Chapter 1: Data Cleaning and Modeling on Python

Data Gathering

In [1]:
```
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Data Import and Display

In [2]:
```
#Importing and Displaying Data
headers = ["DateTime (dd/mm/yyyyy hh:mm:ss)", "Servo Lower Angle (°)","Servo Up
          "Roll Angle (°)", "Pitch Angle (°)", "Humidity (%)", "Temperature (°C
          "Irradiance (W/m2)", "Voltage (V)", "Current (mA)"]
data = pd.read_csv("DATA 19_05_22.txt", header=None, index_col=False,
    names=headers, parse_dates= ["DateTime (dd/mm/yyyyy hh:mm:ss)"])
display(data.head())
print("Data Total Rows: {}\nData Total Columns: {}".format(data.shape[0], data
```

	DateTime (dd/mm/yyyyy hh:mm:ss)	Servo Lower Angle (°)	Servo Upper Angle (°)	Roll Angle (°)	Pitch Angle (°)	Humidity (%)	Temperature (°C)	Heat Index (°C)	Irradiance (W/m2)	V
0	2022-05-19 04:56:00	0	0	15.5504	-66.8076	93.0	27.2	32.2115	0.0	
1	2022-05-19 04:56:05	0	23	18.0047	-47.4466	93.7	27.2	32.3448	0.0	
2	2022-05-19 04:56:10	0	46	17.8869	-24.9693	93.8	27.2	32.3639	0.0	
3	2022-05-19 04:56:15	0	69	20.1395	-6.8439	93.7	27.1	32.0455	0.0	
4	2022-05-19 04:56:20	0	92	18.2653	16.4409	93.8	27.1	32.0641	0.0	

```
Data Total Rows: 10246
Data Total Columns: 11
```

In [3]:
```
data.describe()
```

Out[3]:

	DateTime (dd/mm/yyyyy hh:mm:ss)	Servo Lower Angle (°)	Servo Upper Angle (°)	Roll Angle (°)	Pitch Angle (°)	Humidity (%)
count	10246	10246.000000	10246.000000	10246.000000	10246.000000	10100.000000
mean	2022-05-19 12:02:53.806070784	89.705739	45.988776	2.932538	-27.246695	59.662436
min	2022-05-19 04:56:00	0.000000	0.000000	-15.914300	-88.719000	28.800000
25%	2022-05-19 08:29:26.249999872	45.000000	23.000000	-7.956250	-58.117750	38.800000
50%	2022-05-19 12:02:52.500000	90.000000	46.000000	2.863500	-26.004200	57.600000
75%	2022-05-19 15:36:19.750000128	135.000000	69.000000	14.529500	3.724350	75.100000
max	2022-05-19 19:10:07	180.000000	92.000000	21.027800	27.078000	99.900000
std	NaN	63.702569	32.527704	12.180201	33.273733	21.728205

In [4]:
```
display(pd.DataFrame(data.isna().sum(), columns=["Total Nan Values"]).T)
```

	DateTime (dd/mm/yyyyy hh:mm:ss)	Servo Lower Angle (°)	Servo Upper Angle (°)	Roll Angle (°)	Pitch Angle (°)	Humidity (%)	Temperature (°C)	Heat Index (°C)	Irradiance (W/m2)	Vo
Total Nan Values	0	0	0	0	0	146	146	146	0	

~ The nan/missing values from the "Humidity", "Temperature", and "Heat Index" columns are caused by the low sampling rate capability of the sensor and the library used which is expected.

~ The nan/missing values from the "Voltage" and "Current" columns mostly occur when the sun is down or no current was produced from the solar panel, the developers of the product ensures that quality data is being recorded so a Nan value was used to record instead for this scenario.

Data Cleaning

~ Imputation process for "Temperature", "Humidity", and "Heat Index" columns is to find the average of the nearest previous not-Nan value and nearest next not-Nan value since these values don't really much differ from each other within a minute of timeframe.

In [5]:
```
col_to_clean = ["Humidity (%)", "Temperature (°C)", "Heat Index (°C)"]
display(data[col_to_clean])
```

	Humidity (%)	Temperature (°C)	Heat Index (°C)
0	93.0	27.2	32.2115
1	93.7	27.2	32.3448
2	93.8	27.2	32.3639
3	93.7	27.1	32.0455
4	93.8	27.1	32.0641
...	...	...	...
10241	91.9	27.5	32.8921
10242	91.8	27.4	32.5728
10243	91.8	27.4	32.5728
10244	91.9	27.4	32.5927
10245	92.0	27.4	32.6126

10246 rows × 3 columns

In [6]:
```
#Find closest previous value that is not a Nan value relative to the row where
def FindPreviousNotNan(current_row, pd_series): #
    i=current_row-1
    val = np.nan
    pd_series_min_pos = 0
    while i>=pd_series_min_pos:
        if np.isnan(pd_series.values[i]):
            i-=1
        else:
            val = pd_series.values[i]
            break
    return val

#Find closest next value that is not a Nan value relative to the row where a Nc
def FindNextNotNan(current_row, pd_series):
    i=current_row+1
    val=np.nan
    pd_series_max_pos = len(pd_series)-1
    while i<=pd_series_max_pos:
        if np.isnan(pd_series.values[i]):
            i+=1
        else:
            val = pd_series.values[i]
            break
    return val
```

In [7]:

```
#Impute rows where Nan values are found
#It will get the average of previous and next row values that are not Nan
#If all of the previous row values are Nan but next row value is not Nan then t
def ImputeColumn(pd_dataframe, column):
    for i in range(len(pd_dataframe)):
        current_val = pd_dataframe[column].values[i]
        previous_val = 0
        next_val = 0
        if np.isnan(current_val):
            previous_val = FindNextNotNan(i,pd_dataframe[column])
            next_val = FindPreviousNotNan(i,pd_dataframe[column])
            if not np.isnan(previous_val) and not np.isnan(next_val):
                pd_dataframe[column].values[i] = np.mean([previous_val,next_va
            elif np.isnan(previous_val) and np.isnan(next_val):
                pd_dataframe[column].values[i] = np.nan
            else:
                if np.isnan(previous_val):
                    pd_dataframe[column].values[i] = next_val
                else:
                    pd_dataframe[column].values[i] = previous_val
```

In [8]:
```
print("Sample Rows Before Data Imputation")
display(data.loc[139:141,col_to_clean])
display(data.loc[199:201,col_to_clean])

for col in col_to_clean:
    ImputeColumn(data, col)

display(pd.DataFrame(data.isna().sum(), columns=["Total Nan Values"]).T)
print("Sample Rows After Data Imputation")
display(data.loc[139:141,col_to_clean])
display(data.loc[199:201,col_to_clean])
```

```
Sample Rows Before Data Imputation
```

	Humidity (%)	Temperature (°C)	Heat Index (°C)
139	97.5	25.8	27.7138
140	NaN	NaN	NaN
141	97.6	25.8	27.7161

	Humidity (%)	Temperature (°C)	Heat Index (°C)
199	98.4	25.7	27.4298
200	NaN	NaN	NaN
201	98.5	25.7	27.4313

	DateTime (dd/mm/yyyyy hh:mm:ss)	Servo Lower Angle (°)	Servo Upper Angle (°)	Roll Angle (°)	Pitch Angle (°)	Humidity (%)	Temperature (°C)	Heat Index (°C)	Irradiance (W/m2)	Vo
Total Nan Values	0	0	0	0	0	0	0	0	0	

```
Sample Rows After Data Imputation
```

	Humidity (%)	Temperature (°C)	Heat Index (°C)
139	97.50	25.8	27.71380
140	97.55	25.8	27.71495
141	97.60	25.8	27.71610

	Humidity (%)	Temperature (°C)	Heat Index (°C)
199	98.40	25.7	27.42980
200	98.45	25.7	27.43055
201	98.50	25.7	27.43130

~ Imputation process for "Voltage" and "Current" columns is to find the average of the nearest previous not-Nan value and nearest next not-Nan value (just like the same with the "Humidity", "Temperature", and "Heat Index" columns) since these values don't really much differ from when the sun is down and is more likely to be approximately equal to zero.

In [9]:
```
col_to_clean = ["Voltage (V)", "Current (mA)"]

print("Sample Rows Before Data Imputation")
display(data.loc[132:134,col_to_clean])
display(data.loc[9441:9445,col_to_clean])

for col in col_to_clean:
    ImputeColumn(data, col)

display(pd.DataFrame(data.isna().sum(), columns=["Total Nan Values"]).T)
print("Sample Rows After Data Imputation")
display(data.loc[132:134,col_to_clean])
display(data.loc[9441:9445,col_to_clean])
```

```
Sample Rows Before Data Imputation
```

	Voltage (V)	Current (mA)
132	0.0	0.1
133	NaN	NaN
134	0.0	0.0

	Voltage (V)	Current (mA)
9441	0.0	0.1
9442	NaN	NaN
9443	NaN	NaN
9444	NaN	NaN
9445	0.0	0.0

	DateTime (dd/mm/yyyyy hh:mm:ss)	Servo Lower Angle (°)	Servo Upper Angle (°)	Roll Angle (°)	Pitch Angle (°)	Humidity (%)	Temperature (°C)	Heat Index (°C)	Irradiance (W/m2)	Vo
Total Nan Values	0	0	0	0	0	0	0	0	0	

