Wind Turbine Energy Prediction Model

Objective

Created an energy model using a multiple linear regression function, Random forest regressor and XGB regresson function to predict the energy generation of a wind turbine based on 2018 Scada Data of a Wind Turbine in Turkey. Visualise the dataset and results. Compare between these three models.

About Dataset

Context:

In Wind Turbines, Scada Systems measure and save data's like wind speed, wind direction, generated power etc. for 10 minutes intervals. This file was taken from a wind turbine's scada system that is working and generating power in Turkey.

Content:

The data's in the file are:

- Date/Time (for 10 minutes intervals).
- LV ActivePower (kW): The power generated by the turbine for that moment.
- Wind Speed (m/s): The wind speed at the hub height of the turbine (the wind speed that turbine use for electricity generation).
- Theoretical_Power_Curve (KWh): The theoretical power values that the turbine generates with that wind speed which is given by the turbine manufacturer.
- Wind Direction (°): The wind direction at the hub height of the turbine (wind turbines turn to this direction automaticly).

1. Import the relevant libraries

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats

from sklearn.linear_model import LinearRegression

from sklearn.ensemble import RandomForestRegressor


from sklearn.model_selection import train_test_split
from mpl_toolkits.mplot3d import Axes3D
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

```
print("Libraries Imported...Go Ahead!!")
```

```
Libraries Imported...Go Ahead!!
```

2. Load the data

In [2]:
```
mydata = pd.read_csv("T1.csv")

#renaming the column name
mydata.rename(columns={'Theoretical_Power_Curve (KWh)': 'Theoretical Power Curve (I

mydata.head()
```

Out[2]:

	Date/Time	LV ActivePower (kW)	Wind Speed (m/s)	Theoretical Power Curve (KWh)	Wind Direction (°)
0	01 01 2018 00:00	380.047791	5.311336	416.328908	259.994904
1	01 01 2018 00:10	453.769196	5.672167	519.917511	268.641113
2	01 01 2018 00:20	306.376587	5.216037	390.900016	272.564789
3	01 01 2018 00:30	419.645905	5.659674	516.127569	271.258087
4	01 01 2018 00:40	380.650696	5.577941	491.702972	265.674286

In [3]:
```
print(mydata.describe())
print(mydata.info())
```

```
       LV ActivePower (kW)  Wind Speed (m/s)  Theoretical Power Curve (KWh)  \
count         50530.000000      50530.000000                   50530.000000   
mean           1307.684332          7.557952                    1492.175463   
std            1312.459242          4.227166                    1368.018238   
min              -2.471405          0.000000                       0.000000   
25%              50.677890          4.201395                     161.328167   
50%             825.838074          7.104594                    1063.776283   
75%            2482.507568         10.300020                    2964.972462   
max            3618.732910         25.206011                    3600.000000   

       Wind Direction (°)  
count        50530.000000  
mean           123.687559  
std             93.443736  
min              0.000000  
25%             49.315437  
50%             73.712978  
75%            201.696720  
max            359.997589  
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50530 entries, 0 to 50529
Data columns (total 5 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   Date/Time                      50530 non-null  object 
 1   LV ActivePower (kW)            50530 non-null  float64
 2   Wind Speed (m/s)               50530 non-null  float64
 3   Theoretical Power Curve (KWh)  50530 non-null  float64
 4   Wind Direction (°)             50530 non-null  float64
dtypes: float64(4), object(1)
memory usage: 1.9+ MB
None
```

3. Preparing the data

In [4]:

