# calibration

September 9, 2024

## 1 Calibration data analysis from one motor

Running single motor from full to empty 4x 1.5V rechargeable Lithium batteries.

Algorithm: 1. Measure voltage 2. Run motor for 3 seconds at random PWM 3. Measure speed 4. Stop motor for 100ms 5. Repeat until battery is empty

[77]:
```
import pandas as pd

df = pd.read_csv('left_calibration.csv')
df.head()
```

[77]:

| | pwm | voltage | speed |
|---|---|---|---|
| 0 | 176 | 2.202417 | 12.459220 |
| 1 | 163 | 2.204834 | 11.058830 |
| 2 | 42 | 2.194360 | 1.314481 |
| 3 | 240 | 2.200000 | 18.390820 |
| 4 | 202 | 2.195972 | 14.286200 |

#### 1.0.1 Data statistics

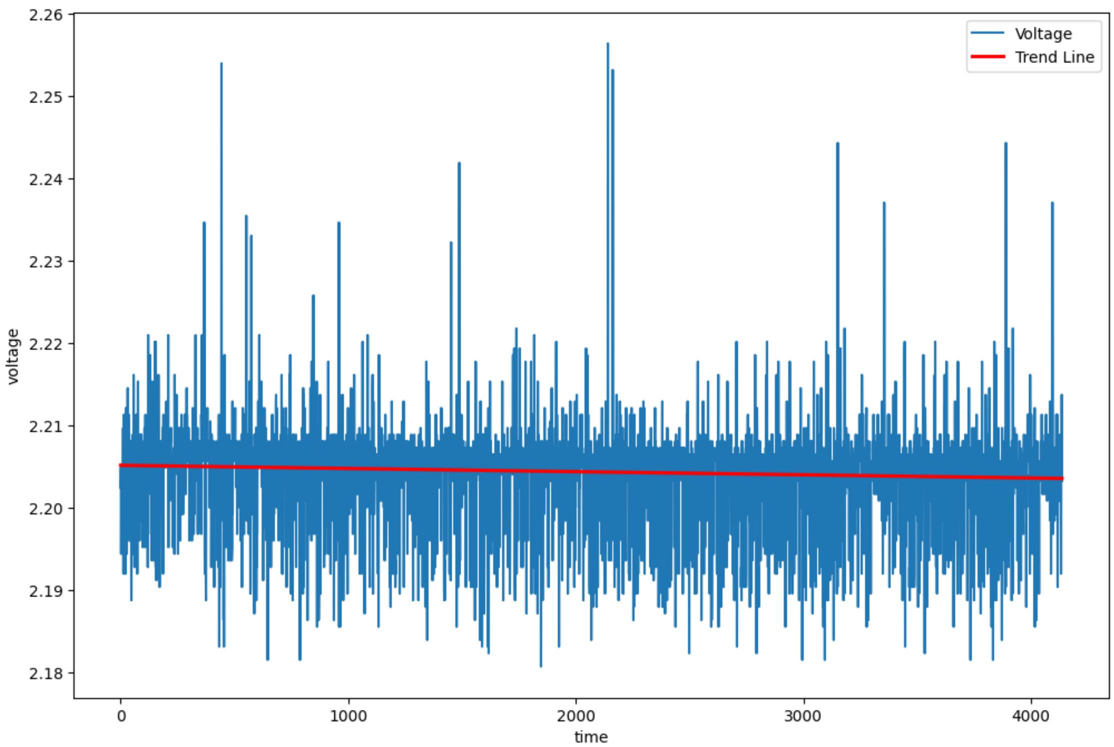
[78]:
```
# Display df statistics
df.describe()
```

[78]:

| | pwm | voltage | speed |
|---|---|---|---|
| count | 4137.000000 | 4137.000000 | 4137.000000 |
| mean | 124.857868 | 2.204326 | 8.170662 |
| std | 74.454052 | 0.006228 | 6.153037 |
| min | 0.000000 | 2.180664 | 0.000000 |
| 25% | 60.000000 | 2.203223 | 2.677155 |
| 50% | 123.000000 | 2.205640 | 7.877773 |
| 75% | 190.000000 | 2.207251 | 13.351660 |
| max | 255.000000 | 2.256397 | 21.490380 |