```
Sample Rows After Data Imputation
```

	Voltage (V)	Current (mA)
132	0.0	0.10
133	0.0	0.05
134	0.0	0.00

	Voltage (V)	Current (mA)
9441	0.0	0.1000
9442	0.0	0.0500
9443	0.0	0.0250
9444	0.0	0.0125
9445	0.0	0.0000

Exploratory Data Analysis

In [10]:
```
data["Power (mW)"] = data["Voltage (V)"]*data["Current (mA)"]
display(data)
```

	DateTime (dd/mm/yyyyy hh:mm:ss)	Servo Lower Angle (°)	Servo Upper Angle (°)	Roll Angle (°)	Pitch Angle (°)	Humidity (%)	Temperature (°C)	Heat Index (°C)	Irradianc (W/m:
0	2022-05-19 04:56:00	0	0	15.5504	-66.8076	93.0	27.2	32.2115	0.
1	2022-05-19 04:56:05	0	23	18.0047	-47.4466	93.7	27.2	32.3448	0.
2	2022-05-19 04:56:10	0	46	17.8869	-24.9693	93.8	27.2	32.3639	0.
3	2022-05-19 04:56:15	0	69	20.1395	-6.8439	93.7	27.1	32.0455	0.
4	2022-05-19 04:56:20	0	92	18.2653	16.4409	93.8	27.1	32.0641	0.
...	...	...	...	...	...	...	...	...	.
10241	2022-05-19 19:09:47	0	92	20.5672	24.4719	91.9	27.5	32.8921	0.
10242	2022-05-19 19:09:52	45	0	12.3812	-74.3377	91.8	27.4	32.5728	0.
10243	2022-05-19 19:09:57	45	23	11.3962	-51.3019	91.8	27.4	32.5728	0.
10244	2022-05-19 19:10:02	45	46	14.6790	-24.8913	91.9	27.4	32.5927	0.
10245	2022-05-19 19:10:07	45	69	14.2961	-4.0299	92.0	27.4	32.6126	0.

10246 rows × 12 columns

In [11]:
```
power_pd = pd.pivot_table(data, values = "Power (mW)", index="Servo Lower Angle
display(power_pd.style.set_caption("Average Power (mW) Delivered based on Servo
```

Average Power (mW) Delivered based on Servo Angle Positions

Servo Upper Angle (°)	0	23	46	69	92
Servo Lower Angle (°)					
0	18.339827	25.189814	27.510043	26.540156	22.891166
45	19.411268	25.378231	27.935678	26.228431	21.922363
90	18.139075	24.721523	27.536104	26.373132	22.013466
135	14.883955	23.227739	27.063587	27.014111	23.741312
180	10.729783	19.683897	25.531714	27.449549	26.176851

In [12]:
```
row,col = np.where(power_pd.values==power_pd.values.max())
print("According to data gathered (on the basis of maximum average power delive
print("Servo Lower Angle: {}°".format(power_pd.index[row[0]]))
print("Servo Upper Angle: {}°".format(power_pd.columns[col[0]]))
print("Max Average Power: {:.4f}mW".format(power_pd.values.max()))

row,col = np.where(power_pd.values==power_pd.values.min())
print("\n\nMeanwhile the sets of Servo Angle that delivers the lowest average p
print("Servo Lower Angle: {}°".format(power_pd.index[row[0]]))
print("Servo Upper Angle: {}°".format(power_pd.columns[col[0]]))
print("Min Average Power: {:.4f}mW".format(power_pd.values.min()))
```

```
According to data gathered (on the basis of maximum average power delivered),
the solar panel holder can be designed on these following servo angles:

Servo Lower Angle: 45°
Servo Upper Angle: 46°
Max Average Power: 27.9357mW


Meanwhile the sets of Servo Angle that delivers the lowest average power:

Servo Lower Angle: 180°
Servo Upper Angle: 0°
Min Average Power: 10.7298mW
```

In [13]:
```
#To see what are the corresponding Pitch and Roll angles of each sets/pair of s
# This can be used as the basis to design the inclination of the solar panel ho
# must also take into consideration the inclincation of the base/roof/ground wh
pitch_roll_pd = pd.pivot_table(data, values =["Roll Angle (°)", "Pitch Angle (°
pitch_roll_pd.style.set_caption("Average Roll and Pitch Angles based on Servo A
```

Out[13]:

Average Roll and Pitch Angles based on Servo Angle Positions

	Pitch Angle (°)							
Servo Upper Angle (°)	0	23	46	69	92	0	23	
Servo Lower Angle (°)								
0	-62.504728	-39.239285	-16.911226	4.182781	23.818237	16.916821	18.558999	19.3093
45	-75.494604	-53.981351	-27.755364	-5.923742	14.575541	11.685777	12.028940	13.8525
90	-84.652065	-60.413839	-33.468829	-11.329598	11.276907	1.419187	1.955682	2.8598
135	-78.251013	-56.504445	-29.341165	-7.318470	14.308224	-8.691554	-7.836315	-6.4729
180	-67.439975	-44.399341	-18.919719	1.648204	22.664773	-14.872325	-14.438797	-13.9571

In [14]:
```
print("Pitch Angle: {:.4f}°".format(pitch_roll_pd['Pitch Angle (°)'][46][45]))
print("Roll Angle: {:.4f}°".format(pitch_roll_pd['Roll Angle (°)'][46][45])) #
```

```
Pitch Angle: -27.7554°
Roll Angle: 13.8526°
```

In [15]:
```
#Now lets look if the servo angles which delivered the max average power will d
irradiance_pd = pd.pivot_table(data, values = "Irradiance (W/m2)", index="Servo
irradiance_pd.style.set_caption("Average Irradiance (W/m2) based on Servo Angle
```

Out[15]:

Average Irradiance (W/m2) based on Servo Angle Positions

Servo Upper Angle (°)	0	23	46	69	92
Servo Lower Angle (°)					
0	87.708637	105.832895	113.995901	112.480507	102.923733
45	90.463229	106.511786	114.941417	111.826011	99.273751
90	86.736455	104.551842	114.279525	112.167286	99.517700
135	78.990350	99.784179	112.267149	112.665229	103.919787
180	69.733758	91.900020	108.132492	112.527074	108.892678

In [16]:
```
row,col = np.where(irradiance_pd.values==irradiance_pd.values.max())
print("According to data gathered (on the basis of maximum average irradiance),
print("Servo Lower Angle: {}°".format(irradiance_pd.index[row[0]]))
print("Servo Upper Angle: {}°".format(irradiance_pd.columns[col[0]]))
print("Max Irradiance: {:.4f}W/m2".format(irradiance_pd.values.max()))

row,col = np.where(irradiance_pd.values==irradiance_pd.values.min())
print("\n\nMeanwhile the sets of Servo Angle that has the lowest average irradi
print("Servo Lower Angle: {}°".format(irradiance_pd.index[row[0]]))
print("Servo Upper Angle: {}°".format(irradiance_pd.columns[col[0]]))
print("Min Irradiance: {:.4f}W/m2".format(irradiance_pd.values.min()))
```

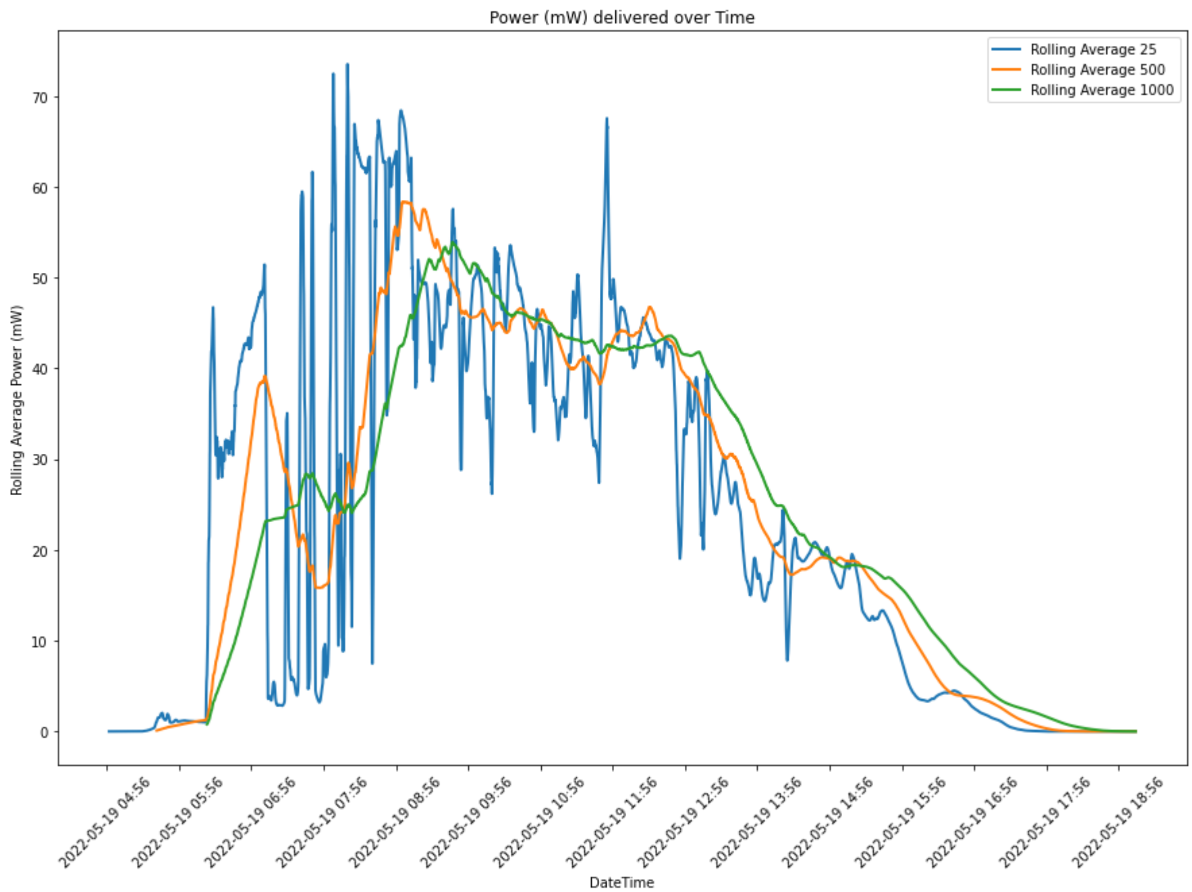
```
According to data gathered (on the basis of maximum average irradiance),
the solar panel holder can be designed on these following servo angles:

Servo Lower Angle: 45°
Servo Upper Angle: 46°
Max Irradiance: 114.9414W/m2


Meanwhile the sets of Servo Angle that has the lowest average irradiance:

Servo Lower Angle: 180°
Servo Upper Angle: 0°
Min Irradiance: 69.7338W/m2
```

In [17]:
```
#Let's visualize the power delivered all throughout the day by the module throu
data_power_roll = data[["DateTime (dd/mm/yyyyy hh:mm:ss)","Power (mW)"]].copy(
data_power_roll["Power (mW) Roll Ave 25"] = data["Power (mW)"].rolling(25).mear
data_power_roll["Power (mW) Roll Ave 500"] = data["Power (mW)"].rolling(500).me
data_power_roll["Power (mW) Roll Ave 1000"] = data["Power (mW)"].rolling(1000)
data_power_roll.rename(columns={"DateTime (dd/mm/yyyyy hh:mm:ss)":"DateTime"},
data_power_roll.set_index("DateTime", inplace=True)
display(data_power_roll.head())
```

DateTime	Power (mW)	Power (mW) Roll Ave 25	Power (mW) Roll Ave 500	Power (mW) Roll Ave 1000
2022-05-19 04:56:00	0.0	NaN	NaN	NaN
2022-05-19 04:56:05	0.0	NaN	NaN	NaN
2022-05-19 04:56:10	0.0	NaN	NaN	NaN
2022-05-19 04:56:15	0.0	NaN	NaN	NaN
2022-05-19 04:56:20	0.0	NaN	NaN	NaN

In [18]:

```
plt.figure(figsize=(15,10))
x_ticks = pd.date_range(start=data_power_roll.index.min(), end=data_power_roll
plt.xticks(x_ticks, x_ticks.strftime("%Y-%m-%d %H:%M"), rotation=45, ha="cente
plt.plot(data_power_roll["Power (mW) Roll Ave 25"], linewidth=2, label="Rolling
plt.plot(data_power_roll["Power (mW) Roll Ave 500"], linewidth=2, label="Rollin
plt.plot(data_power_roll["Power (mW) Roll Ave 1000"], linewidth=2, label="Roll
plt.title("Power (mW) delivered over Time")
plt.xlabel("DateTime")
plt.ylabel("Rolling Average Power (mW)")
plt.legend(loc="best")
plt.show()
```



The fluctuation of data in the line plot of "Rolling Ave 25" higlights how different servo positions will deliver different amounts of power and the fluctuation is also caused by partial shading of the clouds. To visualize this properly, let's create a graph of different pairs of servo position (both from Lower and Upper).

In [19]:
```python
col_to_use = ["DateTime (dd/mm/yyyyy hh:mm:ss)", "Servo Lower Angle (°)","Servo
servo_pair_all_list = list()
servo_lower = data["Servo Lower Angle (°)"].unique()
servo_upper = data["Servo Upper Angle (°)"].unique()
print("Servo Lower Angles: ", servo_lower)
print("Servo Upper Angles: ", servo_upper)

for servo_lower_angle in servo_lower:
    servo_pairings = list()
    for servo_upper_angle in servo_upper:
        servo_pair_filtered = data[(data["Servo Lower Angle (°)"]==servo_lower_
        servo_pair_filtered.rename(columns={"DateTime (dd/mm/yyyyy hh:mm:ss)":'
        servo_pair_filtered.set_index("DateTime", inplace=True)
        servo_pairings.append(servo_pair_filtered)
    servo_pair_all_list.append(servo_pairings)