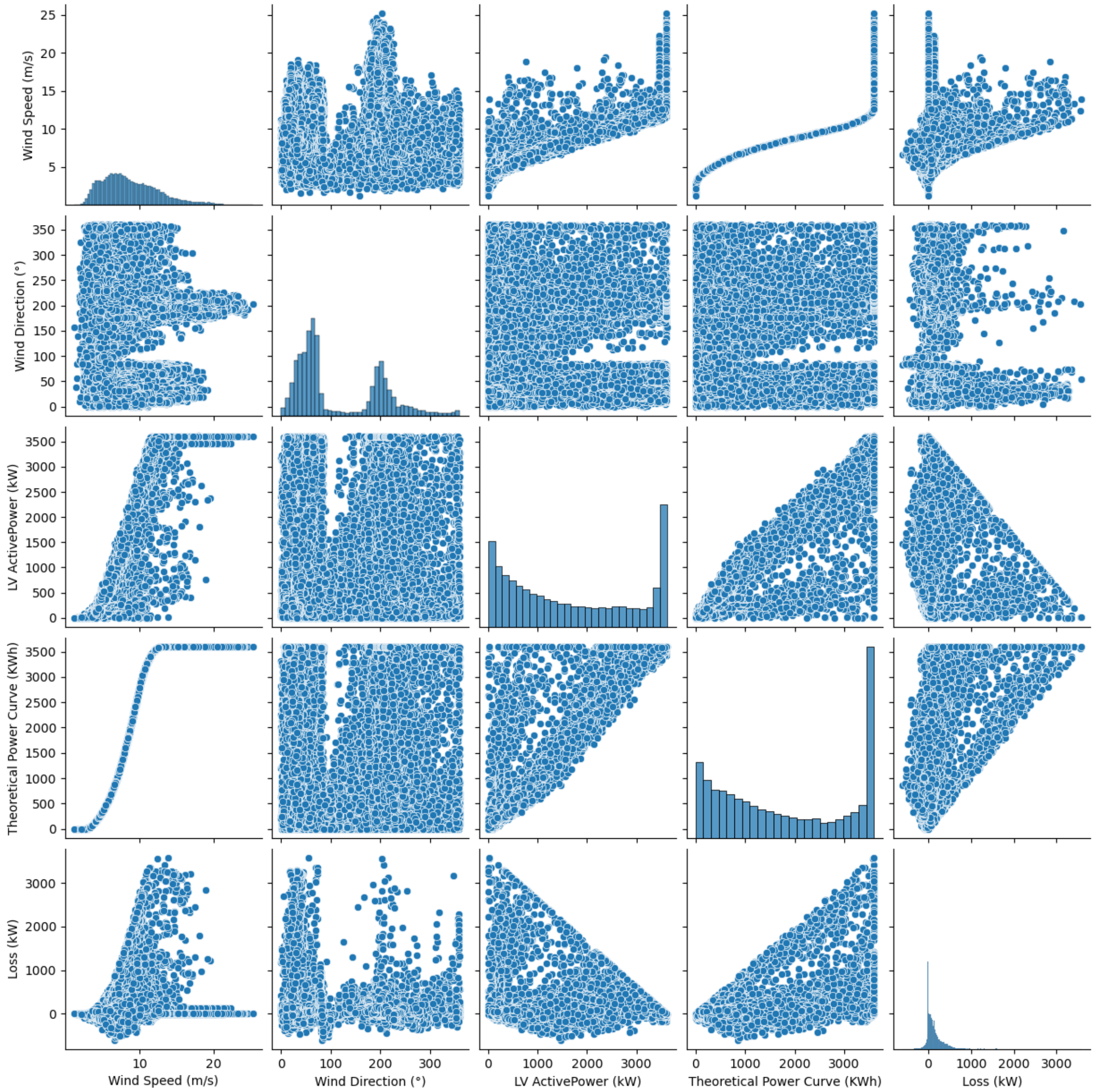
```
# removing negative or zero LV Active Power from data
mydata = mydata[mydata['LV ActivePower (kW)'] > 0]

mydata2= mydata.copy()

# Convert Date/Time to datetime format
mydata['Date/Time'] = pd.to_datetime(mydata['Date/Time'])
mydata['YEAR'] = mydata['Date/Time'].dt.year
mydata['MONTH'] = mydata['Date/Time'].dt.month
mydata['DAY'] = mydata['Date/Time'].dt.day
mydata['hour'] = mydata['Date/Time'].dt.hour
mydata = mydata.drop(['Date/Time'], axis=1)

# Adding the column loss, loss= theoretical power - active power
mydata['Loss (kW)'] = mydata['Theoretical Power Curve (KWh)'] -mydata['LV ActivePo

#remove missing values using dropna() function
mydata.dropna()

print(mydata.describe())
```

```
       LV ActivePower (kW)  Wind Speed (m/s)  Theoretical Power Curve (KWh)  \
count         39692.000000      39692.000000                   39692.000000   
mean           1664.751281          8.769781                    1829.739672   
std            1264.303861          3.773594                    1306.418817   
min               0.000200          1.208934                       0.000000   
25%             481.681473          5.911951                     595.684321   
50%            1394.047974          8.114283                    1596.105035   
75%            2908.239746         11.099597                    3306.484805   
max            3618.732910         25.206011                    3600.000000   

       Wind Direction (°)     YEAR         MONTH           DAY          hour  \
count        39692.000000  39692.0  39692.000000  39692.000000  39692.000000   
mean           115.532274   2018.0      6.611231     15.604127     11.693339   
std             86.276846      0.0      3.341150      8.604754      6.982266   
min              0.000000   2018.0      1.000000      1.000000      0.000000   
25%             49.041458   2018.0      4.000000      8.000000      5.000000   
50%             70.241829   2018.0      7.000000     16.000000     12.000000   
75%            197.156849   2018.0      9.000000     23.000000     18.000000   
max            359.997589   2018.0     12.000000     31.000000     23.000000   

          Loss (kW)  
count  39692.000000  
mean     164.988391  
std      294.311167  
min     -598.741011  
25%       18.378057  
50%       93.968847  
75%      214.783881  
max     3581.179300  
```