### 1.0.2 Voltage over time

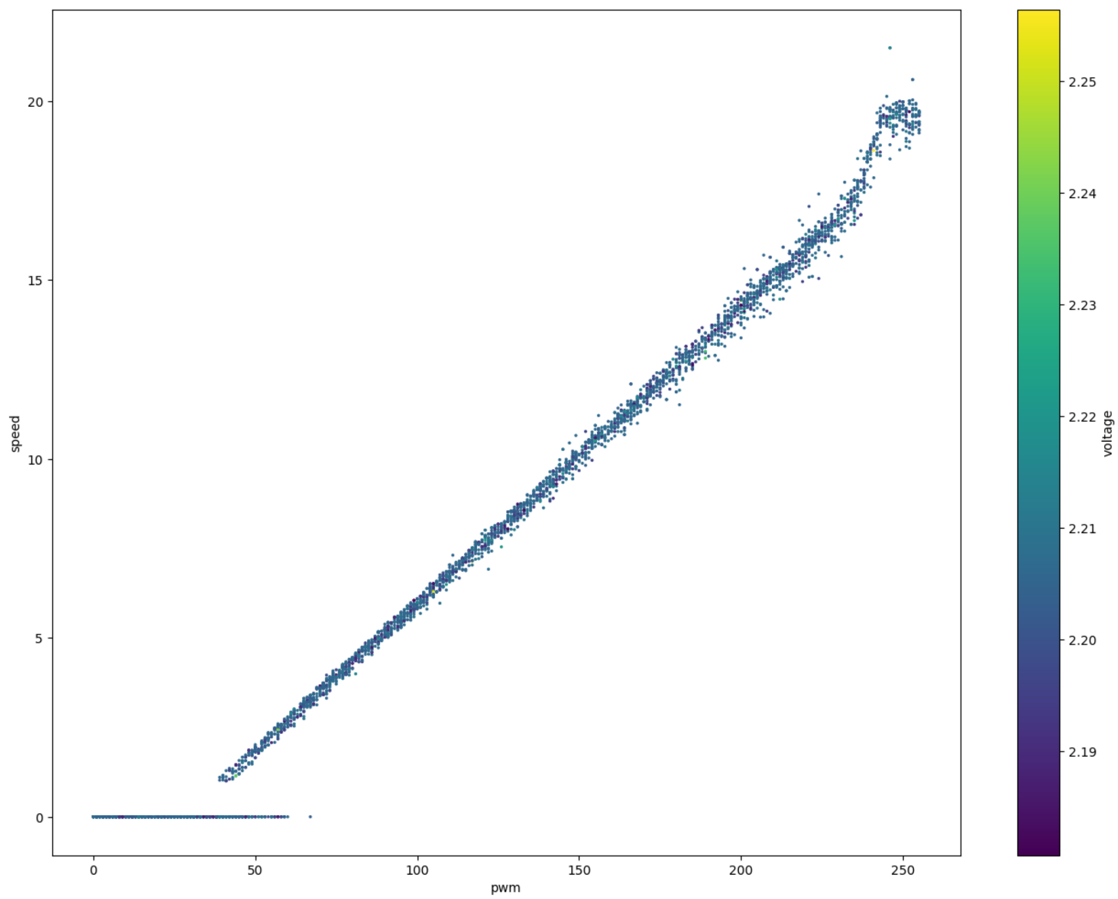
[79]:
```
# Line plot voltage over time

import seaborn as sns
import matplotlib.pyplot as plt

df['time'] = range(0, len(df))

# Create a figure and axis
fig, ax = plt.subplots(figsize=(12, 8))

# Line plot voltage over time
sns.lineplot(data=df, x='time', y='voltage', ax=ax, label='Voltage')

# Plot trend line
sns.regplot(data=df, x='time', y='voltage', ax=ax, scatter=False, color='red',␣
↪label='Trend Line')

# Show plot
plt.legend()
plt.show()
```