display(servo_pair_all_list[0][0].head(5)) # Servo Lower: 0°, Servo Upper 0°
display(servo_pair_all_list[2][3].head(5)) # Servo Lower: 90°, Servo Upper 69°
```

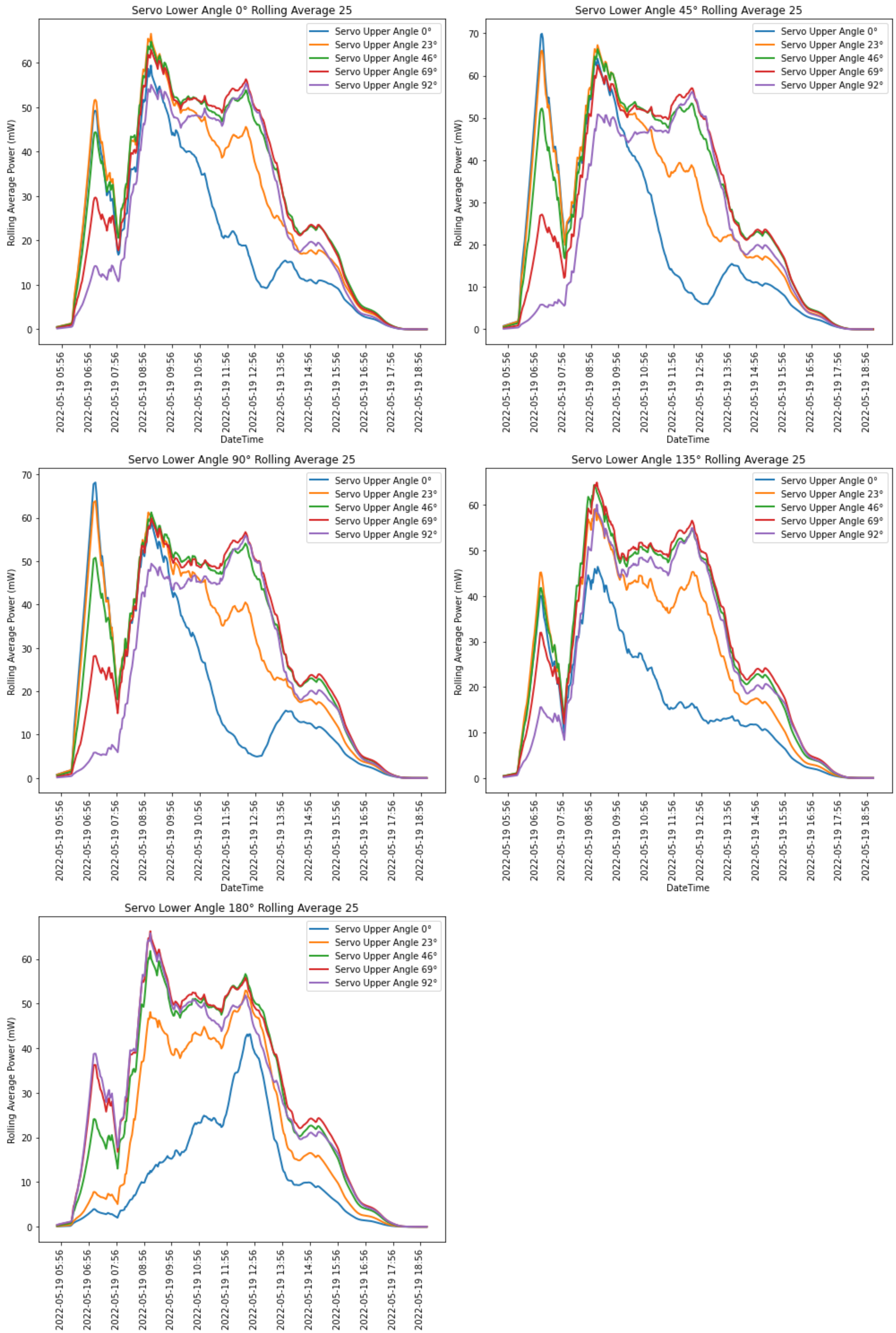
```
Servo Lower Angles:  [  0  45  90 135 180]
Servo Upper Angles:  [ 0 23 46 69 92]
```

DateTime	Servo Lower Angle (°)	Servo Upper Angle (°)	Irradiance (W/m2)	Power (mW)
2022-05-19 04:56:00	0	0	0.0	0.0
2022-05-19 04:58:05	0	0	0.0	0.0
2022-05-19 05:00:10	0	0	0.0	0.0
2022-05-19 05:02:15	0	0	0.0	0.0
2022-05-19 05:04:20	0	0	0.0	0.0

DateTime	Servo Lower Angle (°)	Servo Upper Angle (°)	Irradiance (W/m2)	Power (mW)
2022-05-19 04:57:05	90	69	0.000	0.0
2022-05-19 04:59:10	90	69	0.000	-0.0
2022-05-19 05:01:15	90	69	0.000	-0.0
2022-05-19 05:03:20	90	69	0.000	0.0
2022-05-19 05:05:25	90	69	0.233	0.0

-- Graphing Rolling Average of Power (mW) of Different Servo Angle Pairs --

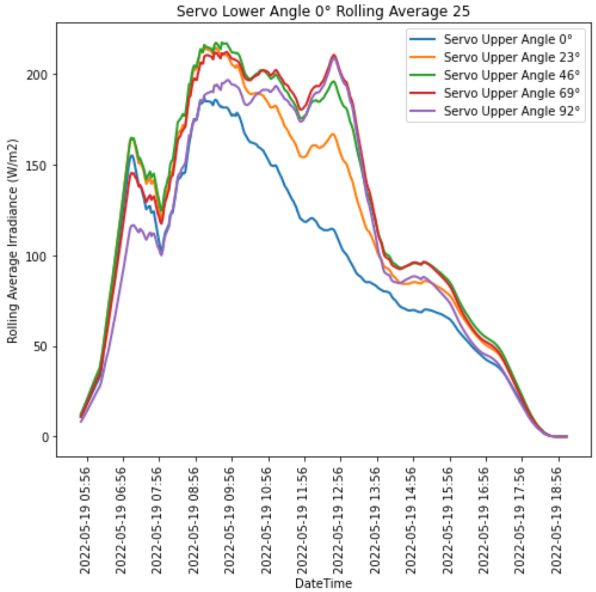
In [20]:
```
fig = plt.figure(figsize=(14, 21))
for i in range(len(servo_pair_all_list)):
    ax = fig.add_subplot(3,2,i+1)
    ax.set_title("Servo Lower Angle {}° Rolling Average 25".format(servo_lower
    ax.set_xlabel("DateTime")
    ax.set_ylabel("Rolling Average Power (mW)")
    ax.set_xticks(x_ticks)
    ax.set_xticklabels(x_ticks.strftime("%Y-%m-%d %H:%M"))
    plt.setp(ax.get_xticklabels(), rotation=90, horizontalalignment='center')
    for j in range(len(servo_pair_all_list[i])):
        ax.plot(servo_pair_all_list[i][j]["Power (mW)"].rolling(25).mean(), li
    ax.legend(loc="best")
fig.tight_layout()
plt.show()
```

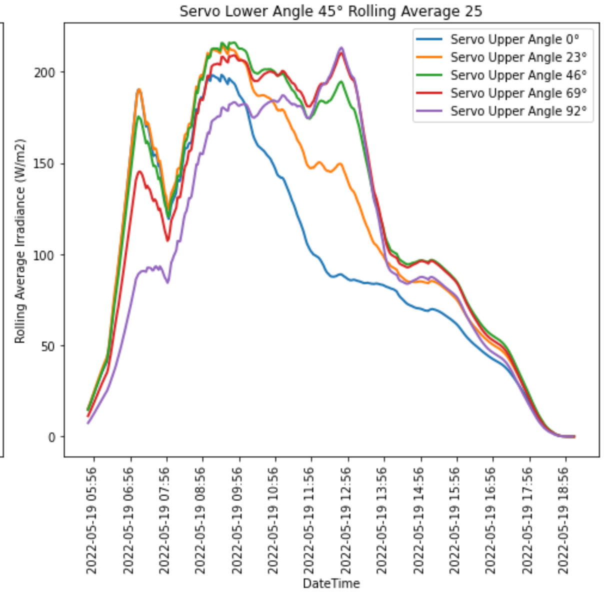


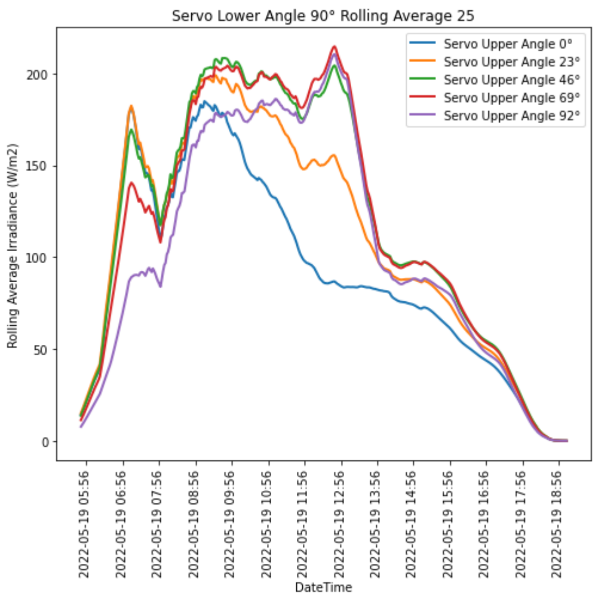
-- Graphing Rolling Average of Irradiance (W/m2) of Different Servo Angle Pairs --

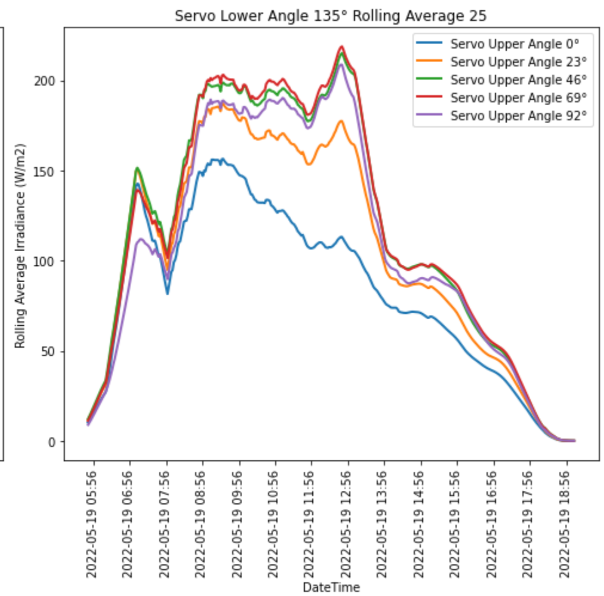
In [21]:

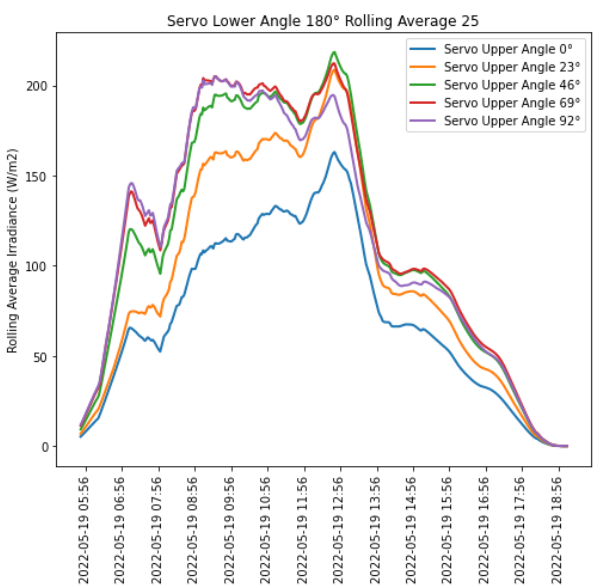
```
fig = plt.figure(figsize=(14, 21))
for i in range(len(servo_pair_all_list)):
    ax = fig.add_subplot(3,2,i+1)
    ax.set_title("Servo Lower Angle {}° Rolling Average 25".format(servo_lower
    ax.set_xlabel("DateTime")
    ax.set_ylabel("Rolling Average Irradiance (W/m2)")
    ax.set_xticks(x_ticks)
    ax.set_xticklabels(x_ticks.strftime("%Y-%m-%d %H:%M"))
    plt.setp(ax.get_xticklabels(), rotation=90, horizontalalignment='center')
    for j in range(len(servo_pair_all_list[i])):
        ax.plot(servo_pair_all_list[i][j]["Irradiance (W/m2)"].rolling(25).mear
    ax.legend(loc="best")
fig.tight_layout()
plt.show()
```


Servo Lower Angle 0° Rolling Average 25
Rolling Average Irradiance (W/m2)
DateTime
Servo Upper Angle 0°
Servo Upper Angle 23°
Servo Upper Angle 46°
Servo Upper Angle 69°
Servo Upper Angle 92°


Servo Lower Angle 45° Rolling Average 25
Rolling Average Irradiance (W/m2)
DateTime
Servo Upper Angle 0°
Servo Upper Angle 23°
Servo Upper Angle 46°
Servo Upper Angle 69°
Servo Upper Angle 92°


Servo Lower Angle 90° Rolling Average 25
Rolling Average Irradiance (W/m2)
DateTime
Servo Upper Angle 0°
Servo Upper Angle 23°
Servo Upper Angle 46°
Servo Upper Angle 69°
Servo Upper Angle 92°


Servo Lower Angle 135° Rolling Average 25
Rolling Average Irradiance (W/m2)
DateTime
Servo Upper Angle 0°
Servo Upper Angle 23°
Servo Upper Angle 46°
Servo Upper Angle 69°
Servo Upper Angle 92°


Servo Lower Angle 180° Rolling Average 25
Rolling Average Irradiance (W/m2)
DateTime
Servo Upper Angle 0°
Servo Upper Angle 23°
Servo Upper Angle 46°
Servo Upper Angle 69°
Servo Upper Angle 92°

Model Development

In [22]:
```
from sklearn.model_selection import train_test_split

columns_rename=["DateTime","Hour","Minute","Second","Servo Lower","Servo Upper'
data_to_model =pd.concat([data["DateTime (dd/mm/yyyyy hh:mm:ss)"],
                          data["DateTime (dd/mm/yyyyy hh:mm:ss)"].dt.hour,
                          data["DateTime (dd/mm/yyyyy hh:mm:ss)"].dt.minute,
                          data["DateTime (dd/mm/yyyyy hh:mm:ss)"].dt.second,
                          data.iloc[:,1:3],data["Power (mW)"]], axis=1)
data_to_model.columns = columns_rename
data_to_model.set_index("DateTime", inplace=True)
display(data_to_model.iloc[:,:-1].head().style.set_caption("Predictor Variables

