage*cross_sectional_area*specific_conductance)/length
    ohm_law_df = pd.DataFrame([[voltage, current, current/voltage]], columns = ['Voltage','Current','Current/Voltage'])
    return ohm_law_df
```

0.0.2 Creating 2 parameter sets

[2]:
```python
#Creating dataset 1
df_1 = ohm_law_model(24, 3.1, 0.14, 9, 0.175, 0.42, 0.07, 0.081, 0.032, 0.011, 0.039)
```

[3]:
```python
df_1
```

[3]:

	Voltage	Current	Current/Voltage
0	24	1.303914	0.05433

[4]:
```python
#Creating dataset2
df_2 = ohm_law_model(94, 10, 0.4, 7, 0.125, 0.82, 0.07, 0.61, 0.5, 0.0121, 0.39)
```

[5]:
```python
df_2
```

[5]:

	Voltage	Current	Current/Voltage
0	94	8.703737	0.092593

[6]:
```
#Appending dataset2 to dataset1
df_final = df_1.append(df_2, ignore_index=True)
df_final
```

[6]:

	Voltage	Current	Current/Voltage
0	24	1.303914	0.054330
1	94	8.703737	0.092593

0.0.3 Estimating g for the 2 parameter sets generated above

[7]:
```
#Estimating g by calculating the average
g_average = df_final['Current/Voltage'].mean()
g_average
```

[7]: 0.07346134461538863

[8]:
```
#Estimating g using min-square method
#As (((I1-(g*V1))^2)+((I2-(g*V2))^2)) should be minimum, g = (I2*V2 + I1*V1)/
↪((V1^2)+(V2^2)
g_min_square =␣
↪((df_final['Current'][0]*df_final['Voltage'][0])+(df_final['Current'][1]*df_final['Voltage'
↪((df_final['Voltage'][0]**2)+(df_final['Voltage'][1]**2))
g_min_square
```

[8]: 0.09025129631868442

[9]:
```
#Estimating g by doing (total_current)/(total_voltage)
g_est = (df_final['Current'].sum())/(df_final['Voltage'].sum())
g_est
```

[9]: 0.08481059953002666

[10]:
```
#Initialising empty dataframe for future use
df = pd.DataFrame(columns=['Voltage','Current','Current/Voltage'])
df
```

[10]:
```
Empty DataFrame
Columns: [Voltage, Current, Current/Voltage]
Index: []
```

0.0.4 Using the model for 100 parameter sets

[11]:
```
#Creating 100 parameter sets
import random
for x in range (0,100):
    volt = random.uniform(5,7)
    spec_conductance = random.uniform(2, 4)
    length = random.uniform(3,5)
    variables = np.random.rand(1,8)
    df_entry = ohm_law_model(volt, spec_conductance, variables[0][0], length,␣
 ↪variables[0][1], variables[0][2], variables[0][3], variables[0][4],␣
 ↪variables[0][5], variables[0][6], variables[0][7])
    df = df.append(df_entry, ignore_index=True)
```

[12]:
```
df
```

[12]:
```
     Voltage   Current  Current/Voltage
0   5.690774  0.674748         0.118569
1   5.296815  0.731416         0.138086
2   5.649467  0.292333         0.051745
3   6.483099  0.981675         0.151421
