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Importing the basic libraries

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
```

Importing the datasets

In [2]:
```
plant1 = pd.read_csv("plant1_merged.csv")
plant1
```

Out[2]:

	Unnamed: 0	DATE_TIME	INVERTER_ID	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD	AMBIENT_TEM
0	0	2020-05-15 00:00:00	1BY6WEcLGh8j5v7	0.0	0.0	0.000	6259559.0	
1	1	2020-05-15 00:00:00	1BY6WEcLGh8j5v7	0.0	0.0	0.000	6259559.0	
2	2	2020-05-15 00:00:00	1BY6WEcLGh8j5v7	0.0	0.0	0.000	6259559.0	
3	3	2020-05-15 00:00:00	1BY6WEcLGh8j5v7	0.0	0.0	0.000	6259559.0	
4	4	2020-05-15 00:00:00	1BY6WEcLGh8j5v7	0.0	0.0	0.000	6259559.0	
...	...	...	...	...	...	...	...	
134125	134125	2020-06-17 23:45:00	uHbuxQJl8lW7ozc	0.0	0.0	5967.000	7287002.0	
134126	134126	2020-06-17 23:45:00	wCURE6d3bPkepu2	0.0	0.0	5147.625	7028601.0	
134127	134127	2020-06-17 23:45:00	z9Y9gH1T5YWrNuG	0.0	0.0	5819.000	7251204.0	
134128	134128	2020-06-17 23:45:00	zBIq5rxdHJRwDNY	0.0	0.0	5817.000	6583369.0	
134129	134129	2020-06-17 23:45:00	zVJPv84UY57bAof	0.0	0.0	5910.000	7363272.0	

134130 rows × 10 columns

In [3]:
```
plant2 = pd.read_csv("plant2_merged.csv")
plant2
```

Out[3]:

	Unnamed: 0	DATE_TIME	INVERTER_ID	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD	AMBIENT_TEI
0	0	2020-05-15 00:00:00	4UPUqMRk7TRMgml	0.0	0.0	9425.0	2429011.0	
1	1	2020-05-15 00:00:00	4UPUqMRk7TRMgml	0.0	0.0	9425.0	2429011.0	
2	2	2020-05-15 00:00:00	4UPUqMRk7TRMgml	0.0	0.0	9425.0	2429011.0	
3	3	2020-05-15 00:00:00	4UPUqMRk7TRMgml	0.0	0.0	9425.0	2429011.0	
4	4	2020-05-15 00:00:00	4UPUqMRk7TRMgml	0.0	0.0	9425.0	2429011.0	
...	...	...	...	...	...	...	...	
134651	134651	2020-06-17 11:30:00	q49J1IKaHRwDQnt	0.0	0.0	4157.0	520758.0	
134652	134652	2020-06-17 11:30:00	rrq4fwE8jgrTyWY	0.0	0.0	3931.0	121131356.0	
134653	134653	2020-06-17 11:30:00	vOuJvMaM2sgwLmb	0.0	0.0	4322.0	2427691.0	
134654	134654	2020-06-17 11:30:00	xMbIugepa2P7lBB	0.0	0.0	4218.0	106896394.0	
134655	134655	2020-06-17 11:30:00	xoJJ8DcxJEcupym	0.0	0.0	4316.0	209335741.0	

134656 rows × 10 columns

In [4]:
```
plant1.drop(["Unnamed: 0", "INVERTER_ID"], axis=1, inplace=True)
plant2.drop(["Unnamed: 0", "INVERTER_ID"], axis=1, inplace=True)
```

In [5]:
```
plant1.dtypes
```

Out[5]:
```
DATE_TIME               object
DC_POWER               float64
AC_POWER               float64
DAILY_YIELD            float64
TOTAL_YIELD            float64
AMBIENT_TEMPERATURE    float64
MODULE_TEMPERATURE     float64
IRRADIATION            float64
dtype: object
```

In [6]:
```
plant1["DATE_TIME"] = pd.to_datetime(plant1["DATE_TIME"], format="%Y-%m-%d %H:%M:%S")
plant2["DATE_TIME"] = pd.to_datetime(plant2["DATE_TIME"], format="%Y-%m-%d %H:%M:%S")
```

In [7]:
```
plant1.dtypes
```

Out[7]:
```
DATE_TIME              datetime64[ns]
DC_POWER                      float64
AC_POWER                      float64
DAILY_YIELD                   float64
TOTAL_YIELD                   float64
AMBIENT_TEMPERATURE           float64
MODULE_TEMPERATURE            float64
IRRADIATION                   float64
dtype: object
```

In [8]:
```
plant2.dtypes
```

Out[8]:
```
DATE_TIME              datetime64[ns]
DC_POWER                      float64
AC_POWER                      float64
DAILY_YIELD                   float64
TOTAL_YIELD                   float64
AMBIENT_TEMPERATURE           float64
MODULE_TEMPERATURE            float64
IRRADIATION                   float64
dtype: object
```

Some Assumptions:

We're going to keep DAILY_YIELD as our target variable. So in a real life scenario, we'd just have the weather sensor data to predict the daily yield of a power plant and so we'll move forward with just that.

Train Test Split

In [9]:
```
reduced_plant1 = plant1[["AMBIENT_TEMPERATURE", "MODULE_TEMPERATURE", "IRRADIATION", "DAILY_YIELD"]]
```

In [10]:
```
reduced_plant2 = plant2[["AMBIENT_TEMPERATURE", "MODULE_TEMPERATURE", "IRRADIATION", "DAILY_YIELD"]]
```

In [11]:
```
reduced_plant1.isnull().sum()
```

Out[11]:
```
AMBIENT_TEMPERATURE    65594
MODULE_TEMPERATURE     65594
IRRADIATION            65594
DAILY_YIELD                0
dtype: int64
```

In [12]:
```
reduced_plant1.fillna(value=0, inplace=True)
reduced_plant2.fillna(value=0, inplace=True)
```