### 1.0.3 PWM to speed scattered plot with voltage as color

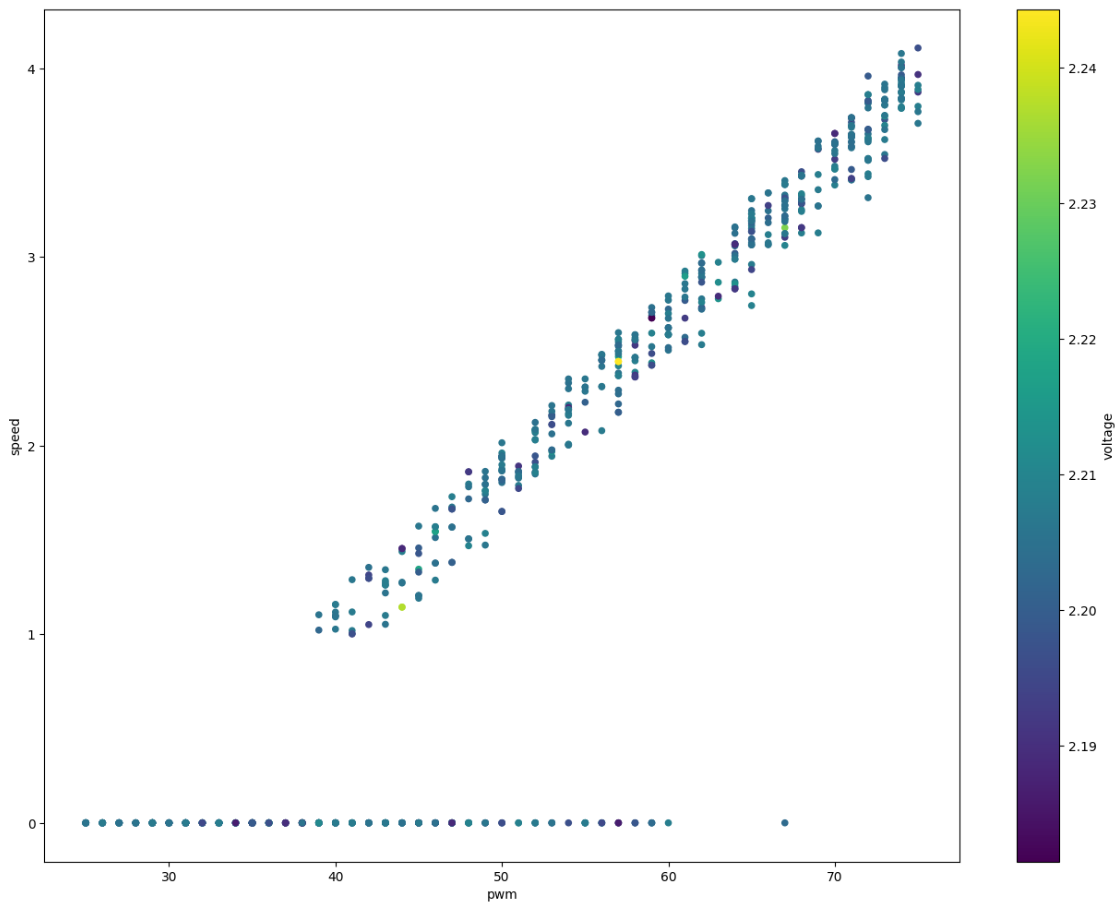
- When wheel starts spinning, function is almost linear except for high PWM. It seems PWM over 230 is like run at max speed, there is non-linear jump and than plateau.

[80]:
```
# Scattered plot of pwm, voltage and speed
import matplotlib.pyplot as plt
fig, ax = plt.subplots(figsize=(16, 12))
df.plot.scatter(x='pwm', y='speed', c='voltage', colormap='viridis', s=2, ax=ax)
plt.show()
```