x_ticks = pd.date_range(start=data_to_model.index.min(), end=data_to_model.inde
X_trainval, X_test, y_trainval, y_test = train_test_split(data_to_model.iloc[:
```

Predictor Variables to Use

DateTime	Hour	Minute	Second	Servo Lower	Servo Upper
2022-05-19 04:56:00	4	56	0	0	0
2022-05-19 04:56:05	4	56	5	0	23
2022-05-19 04:56:10	4	56	10	0	46
2022-05-19 04:56:15	4	56	15	0	69
2022-05-19 04:56:20	4	56	20	0	92

In [23]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_absolute_error

def grid_search_report(regressor, param_grid, X_trainval, X_test, y_trainval, y
                       refit="r2", scoring=["r2","neg_mean_absolute_error"], cv
                        #setting default values

    grid = GridSearchCV(regressor, param_grid=param_grid, scoring=scoring, refi
    grid.fit(X_trainval, y_trainval)
    print("Regression Model used: {}".format(regressor.__class__.__name__ ))
    print("Grid Search Scorer/s used: {}".format(scoring))
    print("Grid Search Scorer used to find best parameters: {}".format(refit))
    print("Best parameters: ", grid.best_params_)
    print("Best cross-validation score ({}): {:.4f}\n...".format(refit,grid.bes

    #Predict both X_trainval and X_test for scoring and plotting
    y_trainval_pred=grid.predict(X_trainval)
    y_test_pred=grid.predict(X_test)

    #Print Metrics
    print("R2 Score:")
    print("Train-Validation Set: {:.4f}".format(grid.score(X_trainval, y_trainv
    print("Test Set: {:.4f}".format(grid.score(X_test, y_test)))
    print("Mean Absolute Error:")
    print("Train-Validation Set: {:.4f}mW".format(mean_absolute_error(y_trainva
    print("Test Set: {:.4f}mW".format(mean_absolute_error(y_test, y_test_pred))

    #Create dataframe with columns y_trainval_actual and y_trainval_predict wit
        #from X_trainval.index which is the corresponding DateTime
    y_trainval_actual_pred = pd.DataFrame({"Power (mW) Actual":y_trainval.value
    #Create dataframe with columns y_test_actual and y_test_predict with index
        #from X_test.index which is the corresponding DateTime
    y_test_actual_pred = pd.DataFrame({"Power (mW) Actual":y_test.values, "Powe

    #Display DataFrame both from TrainVal set and Test set
    display(y_trainval_actual_pred.head().style.set_caption("TrainValidation Se
    display(y_test_actual_pred.head().style.set_caption("Test Set: Actual vs. P

    #Plot both TrainValidation and Test Set: Actual vs. Predicted
    fig = plt.figure(figsize=(14,7))
    for (subplot, y_set) in zip([1,2],[y_trainval_actual_pred,y_test_actual_pre
        ax = fig.add_subplot(1,2,subplot)
        if subplot==1 :
            ax.set_title("TrainValidation Set: Actual vs. Predicted (Rolling Av
        elif subplot == 2:
            ax.set_title("Test Set: Actual vs. Predicted (Rolling Average Power
        ax.set_xlabel("DateTime")
        ax.set_ylabel("Rolling Average Power (mW)")
        ax.set_xticks(x_ticks)
        ax.set_xticklabels(x_ticks.strftime("%Y-%m-%d %H:%M"))
        plt.setp(ax.get_xticklabels(), rotation=90, horizontalalignment='center
        #Plot Actual
        ax.plot(y_set.loc[:,"Power (mW) Actual"].sort_index().rolling(25).mean(
        #Plot Predicted
        ax.plot(y_set.loc[:,"Power (mW) Predict"].sort_index().rolling(25).mean
        ax.legend(loc="best")
    fig.tight_layout()
```

```
    plt.show()

    return (grid.best_estimator_, grid.cv_results_) #return best estimator and
```

In [24]:
```python
from sklearn.ensemble import RandomForestRegressor

rf_param_grid = {"n_estimators":[200,500,700],
                "criterion":["squared_error", "absolute_error"],
                "max_depth":[5,None]}

tup_rf=grid_search_report(RandomForestRegressor(random_state=47, n_jobs=-1), r
```

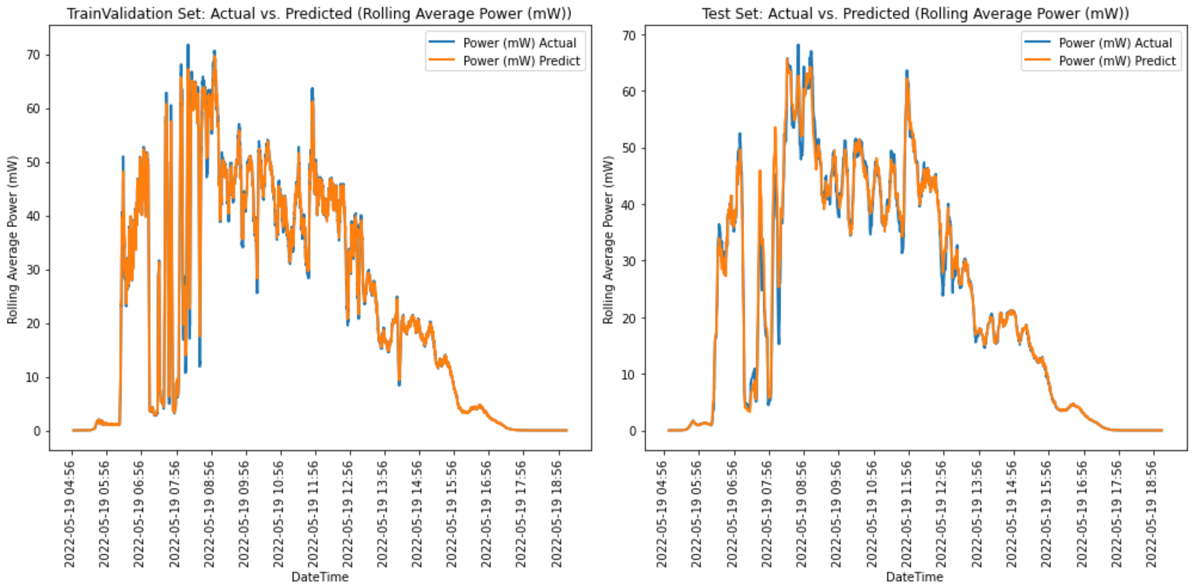
```
Regression Model used: RandomForestRegressor
Grid Search Scorer/s used: ['r2', 'neg_mean_absolute_error']
Grid Search Scorer used to find best parameters: r2
Best parameters:  {'criterion': 'squared_error', 'max_depth': None, 'n_estima
tors': 500}
Best cross-validation score (r2): 0.9340
...
R2 Score:
Train-Validation Set: 0.9920
Test Set: 0.9384
Mean Absolute Error:
Train-Validation Set: 0.8432mW
Test Set: 2.3082mW
```

TrainValidation Set: Actual vs. Predicted Power (mW)

DateTime	Power (mW) Actual	Power (mW) Predict
2022-05-19 05:16:30	0.000050	0.000080
2022-05-19 08:30:50	60.797730	63.327226
2022-05-19 18:54:04	0.000000	0.000000
2022-05-19 06:54:15	19.418050	19.405335
2022-05-19 16:06:51	3.403700	3.257295

Test Set: Actual vs. Predicted Predicted Power (mW)

DateTime	Power (mW) Actual	Power (mW) Predict
2022-05-19 14:21:46	13.092480	11.600516
2022-05-19 08:23:10	72.742500	65.504031
2022-05-19 18:33:27	0.000000	0.000000
2022-05-19 16:09:31	4.313120	4.238830
2022-05-19 17:14:26	1.174860	1.192806


TrainValidation Set: Actual vs. Predicted (Rolling Average Power (mW))
Test Set: Actual vs. Predicted (Rolling Average Power (mW))
Power (mW) Actual
Power (mW) Predict
Rolling Average Power (mW)
DateTime
2022-05-19 04:56
2022-05-19 05:56
2022-05-19 06:56
2022-05-19 07:56
2022-05-19 08:56
2022-05-19 09:56
2022-05-19 10:56
2022-05-19 11:56
2022-05-19 12:56
2022-05-19 13:56
2022-05-19 14:56
2022-05-19 15:56
2022-05-19 16:56
2022-05-19 17:56
2022-05-19 18:56

In [25]:
```python
from sklearn.ensemble import GradientBoostingRegressor

gbr_param_grid = {"learning_rate":[0.5, 0.8],
                  "n_estimators":[500,1000],
                  "max_depth":[5,None]}

tup_gbr=grid_search_report(GradientBoostingRegressor(random_state=47), gbr_para
```

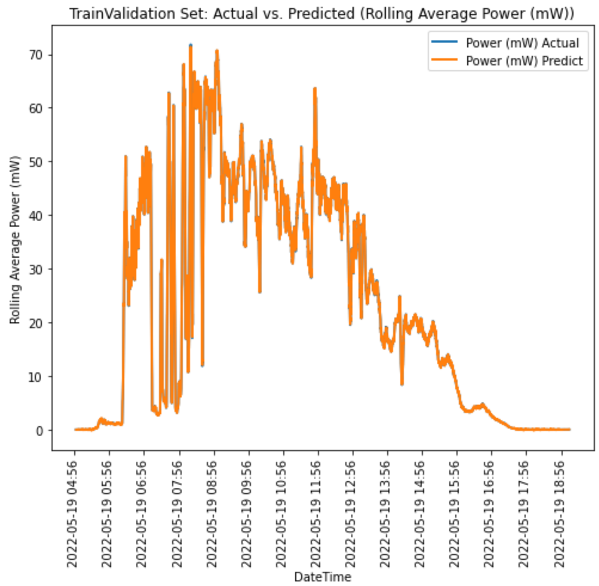
```
Regression Model used: GradientBoostingRegressor
Grid Search Scorer/s used: ['r2', 'neg_mean_absolute_error']
Grid Search Scorer used to find best parameters: r2
Best parameters:  {'learning_rate': 0.5, 'max_depth': 5, 'n_estimators': 100
0}
Best cross-validation score (r2): 0.9372
...
R2 Score:
Train-Validation Set: 0.9989
Test Set: 0.9524
Mean Absolute Error:
Train-Validation Set: 0.5160mW
Test Set: 2.7913mW
```

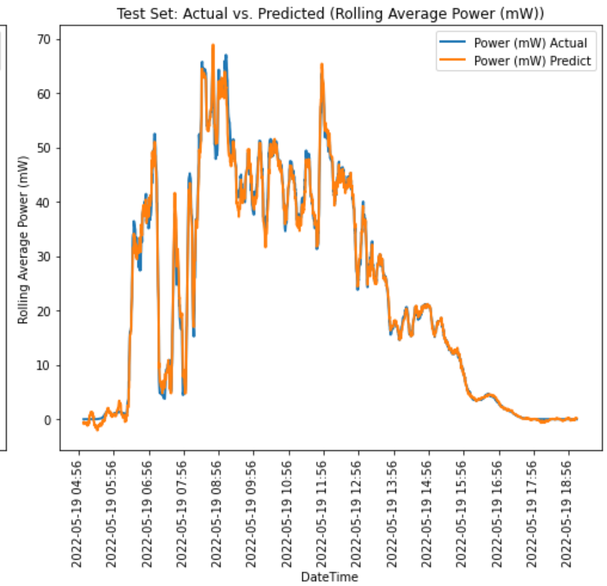
TrainValidation Set: Actual vs. Predicted Power (mW)