```
C:\Users\Ananya\AppData\Local\Temp\ipykernel_18472\3200288954.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexi
ng.html#returning-a-view-versus-a-copy
  reduced_plant1.fillna(value=0, inplace=True)
C:\Users\Ananya\AppData\Local\Temp\ipykernel_18472\3200288954.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexi
ng.html#returning-a-view-versus-a-copy
  reduced_plant2.fillna(value=0, inplace=True)
```

In [13]:
```
train_features = ["AMBIENT_TEMPERATURE", "MODULE_TEMPERATURE", "IRRADIATION"]
X_p1 = reduced_plant1[train_features]
y_p1 = reduced_plant1["DAILY_YIELD"]
```

In [14]:
```
X_p2 = reduced_plant2[train_features]
y_p2 = reduced_plant2["DAILY_YIELD"]
```

In [15]:
```
X_p1_train, X_p1_test, y_p1_train, y_p1_test = train_test_split(X_p1, y_p1, test_size=0.2, random_st
```

In [16]:
```
X_p2_train, X_p2_test, y_p2_train, y_p2_test = train_test_split(X_p2, y_p2, test_size=0.2, random_st
```

LINEAR REGRESSION

In [17]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
```

In [18]:
```
linreg = LinearRegression()
linreg.fit(X_p1_train, y_p1_train)
pred = linreg.predict(X_p1_test)
```

In [19]:
```
mean_squared_error(y_p1_test, pred)
```

Out[19]:
```
7887607.970225091
```

In [20]:
```
linreg2 = LinearRegression() # PLANT 2
linreg2.fit(X_p2_train, y_p2_train)
pred2 = linreg2.predict(X_p2_test)
```

In [21]:
```
mean_squared_error(y_p2_test, pred2)
```

Out[21]:
```
9666845.977933416
```

Default Linear Regression gives a pretty high MSE value which is not good. Now, we know from EDA that Module Temperature, Ambient Temperature and Irradiation are all very highly correlated. So let's try and do Linear Regression with only Irradiation as the other two are a consequence of Irradiation.

In [22]:
```
X_p1_rev = reduced_plant1["IRRADIATION"]
```

In [23]:
```
X_p1_train_rev, X_p1_test_rev, y_p1_train, y_p1_test = train_test_split(X_p1_rev, y_p1, test_size=0.
```

In [24]:
```
X_p1_train_rev = X_p1_train_rev.to_numpy()
X_p1_test_rev = X_p1_test_rev.to_numpy()
X_p1_train_rev = X_p1_train_rev.reshape(-1, 1)
X_p1_test_rev = X_p1_test_rev.reshape(-1, 1)

linreg = LinearRegression()
linreg.fit(X_p1_train_rev, y_p1_train)
pred = linreg.predict(X_p1_test_rev)
```

In [25]:
```
mean_squared_error(y_p1_test, pred)
```

Out[25]:
```
8109974.187599193
```

Okay the mse is still too high.

using GridSearchCV to find the best parameters

In [26]:
```
model = LinearRegression()

param_grid = {
    'fit_intercept': [True, False],
    'copy_X': [True, False]
}

grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=5, scoring='neg_mean_squared_e

grid_search.fit(X_p1_train_rev, y_p1_train)

print("Best hyperparameters:", grid_search.best_params_)

best_model = grid_search.best_estimator_

y_pred = best_model.predict(X_p1_test_rev)
mse = mean_squared_error(y_p1_test, y_pred)
print("Mean Squared Error:", mse)
```

```
Best hyperparameters: {'copy_X': True, 'fit_intercept': True}
Mean Squared Error: 8109974.187599193
```

Even using GridSearchCV the mse is way too big.