4. Visualising the mydata

Creating a pair plot of between all the column to identify correlations.

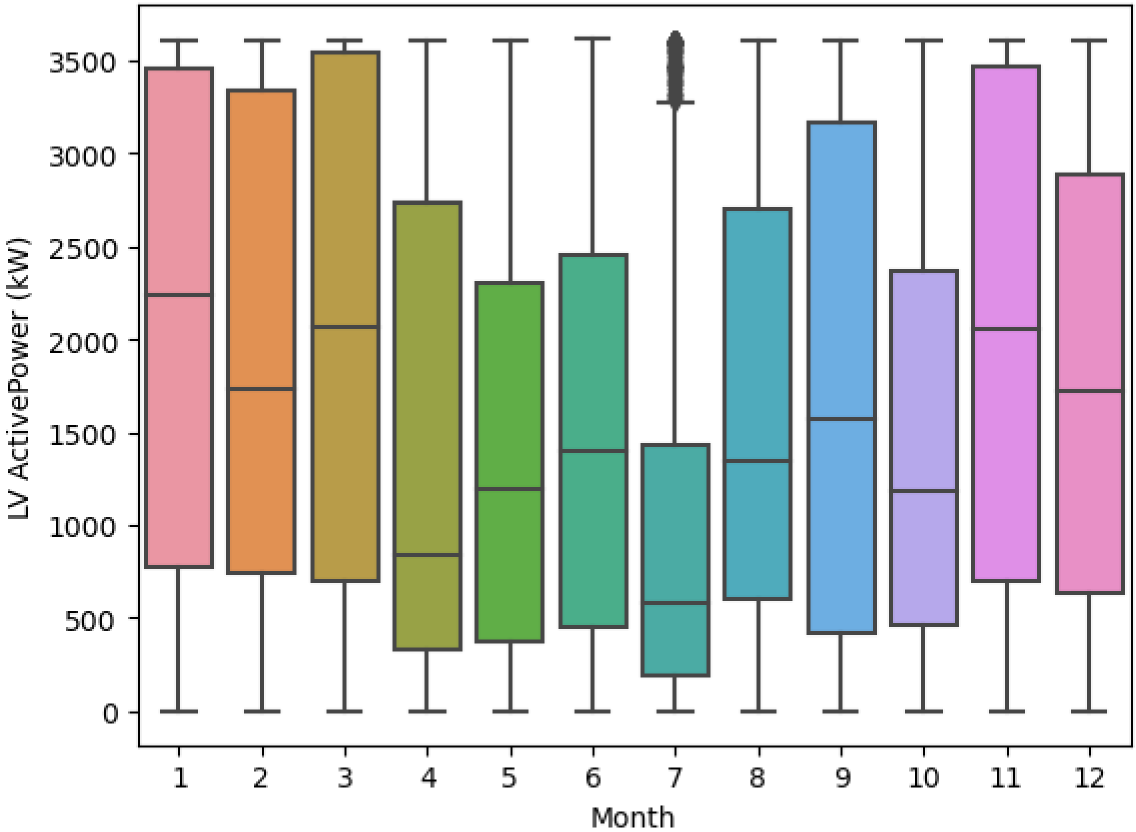
In [5]:
```
sns.pairplot(data=mydata, vars=["Wind Speed (m/s)", "Wind Direction (°)", "LV Acti
plt.show()
```



Evident correlation can be made from above plots.

Creating a Box plot of LV ActivePower by month.