DateTime	Power (mW) Actual	Power (mW) Predict
2022-05-19 05:16:30	0.000050	-0.859534
2022-05-19 08:30:50	60.797730	62.765559
2022-05-19 18:54:04	0.000000	-0.238554
2022-05-19 06:54:15	19.418050	19.688915
2022-05-19 16:06:51	3.403700	3.540735

Test Set: Actual vs. Predicted Predicted Power (mW)

DateTime	Power (mW) Actual	Power (mW) Predict
2022-05-19 14:21:46	13.092480	13.224717
2022-05-19 08:23:10	72.742500	65.401428
2022-05-19 18:33:27	0.000000	-0.252414
2022-05-19 16:09:31	4.313120	4.906825
2022-05-19 17:14:26	1.174860	0.644425





Gradient Boosting Regressor has higher R2 score in the Cross Validation and Test Set compared to Random Forest Regressor but it also has a higher Mean Absolute Error compared to Random Forest Regresssor. Gradient Boosting Regressor also predict negative values while Random Forest only predicts zero as its lowest possible prediction value. To improve gradient boosting regressor's predicting performance and ability to consider zero/close to zero as its lower bounds of prediction, we can do logarithmic transformation but it would also increase/decrease the upper bounds of GBR's prediction and its MAE depending on the constant value applied to the transfromation. To remedy this situation, we will just transform GBR's negative prediction values to zero and see whether the MAE and R2 score of GBR will improve compared to Random Forest Regressor. If not, then we will use Random Forest Regressor as our final model for prediction.

In [26]:
```
#Create unclipped and clipped GBR lower bound prediction to zero
GBR_trainval_predict_clipped = tup_gbr[0].predict(X_trainval).clip(min=0)
GBR_trainval_predict_unclipped = tup_gbr[0].predict(X_trainval)
GBR_test_predict_clipped = tup_gbr[0].predict(X_test).clip(min=0)
GBR_test_predict_unclipped = tup_gbr[0].predict(X_test)
```

In [27]:
```python
print("Mean Absolute Error (Clipped):")
MAE_trainval_clipped = mean_absolute_error(y_trainval, GBR_trainval_predict_cl
MAE_test_clipped = mean_absolute_error(y_test, GBR_test_predict_clipped)
print("Train-Validation Set: {:.4f}mW".format(MAE_trainval_clipped))
print("Test Set: {:.4f}mW\n".format(MAE_test_clipped))

print("Mean Absolute Error (Unclipped):")
MAE_trainval_unclipped = mean_absolute_error(y_trainval, GBR_trainval_predict_
MAE_test_unclipped = mean_absolute_error(y_test, GBR_test_predict_unclipped)
print("Train-Validation Set: {:.4f}mW".format(MAE_trainval_unclipped))
print("Test Set: {:.4f}mW\n".format(MAE_test_unclipped))

print("Based on the Test Set of Clipped and Unclipped Lower Bounds of GBR's Pre
if MAE_test_clipped < MAE_test_unclipped:
    print("Assessment: Clip GBR's Prediction Lower Bounds ")
else:
    print("Assessment: Don't Clip GBR's Prediction Lower Bounds ")
```

```
Mean Absolute Error (Clipped):
Train-Validation Set: 0.4960mW
Test Set: 2.5328mW

Mean Absolute Error (Unclipped):
Train-Validation Set: 0.5160mW
Test Set: 2.7913mW

Based on the Test Set of Clipped and Unclipped Lower Bounds of GBR's Predicti
on...
Assessment: Clip GBR's Prediction Lower Bounds
```

In [28]:

```
from sklearn.metrics import r2_score

print("R2 score (Clipped):")
R2_trainval_clipped = r2_score(y_trainval, GBR_trainval_predict_clipped)
R2_test_clipped = r2_score(y_test, GBR_test_predict_clipped)
print("Train-Validation Set: {:.4f}".format(R2_trainval_clipped))
print("Test Set: {:.4f}\n".format(R2_test_clipped))

print("R2 score (Unclipped):")
R2_trainval_unclipped = r2_score(y_trainval, GBR_trainval_predict_unclipped)
R2_test_unclipped = r2_score(y_test, GBR_test_predict_unclipped)
print("Train-Validation Set: {:.4f}".format(R2_trainval_unclipped))
print("Test Set: {:.4f}\n".format(R2_test_unclipped))

print("Based on the Test Set of Clipped and Unclipped Lower Bounds of GBR's Pre
if R2_test_clipped > R2_test_unclipped:
    print("Assessment: Clip GBR's Prediction Lower Bounds ")
else:
    print("Assessment: Don't Clip GBR's Prediction Lower Bounds ")
```

```
R2 score (Clipped):
Train-Validation Set: 0.9989
Test Set: 0.9571

R2 score (Unclipped):
Train-Validation Set: 0.9989
Test Set: 0.9524

Based on the Test Set of Clipped and Unclipped Lower Bounds of GBR's Predicti
on...
Assessment: Clip GBR's Prediction Lower Bounds
```

Based on the results of clipped and unclipped lower bounds of GBR's prediction, we can see that both MAE and R2 score improves and no scoring type became worse by clipping.

In [29]:
```
#Print CV results of GBR
display(pd.DataFrame(tup_gbr[1]))
```

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_learning_rate	param_max
0	3.351898	0.031714	0.039304	0.007103	0.5	
1	6.688477	0.045830	0.069408	0.005914	0.5	
2	0.837454	0.023958	0.014211	0.003068	0.5	
3	0.983657	0.012567	0.018764	0.006255	0.5	
4	3.329809	0.044907	0.034372	0.006252	0.8	
5	6.666747	0.033734	0.072478	0.007973	0.8	
6	0.487119	0.022181	0.009401	0.007676	0.8	
7	0.659206	0.027875	0.009981	0.005731	0.8	

8 rows × 24 columns

Optimizing Servo Pair Angles

Based on the initial data gathered, we can already identify the best servo pair angles. But we can use the model that we developed to further gain insights or optimize the servo pair angles since the data we gathered only focused on specific sets of steps of servo angles.

```
In [30]: #We previously identified that the pair of servo angles that has highest averag
             #Servo Lower: 45
             #Servo Upper: 46
         #Let's estimate the average power of other sets of servo pair angles (close to
         #We will use the following data points
         #Servo Lower Previous Bounds: 0,  #Servo Lower Next Bounds: 90,
         #Servo Upper Previouse Bounds: 23, #Servo Upper Next Bounds: 69,

         final_model = tup_gbr[0] #set our final model to GBR
         servo_lower_set=np.linspace(0,90, num=11)
         servo_upper_set=np.linspace(23,69, num=5)
         print("Sets of Angle to Pair and Predict")
         print("Servo lower set: ", servo_lower_set)
         print("Servo upper set: ", servo_upper_set)

         #Setup empty dataframe first filled with ones
         servo_pairs_pred_ave_power = pd.DataFrame(1,index=servo_lower_set, columns=serv
         servo_pairs_pred_ave_power.rename_axis("Servo Upper Angle", axis=1, inplace=Tru
         servo_pairs_pred_ave_power.rename_axis("Servo Lower Angle", axis=0, inplace=Tru
         for servo_lower_angle in servo_lower_set:
             for servo_upper_angle in servo_upper_set:
                 data_to_predict=data_to_model.loc[:,:"Servo Upper"].copy() #get all x_p
                 data_to_predict["Servo Lower"] = servo_lower_angle
                 data_to_predict["Servo Upper"] = servo_upper_angle
                 power_predicted = final_model.predict(data_to_predict).clip(min=0) #cl
                 average_power=np.mean(power_predicted)
                 servo_pairs_pred_ave_power.loc[servo_lower_angle,servo_upper_angle] = a


         display(servo_pairs_pred_ave_power.style.set_caption("Average Power (mW) Delive
```

```
Sets of Angle to Pair and Predict
Servo lower set:  [ 0.   9. 18. 27. 36. 45. 54. 63. 72. 81. 90.]
Servo upper set:  [23.   34.5 46.   57.5 69. ]
```

Average Power (mW) Delivered based on Servo Angle Positions

Servo Upper Angle	23.000000	34.500000	46.000000	57.500000	69.000000
Servo Lower Angle					
0.000000	25.593535	25.594966	27.957157	27.951605	26.719754
9.000000	25.593535	25.594966	27.957157	27.951605	26.719754
18.000000	25.593535	25.594966	27.957157	27.951605	26.719754
27.000000	25.594358	25.594790	28.110292	28.107796	26.617448
36.000000	25.594358	25.594790	28.110292	28.107796	26.617448
45.000000	25.594358	25.594790	28.110292	28.107796	26.617448
54.000000	25.587276	25.587709	28.103080	28.100583	26.609840
63.000000	25.587276	25.587709	28.103080	28.100583	26.609840
72.000000	24.593539	24.594033	27.609934	27.607437	26.364032
81.000000	24.593539	24.594033	27.609934	27.607437	26.364032
90.000000	24.593539	24.594033	27.609934	27.607437	26.364032

Conclusions

Based on the prediciton models and data gathered, we can conclude that as for the current physical setup (location, current roofing materials and coatings used) where the device/module gathered the data, we can optimize the average power output of the solar panels during installment phase if we design the inclinations of our panel holders - the same way how the device/module identified its optimal inclinations (with estimated amount of tolerance) through the servo angle pairs which are - Servo Lower: 27°-45° and Servo Upper: 46° - 57.5°. But how can we design it based on pitch and roll angles?

Method 1: We can do these through setting up the device again to the physical location were it gathered the data, and set it up to move towards the optimal servo angle pairs and record its corresponding pitch and roll angles which will then be used to design the solar panel holders.