DECISION TREE REGRESSOR

In [27]:
```
from sklearn.tree import DecisionTreeRegressor
decreg = DecisionTreeRegressor(random_state = 42)
decreg.fit(X_p1_train, y_p1_train) # using all weather sensor features
pred = decreg.predict(X_p1_test)
```

In [28]:
```
mean_squared_error(y_p1_test, pred)
```

Out[28]:
```
5189993.872284841
```

In [29]:
```
decreg = DecisionTreeRegressor(random_state = 42)
decreg.fit(X_p1_train_rev, y_p1_train) # using only irradiation
pred = decreg.predict(X_p1_test_rev)
```

In [30]:
```
mean_squared_error(y_p1_test, pred)
```

Out[30]:
```
6589861.20479132
```

In [31]:
```
tree_reg = DecisionTreeRegressor()

param_grid = {
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

grid_search = GridSearchCV(tree_reg, param_grid, cv=5, scoring='neg_mean_squared_error', verbose=1)

grid_search.fit(X_p1_train, y_p1_train)

print("Best parameters:", grid_search.best_params_)

best_tree_reg = grid_search.best_estimator_

y_pred = best_tree_reg.predict(X_p1_test)
mse = mean_squared_error(y_p1_test, pred)
print("Mean squared error on test set:", mse)
```

```
Fitting 5 folds for each of 36 candidates, totalling 180 fits
Best parameters: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2}
Mean squared error on test set: 6589861.20479132
```

Decision Tree Regressor is a horrible model for this.

LASSO REGRESSION

In [32]:
```
from sklearn.linear_model import Lasso
lasso = Lasso(alpha=0.1)
lasso.fit(X_p1_train, y_p1_train)
pred = lasso.predict(X_p1_test)
```

```
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 5.416e+10, tolerance:
8.788e+07
  model = cd_fast.enet_coordinate_descent(
```

In [33]:
```
mean_squared_error(y_p1_test, pred)
```

Out[33]:
```
7887634.380124176
```

In [34]:
```
lasso_reg = Lasso()

param_grid = {
    'alpha': [0.001, 0.01, 0.1, 1, 10]
}

grid_search = GridSearchCV(lasso_reg, param_grid, cv=5, scoring='neg_mean_squared_error', verbose=1)

grid_search.fit(X_p1_train, y_p1_train)

print("Best parameters:", grid_search.best_params_)

best_lasso_reg = grid_search.best_estimator_

y_pred = best_lasso_reg.predict(X_p1_test)
mse = mean_squared_error(y_p1_test, y_pred)
print("Mean squared error on test set:", mse)
```

```
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 3.257e+11, tolerance:
7.028e+07
  model = cd_fast.enet_coordinate_descent(
Fitting 5 folds for each of 5 candidates, totalling 25 fits
```

```
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 3.248e+11, tolerance:
7.006e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 3.258e+11, tolerance:
7.035e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 3.253e+11, tolerance:
7.035e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 3.256e+11, tolerance:
7.050e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 2.450e+11, tolerance:
7.028e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 2.466e+11, tolerance:
7.006e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 2.469e+11, tolerance:
7.035e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 2.394e+11, tolerance:
7.035e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 2.416e+11, tolerance:
7.050e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 4.413e+10, tolerance:
7.028e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 4.601e+10, tolerance:
7.006e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 4.571e+10, tolerance:
7.035e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 3.975e+10, tolerance:
7.035e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 4.124e+10, tolerance:
7.050e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: Converg
enceWarning: Objective did not converge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. Duality gap: 6.342e+08, tolerance:
7.028e+07
  model = cd_fast.enet_coordinate_descent(
```

```
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: ConvergenceWarning: Objective did not converge. You might want to increase the number of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 6.841e+08, tolerance: 7.006e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: ConvergenceWarning: Objective did not converge. You might want to increase the number of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 6.712e+08, tolerance: 7.035e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: ConvergenceWarning: Objective did not converge. You might want to increase the number of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 5.372e+08, tolerance: 7.035e+07
  model = cd_fast.enet_coordinate_descent(
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: ConvergenceWarning: Objective did not converge. You might want to increase the number of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 5.586e+08, tolerance: 7.050e+07
  model = cd_fast.enet_coordinate_descent(
Best parameters: {'alpha': 0.001}
Mean squared error on test set: 7887607.837941845
C:\Users\Ananya\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:628: ConvergenceWarning: Objective did not converge. You might want to increase the number of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 4.068e+11, tolerance: 8.788e+07
  model = cd_fast.enet_coordinate_descent(
```

RIDGE REGRESSION

In [35]:
```python
from sklearn.linear_model import Ridge
ridge = Ridge(alpha=1.0)
ridge.fit(X_p1_train, y_p1_train)
pred = ridge.predict(X_p1_test)
```

In [36]:
```python
mean_squared_error(y_p1_test, pred)
```

Out[36]:
```
7887612.985658665
```

Both Lasso & Ridge Regression don't work out.

New Training & Testing data (with DATE_TIME)

In [37]:
```python
t_reduced_plant1 = plant1[["DATE_TIME","DAILY_YIELD"]]
t_reduced_plant2 = plant2[["DATE_TIME","DAILY_YIELD"]]
```

In [38]:
```python
t_reduced_plant1.set_index("DATE_TIME", inplace=True)
t_reduced_plant1
```

Out[38]:

DATE_TIME	DAILY_YIELD
2020-05-15 00:00:00	0.000
2020-05-15 00:00:00	0.000
2020-05-15 00:00:00	0.000
2020-05-15 00:00:00	0.000
2020-05-15 00:00:00	0.000
...	...
2020-06-17 23:45:00	5967.000
2020-06-17 23:45:00	5147.625
2020-06-17 23:45:00	5819.000
2020-06-17 23:45:00	5817.000
2020-06-17 23:45:00	5910.000