In [6]:
```
X=mydata['MONTH']
sns.boxplot(x=X, y=mydata['LV ActivePower (kW)'])
plt.xlabel("Month")
plt.ylabel("LV ActivePower (kW)")
plt.show()
```



Observations: We can see that the widest rangest of active power are for the months of January, February, March,September, November, and December. This must align with the a higher wind speed compared to other months during the course of the year.

5.Splitting the data into training and test sets:

In [7]:
```
# defining the desired features(input) as X to use for prediction: wind speed, winc
# theoretical power curve and the target variable as y, which is the LV ActivePowe

X = mydata[['Wind Speed (m/s)', 'Wind Direction (°)','MONTH','DAY','hour']]
y = mydata['LV ActivePower (kW)']

# splitting the data train_test_split() function from the sklearn.model_selection r

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_st
# random_state=0 is an optional parameter that sets the random seed for reproducib
```

6. Linear Regression Model

6.1 Training and testing the model

In [8]:
```
# Building the model:

linear_model = LinearRegression()
linear_model.fit(X_train, y_train)

# Evaluating the model, calculating metrics:

y1_pred = linear_model.predict(X_test)
y1_mse = mean_squared_error(y_test, y1_pred)
```

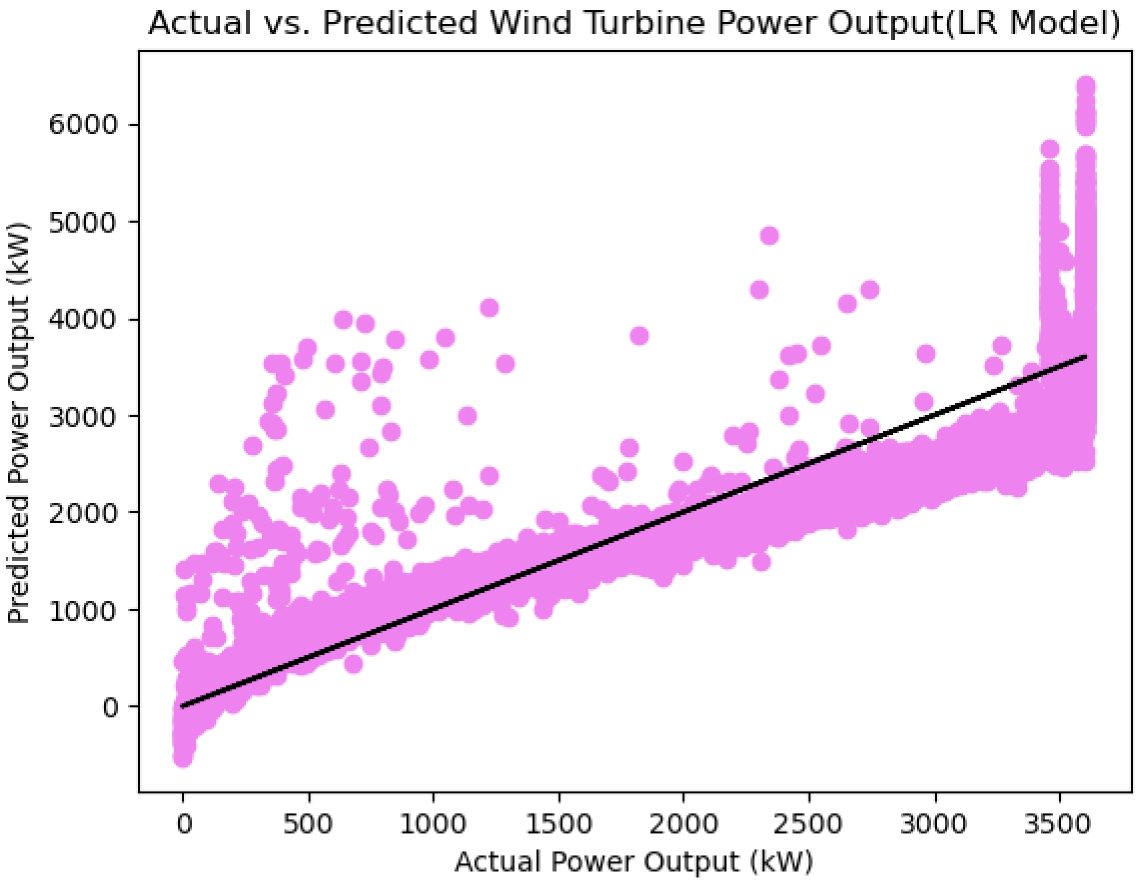
```
y1_mae = mean_absolute_error(y_test, y1_pred)
y1_r2 = r2_score(y_test, y1_pred)

print("Coefficients:", linear_model.coef_) #coefficient of all the features
print("Intercept:", linear_model.intercept_)
print("Mean Squared Error:", y1_mse)
print("Mean Absolute Error:", y1_mae)
print("R-squared:", y1_r2)
Accuracy_LR = 100*y1_r2
print('Accuracy of Linear Regression Model: ',Accuracy_LR)
```

```
Coefficients: [313.64373749  -0.38680755  10.42226576   0.59346052   2.55657314]
Intercept: -1146.9260299745606
Mean Squared Error: 227817.66988870103
Mean Absolute Error: 334.26589942969554
R-squared: 0.8559667280370811
Accuracy of Linear Regression Model:  85.5966728037081
```