Method 2: We can also do these by training another machine learning model where we use Servo Lower and Servo Upper Angles as the predictor/X variables and the Pitch and Roll angles as the response/Y variables and then used the trained model to predict the pitch and roll angles of the optimal servo angle pairs.

But, it is highly recommeded to use Method 1. The results of other servo angle pairs are useful to set the amount of tolerance of the inclination angles on designing our solar panel holders. We can further improve our confidence of these optimization if we also create models where the variable we will be predicting is the Irradiance instead of Power.

Recommendations

If more data and experimentations are done to other location and datetime, we can use the temperature and humidity variables to create a more generalized machine learning model if our goal is to improve efficiency of solar panels by improving temperature conditions. We could use the results to identify whether we need to improve roofing materials, or coatings, or choose the location that already have the best temperature conditions. We also recommend to develop the device even further to also record the yaw angles, and if possible to record the longitude, latitude, and altitude where the device was gathering data. This might be useful if we are to pool the data from different users and locations.

Chapter 2: Transitioning to Cairo

Having successfully trained a model for optimizing solar panel positioning and angles, our next exploration involves investigating the correlation between power output and the irradiance data gathered by our module. Employing a linear regression model with power output as the predictor (X variable) and irradiance data as the response (Y variable), we aim to establish a quantitative relationship. The computed model will enable us to derive the average irradiance associated with each power level (mW) based on servo angle positions obtained in Chapter 1: Data Cleaning and Modeling on Python (Optimizing Servo Pair Angles). To enhance verifiability, we will seamlessly transition to Cairo & Orion, retrain the model, and conduct inferences within Cairo's environment, thereby ensuring the robustness and reliability of our machine learning model and its associated computations.

In [31]:
```
#Lets explore the correlation coefficient of power and irridiance from the raw
corr_matrix = np.corrcoef(power_pd.values.flatten(),irradiance_pd.values.flatte
display(pd.DataFrame(corr_matrix, columns=["Power","Irradiance"], index=["Power
```

	Power	Irradiance
Power	1.00000	0.99509
Irradiance	0.99509	1.00000

This demonstrates that irradiance and power have a strong relationship. As a result, we must optimize the orientation of our solar panel holder so that it receives the most irradiance on average throughout the day.

In [32]:
```
X = power_pd.values.reshape(-1, 1)
Y = irradiance_pd.values.flatten()
```

In [33]:
```
from sklearn.linear_model import LinearRegression

reg = LinearRegression().fit(X, Y)
reg.score(X, Y)
```

Out[33]: 0.9902050433019366

In [34]:
```
servo_pairs_pred_ave_power_stacked = servo_pairs_pred_ave_power.stack().reset_i
servo_pairs_pred_ave_power_stacked = servo_pairs_pred_ave_power_stacked.rename(
display(servo_pairs_pred_ave_power_stacked)
```

	Servo Lower Angle	Servo Upper Angle	Average Power (mW)
0	0.0	23.0	25.593535
1	0.0	34.5	25.594966
2	0.0	46.0	27.957157
3	0.0	57.5	27.951605
4	0.0	69.0	26.719754
5	9.0	23.0	25.593535
6	9.0	34.5	25.594966
7	9.0	46.0	27.957157
8	9.0	57.5	27.951605
9	9.0	69.0	26.719754
10	18.0	23.0	25.593535
11	18.0	34.5	25.594966
12	18.0	46.0	27.957157
13	18.0	57.5	27.951605
14	18.0	69.0	26.719754
15	27.0	23.0	25.594358
16	27.0	34.5	25.594790
17	27.0	46.0	28.110292
18	27.0	57.5	28.107796
19	27.0	69.0	26.617448
20	36.0	23.0	25.594358
21	36.0	34.5	25.594790
22	36.0	46.0	28.110292
23	36.0	57.5	28.107796
24	36.0	69.0	26.617448
25	45.0	23.0	25.594358
26	45.0	34.5	25.594790
27	45.0	46.0	28.110292
28	45.0	57.5	28.107796
29	45.0	69.0	26.617448
30	54.0	23.0	25.587276
31	54.0	34.5	25.587709
32	54.0	46.0	28.103080
33	54.0	57.5	28.100583
34	54.0	69.0	26.609840
35	63.0	23.0	25.587276

	Servo Lower Angle	Servo Upper Angle	Average Power (mW)
36	63.0	34.5	25.587709
37	63.0	46.0	28.103080
38	63.0	57.5	28.100583
39	63.0	69.0	26.609840
40	72.0	23.0	24.593539
41	72.0	34.5	24.594033
42	72.0	46.0	27.609934
43	72.0	57.5	27.607437
44	72.0	69.0	26.364032
45	81.0	23.0	24.593539
46	81.0	34.5	24.594033
47	81.0	46.0	27.609934
48	81.0	57.5	27.607437
49	81.0	69.0	26.364032
50	90.0	23.0	24.593539
51	90.0	34.5	24.594033
52	90.0	46.0	27.609934
53	90.0	57.5	27.607437
54	90.0	69.0	26.364032

In [35]:

```
ave_irridiance = reg.predict(servo_pairs_pred_ave_power_stacked["Average Power
servo_pairs_pred_ave_power_stacked["Average Irradiance (W/m2)"] = ave_irridianc
display(servo_pairs_pred_ave_power_stacked)
```

	Servo Lower Angle	Servo Upper Angle	Average Power (mW)	Average Irradiance (W/m2)
0	0.0	23.0	25.593535	108.385501
1	0.0	34.5	25.594966	108.389398
2	0.0	46.0	27.957157	114.822175
3	0.0	57.5	27.951605	114.807056
4	0.0	69.0	26.719754	111.452449
5	9.0	23.0	25.593535	108.385501
6	9.0	34.5	25.594966	108.389398
7	9.0	46.0	27.957157	114.822175
8	9.0	57.5	27.951605	114.807056
9	9.0	69.0	26.719754	111.452449
10	18.0	23.0	25.593535	108.385501
11	18.0	34.5	25.594966	108.389398
12	18.0	46.0	27.957157	114.822175
13	18.0	57.5	27.951605	114.807056
14	18.0	69.0	26.719754	111.452449
15	27.0	23.0	25.594358	108.387741
16	27.0	34.5	25.594790	108.388919
17	27.0	46.0	28.110292	115.239198
18	27.0	57.5	28.107796	115.232399
19	27.0	69.0	26.617448	111.173846
20	36.0	23.0	25.594358	108.387741
21	36.0	34.5	25.594790	108.388919
22	36.0	46.0	28.110292	115.239198
23	36.0	57.5	28.107796	115.232399
24	36.0	69.0	26.617448	111.173846
25	45.0	23.0	25.594358	108.387741
26	45.0	34.5	25.594790	108.388919
27	45.0	46.0	28.110292	115.239198
28	45.0	57.5	28.107796	115.232399
29	45.0	69.0	26.617448	111.173846
30	54.0	23.0	25.587276	108.368456
31	54.0	34.5	25.587709	108.369634
32	54.0	46.0	28.103080	115.219558
33	54.0	57.5	28.100583	115.212759
34	54.0	69.0	26.609840	111.153127
35	63.0	23.0	25.587276	108.368456

	Servo Lower Angle	Servo Upper Angle	Average Power (mW)	Average Irradiance (W/m2)
36	63.0	34.5	25.587709	108.369634
37	63.0	46.0	28.103080	115.219558
38	63.0	57.5	28.100583	115.212759
39	63.0	69.0	26.609840	111.153127
40	72.0	23.0	24.593539	105.662286
41	72.0	34.5	24.594033	105.663629
42	72.0	46.0	27.609934	113.876609
43	72.0	57.5	27.607437	113.869810
44	72.0	69.0	26.364032	110.483738
45	81.0	23.0	24.593539	105.662286
46	81.0	34.5	24.594033	105.663629
47	81.0	46.0	27.609934	113.876609
48	81.0	57.5	27.607437	113.869810
49	81.0	69.0	26.364032	110.483738
50	90.0	23.0	24.593539	105.662286
51	90.0	34.5	24.594033	105.663629
52	90.0	46.0	27.609934	113.876609
53	90.0	57.5	27.607437	113.869810
54	90.0	69.0	26.364032	110.483738

Now that we have computed the average irridiance per each servo angle positions, let's convert the model we have trained on the python enviroment to cairo.

In [36]:
```
! scarb new sppom_linear_regression
```

```
Created `sppom_linear_regression` package.
```

In [37]:
```
import os
tensor_name =['X_values', 'Y_values']

def decimal_to_fp16x16(decimal_number):
    whole_number = int(decimal_number)
    fractional_part = int((decimal_number - whole_number) * 65536)  # Multiply
    fp_number = (whole_number << 16) + fractional_part
    return fp_number

base_path = os.path.expanduser("sppom_linear_regression/src")

def generate_cairo_files(data, name):

    generated_path = os.path.join(base_path, 'generated')
    os.makedirs(generated_path, exist_ok=True)
    with open(os.path.join(generated_path, f"{name}.cairo"), "w") as f:
            f.write(
                "use array::ArrayTrait;\n" +
                "use orion::operators::tensor::{FP16x16Tensor, TensorTrait, Ter
                "use orion::numbers::{FixedTrait, FP16x16, FP16x16Impl};\n" +
                "\nfn {0}() -> Tensor<FP16x16>  ".format(name) + "{\n" +
                "     let mut shape = ArrayTrait::new();\n"
            )
            for dim in data.shape:
                f.write("     shape.append({0});\n".format(dim))
            f.write(
                "     let mut data = ArrayTrait::new();\n"
            )
            for val in np.nditer(data.flatten()):
                f.write("     data.append(FixedTrait::new({0}, {1} ));\n".format
            f.write(
                "let tensor = TensorTrait::<FP16x16>::new(shape.span(), data.sp
                "return tensor;\n\n"+
                "}\n"
            )
    with open(os.path.join(base_path, 'generated.cairo'), 'w') as f:
        for param_name in tensor_name:
            f.write(f"mod {param_name};\n")
```