134130 rows × 1 columns

In [39]:

```
t_reduced_plant2.set_index("DATE_TIME", inplace=True)
t_reduced_plant2
```

Out[39]:

DATE_TIME	DAILY_YIELD
2020-05-15 00:00:00	9425.0
2020-05-15 00:00:00	9425.0
2020-05-15 00:00:00	9425.0
2020-05-15 00:00:00	9425.0
2020-05-15 00:00:00	9425.0
...	...
2020-06-17 11:30:00	4157.0
2020-06-17 11:30:00	3931.0
2020-06-17 11:30:00	4322.0
2020-06-17 11:30:00	4218.0
2020-06-17 11:30:00	4316.0

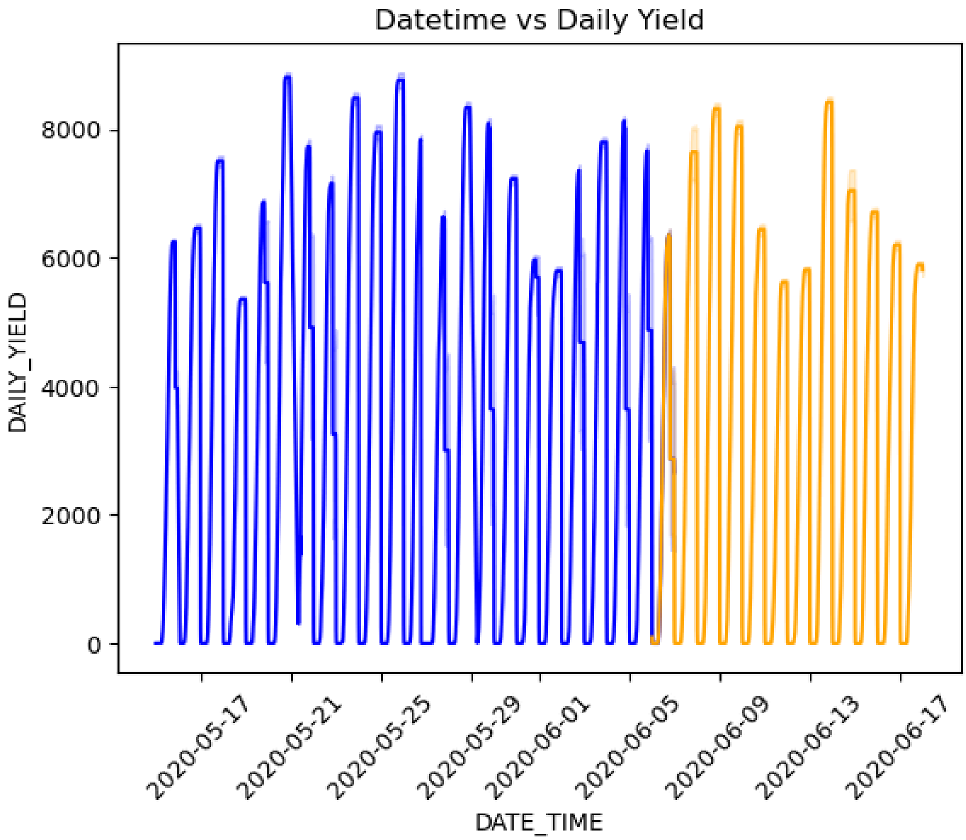
134656 rows × 1 columns

In [40]:

```
split_date = '2020-06-06'
plant1_train = t_reduced_plant1.loc[:split_date]
plant1_test = t_reduced_plant1.loc[split_date:]
```

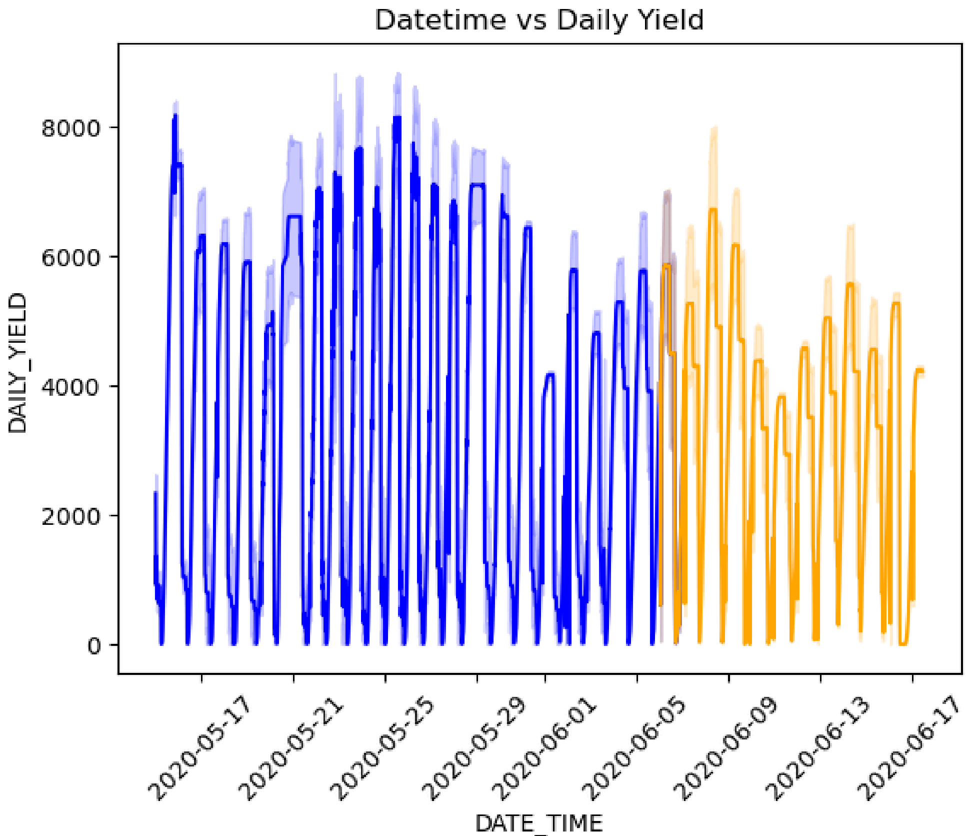
In [41]:

```
sns.lineplot(data=plant1_train, x=plant1_train.index, y=plant1_train["DAILY_YIELD"], c="blue")
sns.lineplot(data=plant1_test, x=plant1_test.index, y=plant1_test["DAILY_YIELD"], c="orange")
plt.title("Datetime vs Daily Yield")
plt.xticks(rotation=45)
plt.show()
```