4   6.400294  0.102385         0.015997
..       ...       ...              ...
95  5.266162  3.035324         0.576383
96  5.894444  0.104021         0.017647
97  5.152702  0.993404         0.192793
98  5.433725  0.021054         0.003875
99  5.666494  0.774496         0.136680

[100 rows x 3 columns]
```

0.0.5 Estimating g for 100 parameter sets

[13]:
```
#Estimating g by calculating average
g_mean = df['Current/Voltage'].mean()
g_mean
```

[13]:
```
0.1517005536171174
```

[14]:
```
#Estimating g using min-square method
sum_of_product = 0
sum_of_squares = 0
for x in range (0,100):
    sum_of_product = sum_of_product + (df['Current'][x]*df['Voltage'][x])
    sum_of_squares = sum_of_squares + (df['Voltage'][x]**2)
g_min_square_2 = sum_of_product/sum_of_squares
g_min_square_2
```

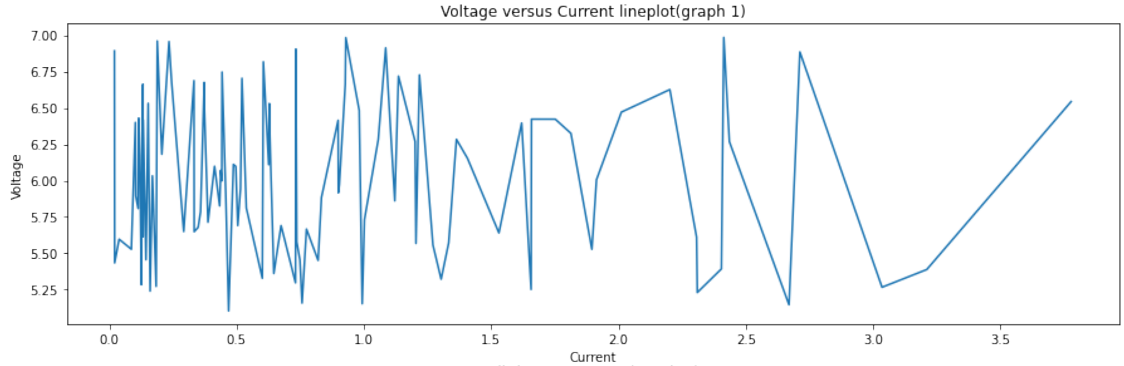
[14]: 0.14831789878804544

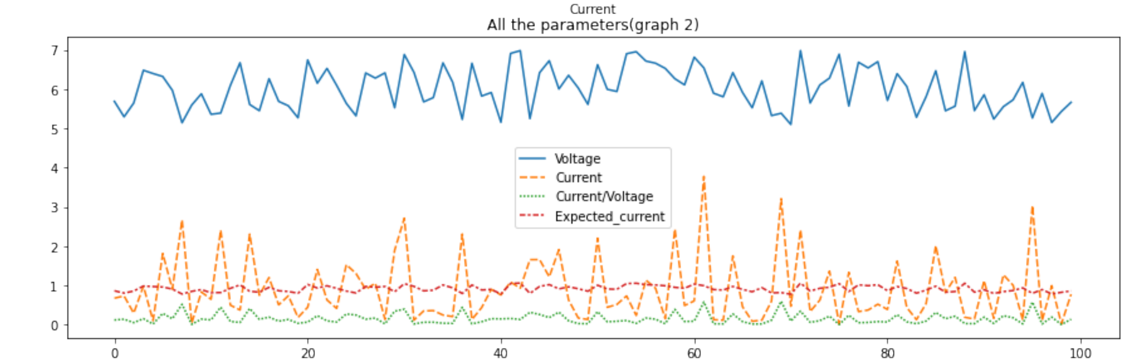
[15]:
```
#Estimating g by doing (total current)/(total voltage)
g_est_avg = df['Current'].sum()/df['Voltage'].sum()
g_est_avg
```

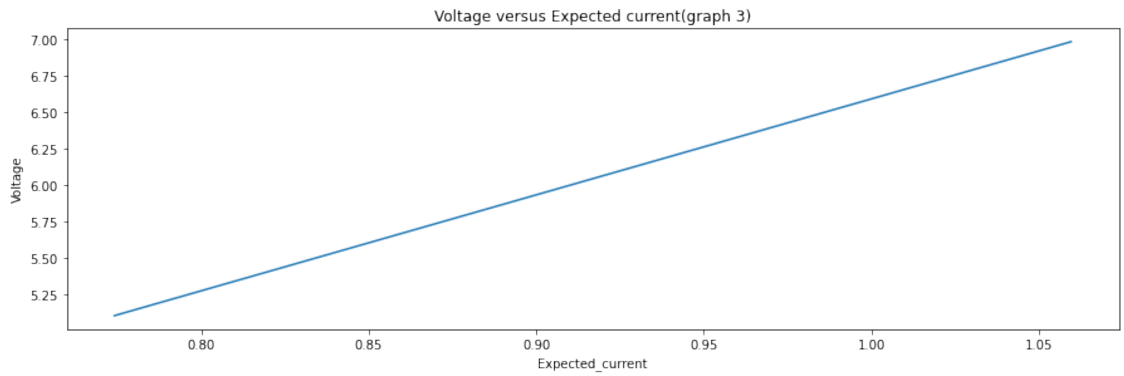
[15]: 0.1499122755284444

0.0.6 Visualizing the 100 parameter sets

[16]:
```
df['Expected_current'] = g_mean*df['Voltage']
fig, axs = plt.subplots(3, figsize=(15,15))
axs[0].set_title("Voltage versus Current lineplot(graph 1)")
axs[1].set_title("All the parameters(graph 2)")
axs[2].set_title("Voltage versus Expected current(graph 3)")
sb.lineplot(x=df['Current'], y=df['Voltage'], ax=axs[0]);
sb.lineplot(data=df, ax=axs[1]);
sb.lineplot(x=df['Expected_current'], y=df['Voltage'],ax=axs[2]);
```







0.0.7 Conclusion from the above graphs

- Current versus Voltage is not a constant in the second graph, which means ohm's law is being violated(from graph 2)
- Expected current matches actual current for higher voltages(from graph-2)
- Variation in actual current is way larger than expected current(from graph-2)
- The value of g estimated from taking the average of (Current/Voltage) is identical to value of g obtained from minimum square method as the Current/Voltage value has significantly low variance.

0.0.8 Learning takeaways from the assignment

- Creating a model with parameters.
- Using the model to get outputs.

- Estimating outputs by taking average and using minimum square method.
- Generating a large number of random parameter sets and incorporating them to the created model.
- Visualizing the output sets to evaluate the difference between the hypothesized model and the actual “scientific” model.