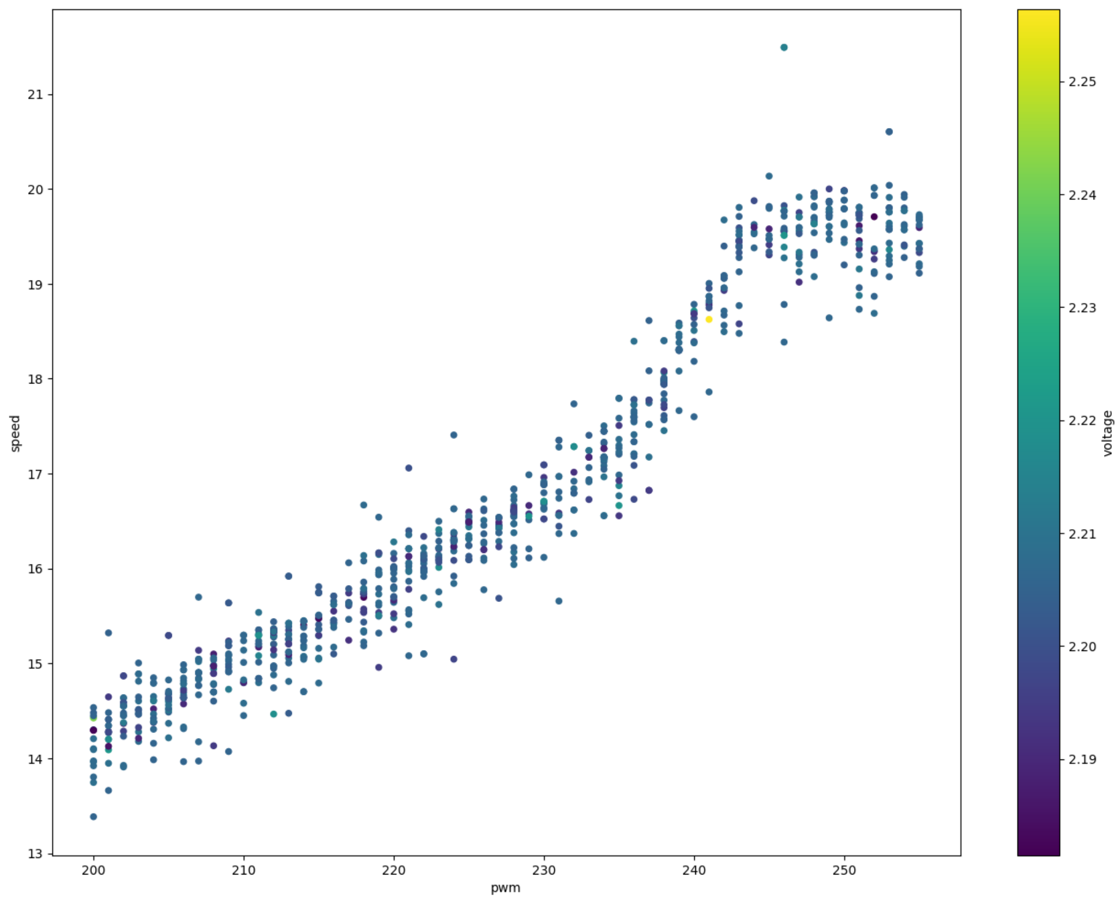

### 1.0.4 Zooming in to interesting section 25 to 75 PWM

[81]:
```
# Zoom to pwm 25 to 75
df_zoom = df[(df['pwm'] >= 25) & (df['pwm'] <= 75)]
fig, ax = plt.subplots(figsize=(16, 12))
df_zoom.plot.scatter(x='pwm', y='speed', c='voltage', colormap='viridis', s=20,␣
↪ax=ax)
plt.show()
```




### 1.0.5 Zooming in to interesting section over 200 PWM

[82]:
```
# Zoom to pwm over 200
df_zoom = df[(df['pwm'] >= 200)]
fig, ax = plt.subplots(figsize=(16, 12))
df_zoom.plot.scatter(x='pwm', y='speed', c='voltage', colormap='viridis', s=20,␣
 ↪ax=ax)
plt.show()
```




### 1.0.6 Let's see extreme values in voltage ignoring others. Highest 10% to be in green, lowest 10% to be in red.

If there is strong correlation between voltage and speed, we should see some pattern here of green being always on top of the line.