In [42]:
```
plant2_train = t_reduced_plant2.loc[:split_date]
plant2_test = t_reduced_plant2.loc[split_date:]
```

In [43]:
```
sns.lineplot(data=plant2_train, x=plant2_train.index, y=plant2_train["DAILY_YIELD"], c="blue")
sns.lineplot(data=plant2_test, x=plant2_test.index, y=plant2_test["DAILY_YIELD"], c="orange")
plt.title("Datetime vs Daily Yield")
plt.xticks(rotation=45)
plt.show()
```



In [44]:
```
def create_features(df):
    df = df.copy()
    df['hour'] = df.index.hour
    df['day_of_week'] = df.index.dayofweek
    df['month'] = df.index.month
    df['year'] = df.index.year
    df['week_of_year'] = df.index.isocalendar().week
    return df

t_reduced_plant1 = create_features(t_reduced_plant1)
plant1_train = create_features(plant1_train)
plant1_test = create_features(plant1_test)

t_reduced_plant2 = create_features(t_reduced_plant2)
plant2_train = create_features(plant2_train)
plant2_test = create_features(plant2_test)
```

In [45]:
```
X_p1_train = plant1_train.iloc[:, 1:]
y_p1_train = plant1_train.iloc[:, 0]

X_p1_test = plant1_test.iloc[:, 1:]
y_p1_test = plant1_test.iloc[:, 0]
```

XG BOOST REGRESSOR:

In [46]:
```
import xgboost as xgb
```

PLANT 1:

In [47]:
```
reg = xgb.XGBRegressor(n_estimators=1000, learning_rate=0.01)
reg.fit(X_p1_train, y_p1_train)
```

Out[47]:
```
▾                              XGBRegressor
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.01, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=1000, n_jobs=None,
             num_parallel_tree=None, random_state=None, ...)
```

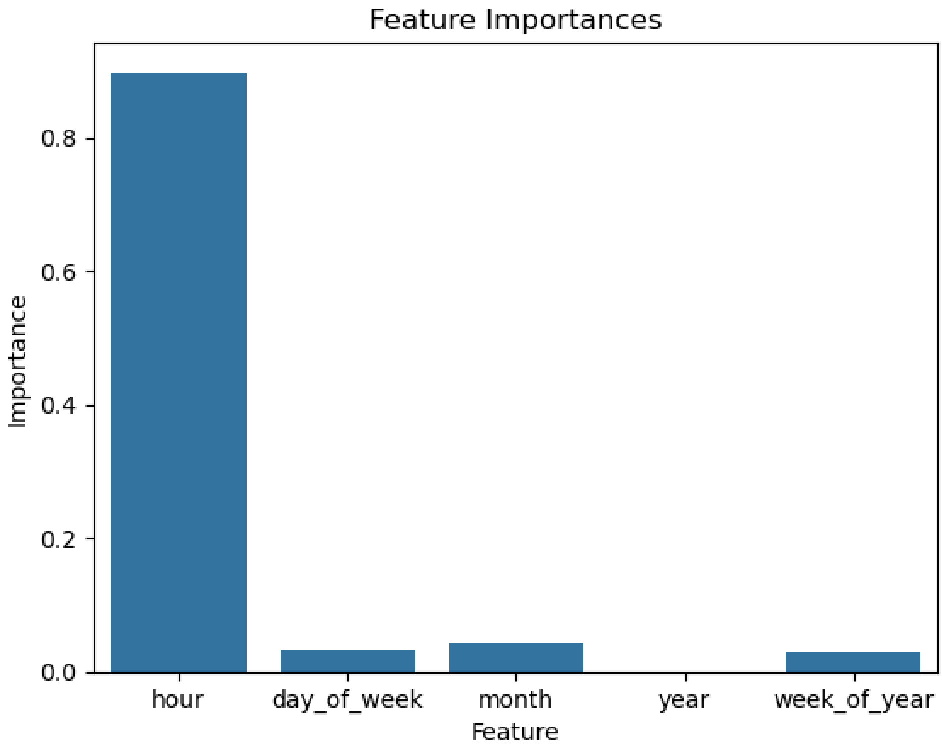
In [48]:
```
predictions = reg.predict(X_p1_test)
predictions
```