6.2 Visualizing the model

Visualizing the model's performance by comparing the actual output with the predicted output on the test set using a scatter plot.

In [9]:
```
plt.scatter(y_test, y1_pred, color='violet')

# Adding a line representing perfect predictions (i.e., y_test = y1_pred)
plt.plot(y_test, y_test, color='black')

plt.xlabel("Actual Power Output (kW)")
plt.ylabel("Predicted Power Output (kW)")
plt.title("Actual vs. Predicted Wind Turbine Power Output(LR Model)")

plt.show()
```



7. Random Forest Regressor Model

7.1 Training and testing the model

In [10]:

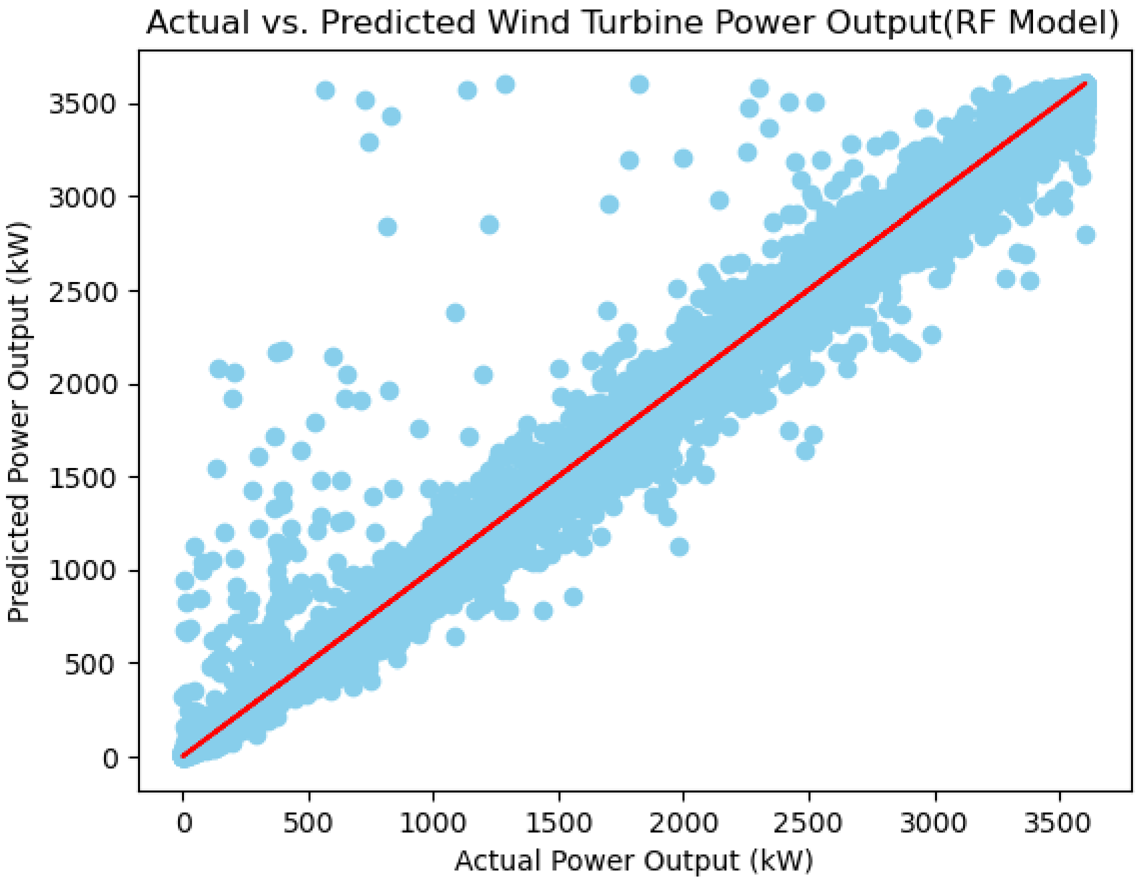
```
# Building the model:

forest_model = RandomForestRegressor(n_estimators=100, max_depth=10)
forest_model.fit(X_train, y_train)

# Evaluating the model, calculating metrics:

y2_pred = forest_model.predict(X_test)
y2_mse = mean_squared_error(y_test, y2_pred)
y2_mae = mean_absolute_error(y_test, y2_pred)
y2_r2 = r2_score(y_test, y2_pred)

print("Mean Squared Error:", y2_mse)
print("Mean Absolute Error:", y2_mae)
print("R-squared:", y2_r2)
Accuracy_RF = 100*y2_r2
print('Accuracy of Random Forest Regressor Model: ',Accuracy_RF)
```

```
Mean Squared Error: 29913.327964674263
Mean Absolute Error: 87.29751482791522
R-squared: 0.9810878826732061
Accuracy of Random Forest Regressor Model:  98.10878826732062
```