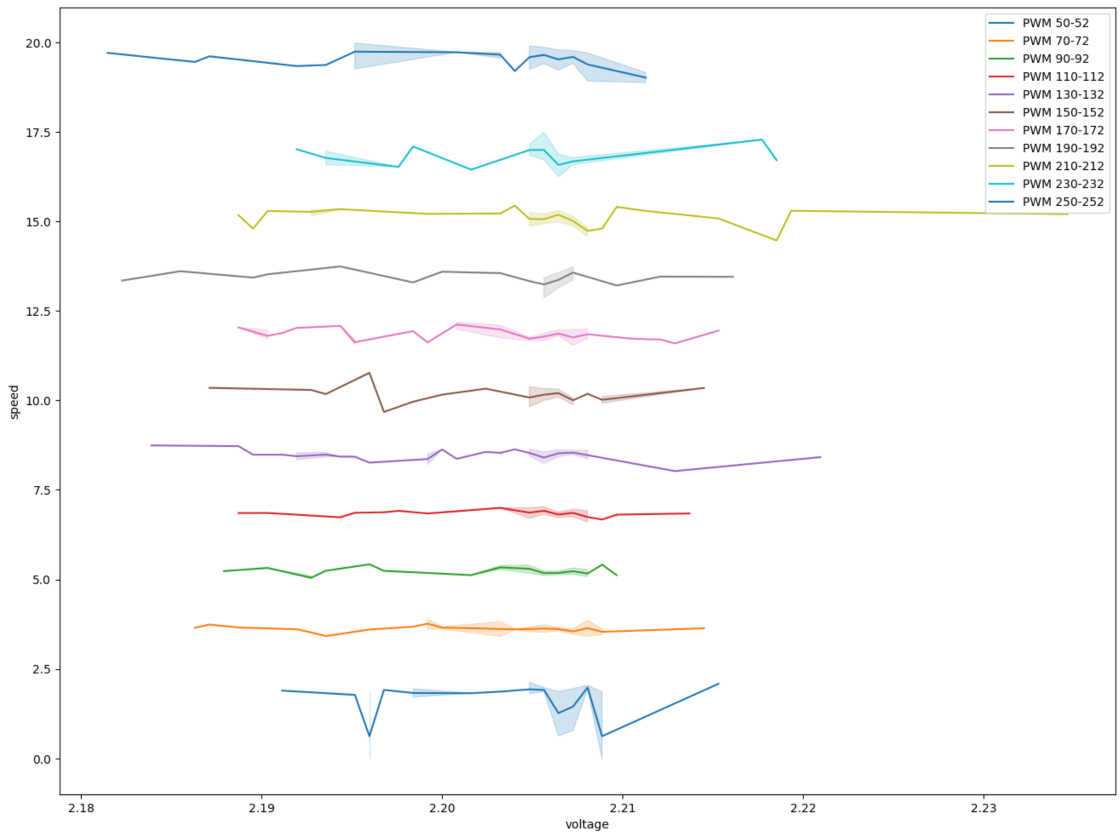
[83]:
```
# Filter df rows to include only top 10% and bottom of voltage values
df_top10 = df[df['voltage'] >= df['voltage'].quantile(0.9)]
df_bottom10 = df[df['voltage'] <= df['voltage'].quantile(0.1)]

# Create a figure and axis
fig, ax = plt.subplots(figsize=(16, 12))

# Scatter plot for df_top10 in green
ax.scatter(df_top10['pwm'], df_top10['speed'], color='green', label='Top 10%␣
↪Voltage', s=10)

# Scatter plot for df_bottom10 in red
```

```
ax.scatter(df_bottom10['pwm'], df_bottom10['speed'], color='red', label='Bottom␣
↪10% Voltage', s=10)

# Set labels
ax.set_xlabel('PWM')
ax.set_ylabel('Speed')
ax.set_title('PWM to Speed Scatter Plot')

# Add legend
ax.legend()

# Show plot
plt.show()
```


Let's see sample of fixed pwm (to have more datapoints we will "fix" in in range of 3) on how speed evolves with voltage

[84]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Define the ranges of pwm
pwm_ranges = [(i, i + 2) for i in range(50, 256, 20)]

# Create a figure and axis
fig, ax = plt.subplots(figsize=(16, 12))

# Plot each range
for pwm_range in pwm_ranges:
    df_zoom = df[(df['pwm'] >= pwm_range[0]) & (df['pwm'] <= pwm_range[1])]
    sns.lineplot(x=df_zoom["voltage"], y=df_zoom["speed"], ax=ax, label=f'PWM␣
 ↪{pwm_range[0]}-{pwm_range[1]}')

# Show plot
plt.show()
```




### 1.0.7 Linear Regretion model training

- Without scaling features -> simplicity of inference on device

[85]:
```
# Linear Regression model - take the pwm and voltage to predict speed
from sklearn.linear_model import LinearRegression
```

```
model = LinearRegression()
model.fit(df[['pwm', 'voltage']], df['speed'])
```

[85]:
```
LinearRegression()
```

[86]:
```
# Predict the speed
pwm = 140
voltage = 2.2
model.predict([[pwm, voltage]])
```

```
c:\Users\tokubica\AppData\Local\miniconda3\envs\robot\Lib\site-
packages\sklearn\base.py:493: UserWarning: X does not have valid feature names,
but LinearRegression was fitted with feature names
  warnings.warn(
```

[86]:
```
array([9.40395494])
```

[87]:
```
# Print model equation
print(f"speed = {model.intercept_} + {model.coef_[0]} * pwm + {model.coef_[1]}␣
↪* voltage")
```