Out[48]:
```
array([  47.04413,   47.04413,   47.04413, ..., 7617.5845 , 7617.5845 ,
       7617.5845 ], dtype=float32)
```

In [49]:
```
mse = mean_squared_error(y_p1_test, predictions)
print(f"MSE = {mse:.2f}")
```

```
MSE = 2536624.12
```

In [50]:
```
sns.barplot(x=reg.feature_names_in_, y=reg.feature_importances_).set(xlabel='Feature', ylabel='Impor
plt.show()
```



In [51]:
```
X_p1_train = plant1_train.iloc[:, 1]
y_p1_train = plant1_train.iloc[:, 0]

X_p1_test = plant1_test.iloc[:, 1]
y_p1_test = plant1_test.iloc[:, 0]
```

In [52]:
```
reg = xgb.XGBRegressor(n_estimators=1000, learning_rate=0.01)
reg.fit(X_p1_train, y_p1_train)
```

Out[52]:

```
XGBRegressor

XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.01, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=1000, n_jobs=None,
             num_parallel_tree=None, random_state=None, ...)
```

In [53]:
```
predictions = reg.predict(X_p1_test)
predictions
```

Out[53]:
```
array([  25.496717,   25.496717,   25.496717, ..., 4983.6963  ,
       4983.6963  , 4983.6963  ], dtype=float32)
```

In [56]:
```
rmse = np.sqrt(mean_squared_error(y_p1_test, predictions))
print(f"RMSE = {rmse:.2f}")
```

```
RMSE = 1128.25
```

In [57]:
```
model = xgb.XGBRegressor()
param_grid = {
    'n_estimators': [100, 500, 1000],
    'learning_rate': [0.01, 0.05, 0.1],
}

grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=5, scoring='neg_mean_squared_e
grid_search.fit(X_p1_train, y_p1_train)

print("Best parameters:", grid_search.best_params_)
```

```python
best_model = grid_search.best_estimator_

test_predictions = best_model.predict(X_p1_test)
mse = np.mean((test_predictions - y_p1_test) ** 2)
print("Mean Squared Error on test set:", mse)
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits
[CV] END ..............learning_rate=0.01, n_estimators=100; total time=   0.0s
[CV] END ..............learning_rate=0.01, n_estimators=100; total time=   0.0s
[CV] END ..............learning_rate=0.01, n_estimators=100; total time=   0.0s
[CV] END ..............learning_rate=0.01, n_estimators=100; total time=   0.0s
[CV] END ..............learning_rate=0.01, n_estimators=100; total time=   0.0s
[CV] END ..............learning_rate=0.01, n_estimators=500; total time=   0.6s
[CV] END ..............learning_rate=0.01, n_estimators=500; total time=   0.6s
[CV] END ..............learning_rate=0.01, n_estimators=500; total time=   0.5s
[CV] END ..............learning_rate=0.01, n_estimators=500; total time=   0.6s
[CV] END ..............learning_rate=0.01, n_estimators=500; total time=   0.5s
[CV] END .............learning_rate=0.01, n_estimators=1000; total time=   1.0s
[CV] END .............learning_rate=0.01, n_estimators=1000; total time=   1.1s
[CV] END .............learning_rate=0.01, n_estimators=1000; total time=   1.5s
[CV] END .............learning_rate=0.01, n_estimators=1000; total time=   1.7s
[CV] END .............learning_rate=0.01, n_estimators=1000; total time=   1.5s
[CV] END ..............learning_rate=0.05, n_estimators=100; total time=   0.2s
[CV] END ..............learning_rate=0.05, n_estimators=100; total time=   0.1s
[CV] END ..............learning_rate=0.05, n_estimators=100; total time=   0.1s
[CV] END ..............learning_rate=0.05, n_estimators=100; total time=   0.1s
[CV] END ..............learning_rate=0.05, n_estimators=100; total time=   0.1s
[CV] END ..............learning_rate=0.05, n_estimators=500; total time=   0.7s
[CV] END ..............learning_rate=0.05, n_estimators=500; total time=   0.7s
[CV] END ..............learning_rate=0.05, n_estimators=500; total time=   0.7s
[CV] END ..............learning_rate=0.05, n_estimators=500; total time=   0.7s
[CV] END ..............learning_rate=0.05, n_estimators=500; total time=   0.7s
[CV] END .............learning_rate=0.05, n_estimators=1000; total time=   1.4s
[CV] END .............learning_rate=0.05, n_estimators=1000; total time=   1.4s
[CV] END .............learning_rate=0.05, n_estimators=1000; total time=   1.4s
[CV] END .............learning_rate=0.05, n_estimators=1000; total time=   1.5s
[CV] END .............learning_rate=0.05, n_estimators=1000; total time=   1.4s
[CV] END ...............learning_rate=0.1, n_estimators=100; total time=   0.1s
[CV] END ...............learning_rate=0.1, n_estimators=100; total time=   0.1s
[CV] END ...............learning_rate=0.1, n_estimators=100; total time=   0.1s
[CV] END ...............learning_rate=0.1, n_estimators=100; total time=   0.2s
[CV] END ...............learning_rate=0.1, n_estimators=100; total time=   0.1s
[CV] END ...............learning_rate=0.1, n_estimators=500; total time=   0.7s
[CV] END ...............learning_rate=0.1, n_estimators=500; total time=   0.9s
[CV] END ...............learning_rate=0.1, n_estimators=500; total time=   0.8s
[CV] END ...............learning_rate=0.1, n_estimators=500; total time=   0.8s
[CV] END ...............learning_rate=0.1, n_estimators=500; total time=   0.7s
[CV] END ..............learning_rate=0.1, n_estimators=1000; total time=   1.6s
[CV] END ..............learning_rate=0.1, n_estimators=1000; total time=   1.5s
[CV] END ..............learning_rate=0.1, n_estimators=1000; total time=   1.6s
[CV] END ..............learning_rate=0.1, n_estimators=1000; total time=   1.4s
[CV] END ..............learning_rate=0.1, n_estimators=1000; total time=   1.6s
Best parameters: {'learning_rate': 0.01, 'n_estimators': 500}
Mean Squared Error on test set: 1282434.1400564422
```