7.2 Visualizing the model

In [11]:

```
plt.scatter(y_test, y2_pred, color='skyblue')

# Adding a line representing perfect predictions (i.e., y_test = y2_pred)
plt.plot(y_test, y_test, color='red')

plt.xlabel("Actual Power Output (kW)")
plt.ylabel("Predicted Power Output (kW)")
plt.title("Actual vs. Predicted Wind Turbine Power Output(RF Model)")

plt.show()
```



8. XGBoost Model

8.1 Training and testing the model

In [12]:
```
from xgboost import XGBRegressor

xgb_model = XGBRegressor(n_estimators=1000, learning_rate=0.05)
```

In [24]:
```
xgb_model.fit(X_train, y_train, early_stopping_rounds=5,
             eval_set=[(X_test, y_test)], verbose=False)

y3_pred = xgb_model.predict(X_test)
y3_mse = mean_squared_error(y_test, y3_pred)
y3_mae = mean_absolute_error(y_test, y3_pred)
y3_r2 = r2_score(y_test, y3_pred)

print("Mean Squared Error:", y3_mse)
print("Mean Absolute Error:", y3_mae)
print("R-squared:", y3_r2)
Accuracy_XGB = 100*y3_r2
print('Accuracy of XGB Regressor Model: ',Accuracy_XGB)
```

```
C:\Users\psk_k\anaconda3\lib\site-packages\xgboost\sklearn.py:835: UserWarning: `e
arly_stopping_rounds` in `fit` method is deprecated for better compatibility with
scikit-learn, use `early_stopping_rounds` in constructor or`set_params` instead.
  warnings.warn(
Mean Squared Error: 19414.11632390108
Mean Absolute Error: 67.25905126183842
R-squared: 0.9877258041583592
Accuracy of XGB Regressor Model:  98.77258041583592
```

In [25]:
```
a=pd.DataFrame([[5,5,5,5,5]], columns = ['Wind Speed (m/s)', 'Wind Direction (°)',
a # data should be in same format with same column name as in training data set
```

Out[25]:

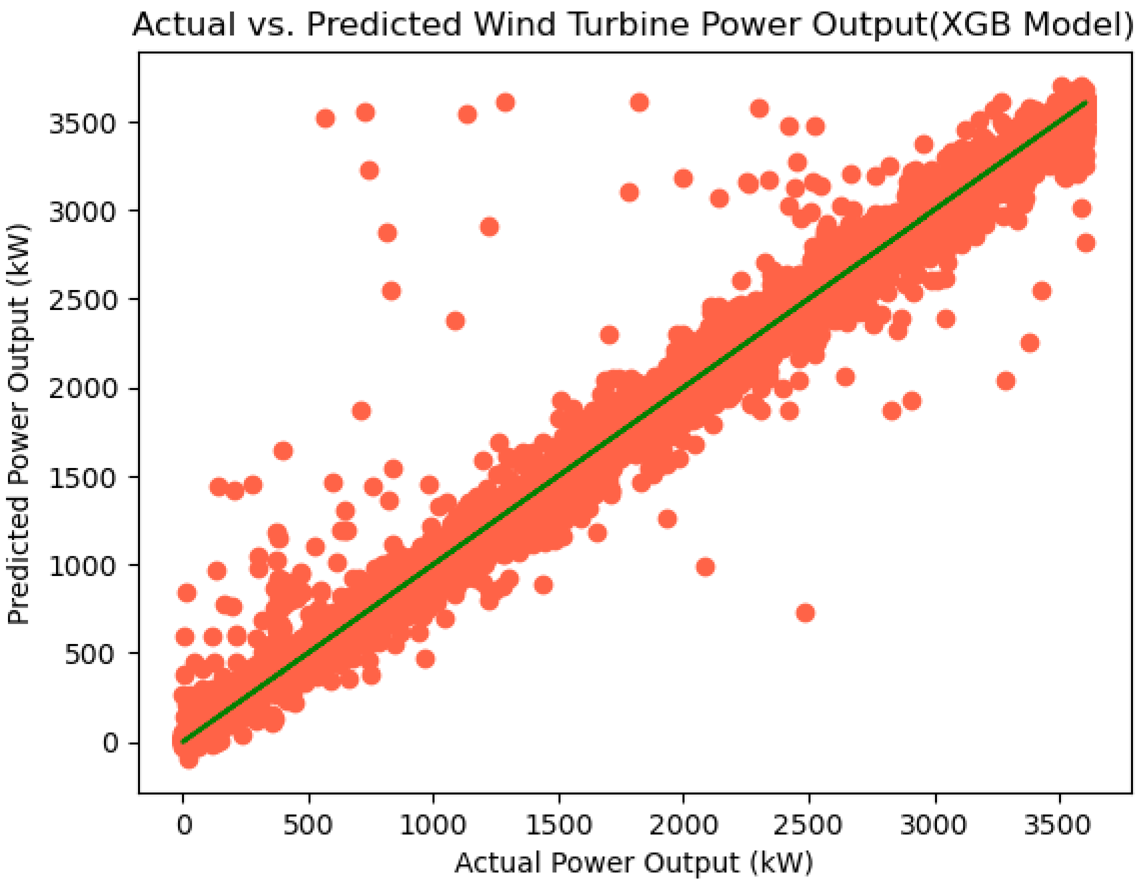
	Wind Speed (m/s)	Wind Direction (°)	MONTH	DAY	hour
0	5	5	5	5	5

In [23]:
```
xgb_model.predict(a)[0]
```

Out[23]: 267.4284

8.2 Visualizing the model

In [14]:
```
plt.scatter(y_test, y3_pred, color='tomato')

# Adding a line representing perfect predictions (i.e., y_test = y3_pred)
plt.plot(y_test, y_test, color='green')

plt.xlabel("Actual Power Output (kW)")
plt.ylabel("Predicted Power Output (kW)")
plt.title("Actual vs. Predicted Wind Turbine Power Output(XGB Model)")

plt.show()
```



Comparison

In [15]:
```
pd.DataFrame({'Model Accuracy' : [Accuracy_LR , Accuracy_RF, Accuracy_XGB], 'Mean S
```

Out[15]:

	Model Accuracy	Mean Squared Error	Mean Absolute Error
Multiple Linear Regression	85.596673	227817.669889	334.265899
Random Forest Regressor	98.089134	30224.202814	87.232401
XG Boost Regressor	98.772580	19414.116324	67.259051

- In this project, three different models are built to predict the energy generation of wind turbine. The project consisted in different steps. First, imported the necessary libraries, then loaded and cleaned the data and prepared it for modelling. Then, splitted the data into training and test sets, built the model, and evaluated its performance on the test set using mean squared error and R-squared metrics.
- Here, XGBoost and Random Forest Model is reliable and effective model to predict the output with high accuracy in compare with Multiple Linear Regression model.

Predict

In [16]:
```
import pickle
```

In [17]:
```
pickle.dump(linear_model,open('linear_model.pkl','wb'))
```

In [18]:
```
pickle.dump(forest_model, open('forest_model.pkl','wb'))
```

In [19]:
```
pickle.dump(xgb_model, open('xgb_model.pkl','wb'))
```

In [20]:
```
detail = [y1_mse, y2_mse, y3_mse,y1_mae, y2_mae, y3_mae]
pickle.dump(detail, open('detail.pkl','wb'))
```