```
speed = -7.557230152331938 + 0.08215664875990293 * pwm + 2.4814792098348186 *
voltage
```

### 1.0.8 Relative importance of pwm vs. voltage to predict speed

Fit the model using scaled features to see relative importance of each feature.

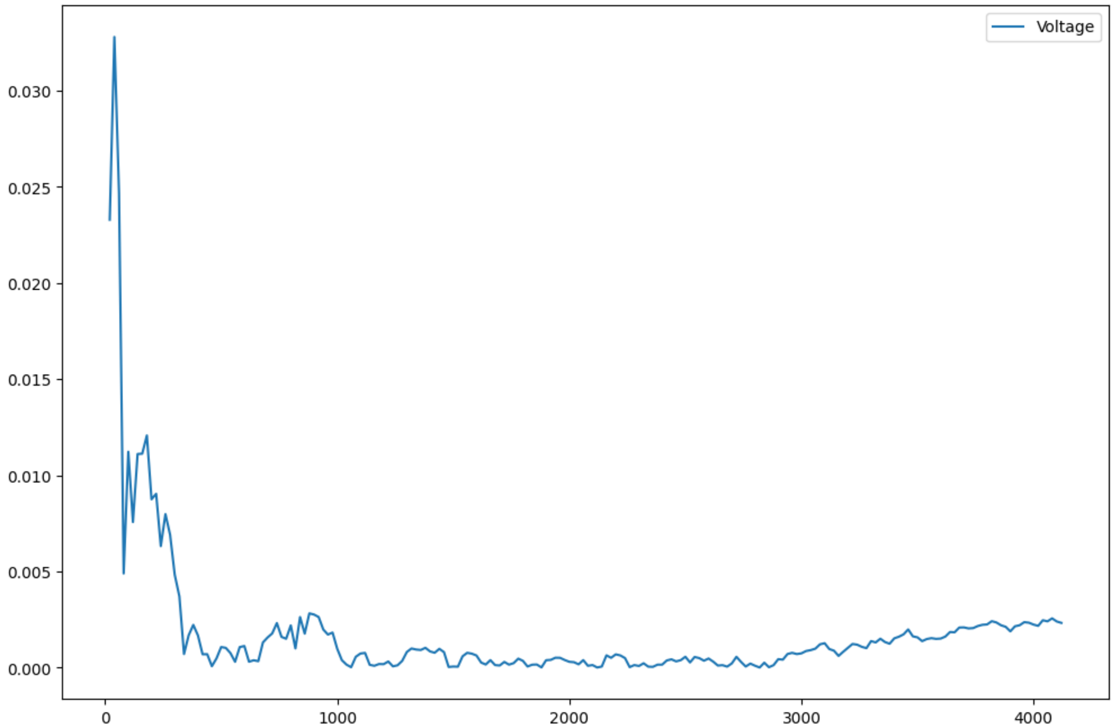
[88]:
```
# Linear Regression model - take the pwm and voltage to predict speed
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline

# Create a pipeline that scales the features and then fits the model
pipeline = make_pipeline(StandardScaler(), LinearRegression())

# Fit the model
pipeline.fit(df[['pwm', 'voltage']], df['speed'])

# Print coefficients
pwm_coef, voltage_coef = pipeline.named_steps['linearregression'].coef_

print(f"speed = {pipeline.named_steps['linearregression'].intercept_} +␣
↪{pwm_coef} * pwm + {voltage_coef} * voltage")

print()
print(f"Relative importance of pwm: {abs(pwm_coef) / (abs(pwm_coef) +␣
↪abs(voltage_coef))}")
```

```
print(f"Relative importance of voltage: {abs(voltage_coef) / (abs(pwm_coef) +␣
↪abs(voltage_coef))}")
```

```
speed = 8.17066179357022 + 6.116156035379288 * pwm + 0.01545208734885098 *
voltage

Relative importance of pwm: 0.9974799290757714
Relative importance of voltage: 0.002520070924228582
```

Plot relative importance of each feature as it evolves over time

[89]:
```
df_size = len(df)
df_step = int(df_size / 200)
df_index = range(df_step, df_size, df_step)

pwm = []
voltage = []
for i in df_index:
    i_df = df.iloc[0:i]
    pipeline.fit(i_df[['pwm', 'voltage']], i_df['speed'])
    pwm_coef, voltage_coef = pipeline.named_steps['linearregression'].coef_
    pwm.append(abs(pwm_coef) / (abs(pwm_coef) + abs(voltage_coef)))
    voltage.append(abs(voltage_coef) / (abs(pwm_coef) + abs(voltage_coef)))

# Plot pwm and voltage over time in line chart
fig, ax = plt.subplots(figsize=(12, 8))
# sns.lineplot(x=df_index, y=pwm, ax=ax, label='PWM')
sns.lineplot(x=df_index, y=voltage, ax=ax, label='Voltage')
plt.show()
```


Voltage
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
1000
2000
3000
4000