The best model for plant 1 is XGBoostRegressor with only the feature hour, n_estimators=1000 and learning rate=0.01

PLANT 2:

In [58]:
```python
plant2_train
```

Out[58]:

	DAILY_YIELD	hour	day_of_week	month	year	week_of_year
DATE_TIME						
2020-05-15 00:00:00	9425.000000	0	4	5	2020	20
2020-05-15 00:00:00	9425.000000	0	4	5	2020	20
2020-05-15 00:00:00	9425.000000	0	4	5	2020	20
2020-05-15 00:00:00	9425.000000	0	4	5	2020	20
2020-05-15 00:00:00	9425.000000	0	4	5	2020	20
...	...	...	...	...	...	...
2020-06-06 23:45:00	1078.000000	23	5	6	2020	23
2020-06-06 23:45:00	4292.428571	23	5	6	2020	23
2020-06-06 23:45:00	4162.533333	23	5	6	2020	23
2020-06-06 23:45:00	4616.133333	23	5	6	2020	23
2020-06-06 23:45:00	1079.000000	23	5	6	2020	23

112548 rows × 6 columns

In [59]:

```
X_p2_train = plant2_train.iloc[:, 1:]
y_p2_train = plant2_train.iloc[:, 0]

X_p2_test = plant2_test.iloc[:, 1:]
y_p2_test = plant2_test.iloc[:, 0]
```

In [60]:

```
reg = xgb.XGBRegressor(n_estimators=1000, learning_rate=0.01)
reg.fit(X_p2_train, y_p2_train)
```

Out[60]:

```
▾ XGBRegressor
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.01, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=1000, n_jobs=None,
             num_parallel_tree=None, random_state=None, ...)
```

In [61]:

```
predictions = reg.predict(X_p2_test)
predictions
```

Out[61]:

```
array([3644.4348, 3644.4348, 3644.4348, ...,  975.2371,  975.2371,
        975.2371], dtype=float32)
```

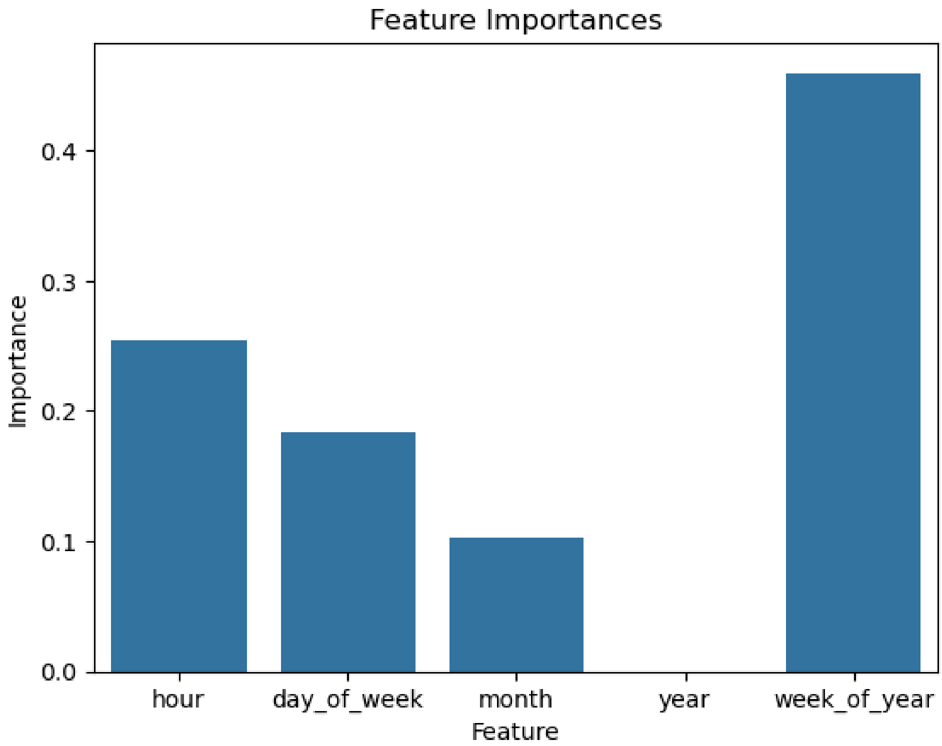
In [62]:

```
rmse = np.sqrt(mean_squared_error(y_p2_test, predictions))
print(f"RMSE = {rmse:.2f}")
```

```
RMSE = 1282434.14
```