In [38]:
```
generate_cairo_files(X, 'X_values')
generate_cairo_files(Y, 'Y_values')
```

In [39]:

```
%%writefile sppom_linear_regression/src/lin_reg_func.cairo

use orion::operators::tensor::{Tensor, TensorTrait, FP16x16Tensor};
use orion::numbers::{FP16x16, FixedTrait};

/// Calculates the mean of a given 1D tensor.
fn calculate_mean(tensor_data: Tensor<FP16x16>) -> FP16x16 {
    let tensor_size = FixedTrait::<FP16x16>::new_unscaled(tensor_data.data.len

    let cumulated_sum = tensor_data.cumsum(0, Option::None(()), Option::None((
    let sum_result = cumulated_sum.data[tensor_data.data.len() - 1];
    let mean = *sum_result / tensor_size;

    return mean;
}

/// Calculates the deviation of each element from the mean of the provided 1D t
fn deviation_from_mean(tensor_data: Tensor<FP16x16>) -> Tensor<FP16x16> {
    let mean_value = calculate_mean(tensor_data);

    let mut tensor_shape = array::ArrayTrait::new();
    tensor_shape.append(tensor_data.data.len());

    let mut deviation_values = array::ArrayTrait::new();

    let mut i: u32 = 0;
    loop {
        if i >= tensor_data.data.len() {
            break ();
        }
        let distance_from_mean = *tensor_data.data.at(i) - mean_value;
        deviation_values.append(distance_from_mean);
        i += 1;
    };

    let distance_from_mean_tensor = TensorTrait::<FP16x16>::new(
        tensor_shape.span(), deviation_values.span()
    );

    return distance_from_mean_tensor;
}


/// Calculates the beta value for linear regression.
fn compute_beta(x_values: Tensor<FP16x16>, y_values: Tensor<FP16x16>) -> FP16x1
    let x_deviation = deviation_from_mean(x_values);
    let y_deviation = deviation_from_mean(y_values);

    let x_y_covariance = x_deviation.matmul(@y_deviation);
    let x_variance = x_deviation.matmul(@x_deviation);

    let beta_value = *x_y_covariance.data.at(0) / *x_variance.data.at(0);

    return beta_value;
}

/// Calculates the intercept for linear regression.
```

```
fn compute_intercept(
    beta_value: FP16x16, x_values: Tensor<FP16x16>, y_values: Tensor<FP16x16>
) -> FP16x16 {
    let x_mean = calculate_mean(x_values);
    let y_mean = calculate_mean(y_values);

    let mx = beta_value * x_mean;
    let intercept = y_mean - mx;

    return intercept;
}

/// Predicts the y values using the provided x values and computed beta and int
fn predict_y_values(
    beta_value: FP16x16, x_values: Tensor<FP16x16>, y_values: Tensor<FP16x16>
) -> Tensor<FP16x16> {
    let beta = compute_beta(x_values, y_values);
    let intercept = compute_intercept(beta_value, x_values, y_values);

    //create a tensor to hold all the y_pred values
    let mut y_pred_shape = array::ArrayTrait::new();
    y_pred_shape.append(y_values.data.len());

    let mut y_pred_vals = array::ArrayTrait::new();

    let mut i: u32 = 0;
    loop {
        if i >= y_values.data.len() {
            break ();
        }
        // (*x_values.data.at(i)).print();
        let predicted_value = beta * *x_values.data.at(i) + intercept;
        y_pred_vals.append(predicted_value);
        i += 1;
    };

    let y_pred_tensor = TensorTrait::<FP16x16>::new(y_pred_shape.span(), y_pred

    return y_pred_tensor;
}


/// Calculates the mean squared error between the true y values and the predict
fn compute_mse(y_values: Tensor<FP16x16>, y_pred_values: Tensor<FP16x16>) -> FP
    let mut squared_diff_shape = array::ArrayTrait::new();
    squared_diff_shape.append(y_values.data.len());

    let mut squared_diff_vals = array::ArrayTrait::new();

    let mut i: u32 = 0;
    loop {
        if i >= y_values.data.len() {
            break ();
        }
        let diff = *y_values.data.at(i) - *y_pred_values.data.at(i);
        let squared_diff = diff * diff;
        squared_diff_vals.append(squared_diff);
```

```
        i += 1;
    };

    let squared_diff_tensor = TensorTrait::<FP16x16>::new(
        squared_diff_shape.span(), squared_diff_vals.span()
    );

    let mse = calculate_mean(squared_diff_tensor);

    return mse;
}

/// Calculates the R squared score.
fn calculate_r_score(y_values: Tensor<FP16x16>, y_pred_values: Tensor<FP16x16>)
    let mean_y_value = calculate_mean(y_values);

    // creating the appropriate tensor shapes and empty arrays to populate valu
    let mut squared_diff_shape = array::ArrayTrait::new();
    squared_diff_shape.append(y_values.data.len());
    let mut squared_diff_vals = array::ArrayTrait::new();

    let mut squared_mean_diff_shape = array::ArrayTrait::new();
    squared_mean_diff_shape.append(y_values.data.len());
    let mut squared_mean_diff_vals = array::ArrayTrait::new();

    let mut i: u32 = 0;
    loop {
        if i >= y_values.data.len() {
            break ();
        }
        let diff_pred = *y_values.data.at(i) - *y_pred_values.data.at(i);
        let squared_diff = diff_pred * diff_pred;
        squared_diff_vals.append(squared_diff);

        let diff_mean = *y_values.data.at(i) - mean_y_value;
        let squared_mean_diff = diff_mean * diff_mean;
        squared_mean_diff_vals.append(squared_mean_diff);
        i += 1;
    };

    let squared_diff_tensor = TensorTrait::<FP16x16>::new(
        squared_diff_shape.span(), squared_diff_vals.span()
    );
    let squared_mean_diff_tensor = TensorTrait::<FP16x16>::new(
        squared_mean_diff_shape.span(), squared_mean_diff_vals.span()
    );

    let sum_squared_diff = squared_diff_tensor.cumsum(0, Option::None(()), Opt
    let sum_squared_mean_diff = squared_mean_diff_tensor
        .cumsum(0, Option::None(()), Option::None(()));

    let r_score = FixedTrait::new_unscaled(1, false)
        - *sum_squared_diff.data.at(y_values.data.len() - 1)
            / *sum_squared_mean_diff.data.at(y_values.data.len() - 1);

    return r_score;
}
```

Writing sppom_linear_regression/src/lin_reg_func.cairo

In [40]:
```
%%writefile sppom_linear_regression/src/test.cairo
use debug::PrintTrait;

use sppom_linear_regression::generated::X_values::X_values;
use sppom_linear_regression::generated::Y_values::Y_values;
use sppom_linear_regression::lin_reg_func::{
    calculate_mean, deviation_from_mean, compute_beta, compute_intercept, pred:
    compute_mse, calculate_r_score
};


#[test]
#[available_gas(99999999999999999)]
fn sppom_linear_regression_test() {
    // Fetching the x and y values
    let y_values = Y_values();
    let x_values = X_values();

    // (*x_values.data.at(18)).print();

    let beta_value = compute_beta(x_values, y_values);
    // beta_value.print();    // calculated gradient value

    let intercept_value = compute_intercept(beta_value, x_values, y_values);
    // intercept_value.print();   // calculated intercept value

    let y_pred = predict_y_values(beta_value, x_values, y_values);

    let mse = compute_mse(y_values, y_pred);
    // mse.print();       // mean squared error ouput

    let r_score = calculate_r_score(y_values, y_pred);
    r_score.print(); // accuracy of model around 0.9902050433019366

    assert(beta_value.mag > 0, 'x & y not positively correlated');
    assert(r_score.mag > 0, 'R-Squared needs to be above 0');
    assert(
        r_score.mag < 65536, 'R-Squared has to be below 65536'
    ); // 65536 represents ONE in fp16x16.
    assert(r_score.mag > 32768, 'Accuracy below 50% ');
}
```

Writing sppom_linear_regression/src/test.cairo

In [41]:
```
%%writefile sppom_linear_regression/src/lib.cairo

mod generated;
mod lin_reg_func;
mod test;
```

Overwriting sppom_linear_regression/src/lib.cairo

In [42]:
```python
current_directory = os.getcwd()
print("Current Working Directory:", current_directory)

# Change the current working directory
new_directory = os.path.join(current_directory, "sppom_linear_regression")
os.chdir(new_directory)

# Verify the change
updated_directory = os.getcwd()
print("Updated Working Directory:", updated_directory)
```

```
Current Working Directory: C:\Users\Predator\Desktop\Personal Files\School Fi
les\Starknet Infra Exploration Hackathon\SPPOM ZKML
Updated Working Directory: C:\Users\Predator\Desktop\Personal Files\School Fi
les\Starknet Infra Exploration Hackathon\SPPOM ZKML\sppom_linear_regression
```

In [43]:
```
! scarb cairo-test -f sppom_linear_regression_test
```

```
   Compiling test(sppom_linear_regression_unittest) sppom_linear_regression v
0.1.0 (C:\Users\Predator\Desktop\Personal Files\School Files\Starknet Infra E
xploration Hackathon\SPPOM ZKML\sppom_linear_regression\Scarb.toml)
    Finished release target(s) in 25 seconds
testing sppom_linear_regression ...
running 1 tests
[DEBUG] false                           (raw: 0x66616c7365

[DEBUG]                                 (raw: 0xfd7f

test sppom_linear_regression::test::sppom_linear_regression_test ... ok (gas
usage est.: 51105060)
test result: ok. 1 passed; 0 failed; 0 ignored; 0 filtered out;
```

Conclusion

Now equipped with a verifiable model on Cairo, we can accurately estimate the corresponding average irradiance for each average power estimation derived from the Solar PV Positioning Optimizer Module (SPPOM) on Cairo. The synergy of Cairo and Orion ensures rigorous verification of our model's estimations and inferences, reinforcing the reliability of our results within the Orion framework.