In [63]:

```
sns.barplot(x=reg.feature_names_in_, y=reg.feature_importances_).set(xlabel='Feature', ylabel='Impor
plt.show()
```



In [64]:
```
X_p2_train = plant2_train.drop(['year', 'month'], axis=1)
y_p2_train = plant2_train.iloc[:, 0]

X_p2_test = plant2_test.drop(['year', 'month'], axis=1)
y_p2_test = plant2_test.iloc[:, 0]
```

In [65]:
```
reg = xgb.XGBRegressor(n_estimators=1000, learning_rate=0.01)
reg.fit(X_p2_train, y_p2_train)
```

Out[65]:
```
XGBRegressor
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.01, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=1000, n_jobs=None,
             num_parallel_tree=None, random_state=None, ...)
```

In [66]:
```
predictions = reg.predict(X_p2_test)
predictions
```

Out[66]:
```
array([1067.047 , 5523.4956, 5374.6084, ..., 4315.8247, 4209.1377,
       4315.8247], dtype=float32)
```

In [76]:
```
rmse = np.sqrt(mean_squared_error(y_p2_test, predictions))
print(f"RMSE = {rmse:.2f}")
```

```
RMSE = 15.60
```

The best model for Plant 2 is XGBoostRegressor with the features: hour, day_of_week, week_of_year, n_Estimators=1000, learning_rate=0.01

FINAL MODEL:

PLANT 1:

In [68]:
```
X_p1_train_final = plant1_train.iloc[:, 1] # only hour data
y_p1_train_final = plant1_train.iloc[:, 0]
```

```python
X_p1_test_final = plant1_test.iloc[:, 1]
y_p1_test_final = plant1_test.iloc[:, 0]
```

In [69]:
```python
reg_final_p1 = xgb.XGBRegressor(n_estimators=1000, learning_rate=0.01)
reg_final_p1.fit(X_p1_train_final, y_p1_train_final)
```

Out[69]:

XGBRegressor

```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.01, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=1000, n_jobs=None,
             num_parallel_tree=None, random_state=None, ...)
```

In [70]:
```python
redictions_final_p1 = reg_final_p1.predict(X_p1_test_final)p
predictions_final_p1
```

Out[70]:
```
array([  25.496717,   25.496717,   25.496717, ..., 4983.6963  ,
       4983.6963  , 4983.6963  ], dtype=float32)
```

In [71]:
```python
rmse_final_p1 = np.sqrt(mean_squared_error(y_p1_test_final, predictions_final_p1))
print(f"RMSE = {rmse_final_p1:.2f}")
```

```
RMSE = 1128.25
```

PLANT 2:

In [72]:
```python
X_p2_train_final = plant2_train.drop(['year', 'month'], axis=1) # using week_of_year, day_of_week, h
y_p2_train_final = plant2_train.iloc[:, 0]

X_p2_test_final = plant2_test.drop(['year', 'month'], axis=1)
y_p2_test_final = plant2_test.iloc[:, 0]
```

In [73]:
```python
reg_final_p2 = xgb.XGBRegressor(n_estimators=1000, learning_rate=0.01)
reg_final_p2.fit(X_p2_train_final, y_p2_train_final)
```

Out[73]:

XGBRegressor

```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.01, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=1000, n_jobs=None,
             num_parallel_tree=None, random_state=None, ...)
```

In [74]:
```python
predictions_final_p2 = reg.predict(X_p2_test_final)
predictions_final_p2
```

Out[74]:
```
array([1067.047 , 5523.4956, 5374.6084, ..., 4315.8247, 4209.1377,
       4315.8247], dtype=float32)
```

In [75]:
```python
rmse_final_p2 = np.sqrt(mean_squared_error(y_p2_test_final, predictions_final_p2))
print(f"RMSE = {rmse_final_p2:.2f}")
```

```
RMSE = 15.60
```

Exporting the final train, test sets:

In [77]:

```
X_p1_train_final.to_csv('X_plant1_train.csv')
X_p1_test_final.to_csv('X_plant1_test.csv')

y_p1_train_final.to_csv('y_plant1_train.csv')
y_p1_test_final.to_csv('y_plant1_test.csv')

X_p2_train_final.to_csv('X_plant2_train.csv')
X_p2_test_final.to_csv('X_plant2_test.csv')

y_p2_train_final.to_csv('y_plant2_train.csv')
y_p2_test_final.to_csv('y_plant2_test.csv')
```

In [ ]:

```

```