Solar Power Generation Prediction & Fault/Abnormalities Analysis

PV Solar Power Plant:

1. Importing Libraries

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

import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
pd.set_option('display.max_columns',None)
pd.set_option('display.max_rows',None)
pd.set_option('precision',3)
```

2. Importing Power Generation & Weather Sensor Data

In [3]:
```
generation_data = pd.read_csv('../input/solar-power/Plant_2_Generat
```

In [4]:
```
weather_data = pd.read_csv('../input/solar-power/Plant_2_Weather_Se
```

In [5]:
```
generation_data.sample(5).style.set_properties(
    **{
        'background-color': 'OliveDrab',
        'color': 'white',
        'border-color': 'darkblack'
    })
```

Out[5]:

	DATE_TIME	PLANT_ID	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD
17162	2020-05-24 00:15:00	4136001	LYwnQax7tkwH5Cb	0.000	0.000	0.000
33475	2020-06-01 18:45:00	4136001	PeE6FRyGXUgsRhN	0.000	0.000	4156.000
65080	2020-06-16 18:15:00	4136001	4UPUqMRk7TRMgml	23.273	22.473	4998.933
44515	2020-06-07 00:30:00	4136001	LYwnQax7tkwH5Cb	0.000	0.000	3489.000
18165	2020-05-24 14:00:00	4136001	xoJJ8DcxJEcupym	1098.047	1073.093	6633.800

In [6]:
```
weather_data.sample(5).style.set_properties(
    **{
        'background-color': 'pink',
        'color': 'Black',
        'border-color': 'darkblack'
    })
```

Out[6]:

	DATE_TIME	PLANT_ID	SOURCE_KEY	AMBIENT_TEMPERATURE	MODULE_TEMI
36	2020-05-15 09:00:00	4136001	iq8k7ZNt4Mwm3w0	29.572	
480	2020-05-20 00:30:00	4136001	iq8k7ZNt4Mwm3w0	24.692	
452	2020-05-19 17:30:00	4136001	iq8k7ZNt4Mwm3w0	23.329	
2958	2020-06-14 20:45:00	4136001	iq8k7ZNt4Mwm3w0	24.681	
2971	2020-06-15 00:00:00	4136001	iq8k7ZNt4Mwm3w0	24.487	

3. Adjust datetime format

In [7]:
```
generation_data['DATE_TIME'] = pd.to_datetime(generation_data['DATE_
weather_data['DATE_TIME'] = pd.to_datetime(weather_data['DATE_TIME'
```

4. Merging generation data and weather sensor data

In [8]:
```
df_solar = pd.merge(generation_data.drop(columns = ['PLANT_ID']), w
df_solar.sample(5).style.background_gradient(cmap='cool')
```

Out[8]:

	DATE_TIME	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_Y
35450	2020-06-02 17:15:00	IQ2d7wF4YD8zU1Q	422.800	415.327	7042.000	2008931
59208	2020-06-13 23:30:00	9kRcWv60rDACzjR	0.000	0.000	2777.000	224789301
6592	2020-05-18 03:00:00	mqwcsP2rE7J0TFp	0.000	0.000	0.000	59360435
55317	2020-06-12 03:15:00	LYwnQax7tkwH5Cb	0.000	0.000	3718.000	179508307
6094	2020-05-17 21:30:00	4UPUqMRk7TRMgml	0.000	0.000	6342.000	244523

5. Adding separate time and date columns

In [9]:
```
# adding separate time and date columns
df_solar["DATE"] = pd.to_datetime(df_solar["DATE_TIME"]).dt.date
df_solar["TIME"] = pd.to_datetime(df_solar["DATE_TIME"]).dt.time
df_solar['DAY'] = pd.to_datetime(df_solar['DATE_TIME']).dt.day
df_solar['MONTH'] = pd.to_datetime(df_solar['DATE_TIME']).dt.month
df_solar['WEEK'] = pd.to_datetime(df_solar['DATE_TIME']).dt.week


# add hours and minutes for ml models
df_solar['HOURS'] = pd.to_datetime(df_solar['TIME'],format='%H:%M:%
df_solar['MINUTES'] = pd.to_datetime(df_solar['TIME'],format='%H:%M
df_solar['TOTAL MINUTES PASS'] = df_solar['MINUTES'] + df_solar['HO

# add date as string column
df_solar["DATE_STRING"] = df_solar["DATE"].astype(str) # add column
df_solar["HOURS"] = df_solar["HOURS"].astype(str)
df_solar["TIME"] = df_solar["TIME"].astype(str)

df_solar.head(2)
```

Out[9]:

	DATE_TIME	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD
0	2020-05-15	4UPUqMRk7TRMgml	0.0	0.0	9425.0	2.429e+06
1	2020-05-15	81aHJ1q11NBPMrL	0.0	0.0	0.0	1.215e+09

In [10]:
```
df_solar.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 67698 entries, 0 to 67697
Data columns (total 18 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   DATE_TIME            67698 non-null  datetime64[ns]
 1   SOURCE_KEY           67698 non-null  object
 2   DC_POWER             67698 non-null  float64
 3   AC_POWER             67698 non-null  float64
 4   DAILY_YIELD          67698 non-null  float64
 5   TOTAL_YIELD          67698 non-null  float64
 6   AMBIENT_TEMPERATURE  67698 non-null  float64
 7   MODULE_TEMPERATURE   67698 non-null  float64
 8   IRRADIATION          67698 non-null  float64
 9   DATE                 67698 non-null  object
 10  TIME                 67698 non-null  object
 11  DAY                  67698 non-null  int64
 12  MONTH                67698 non-null  int64
 13  WEEK                 67698 non-null  int64
 14  HOURS                67698 non-null  object
 15  MINUTES              67698 non-null  int64
 16  TOTAL MINUTES PASS   67698 non-null  int64
 17  DATE_STRING          67698 non-null  object
dtypes: datetime64[ns](1), float64(7), int64(5), object(5)
memory usage: 9.8+ MB
```

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

Out[11]:
```
DATE_TIME              0
SOURCE_KEY             0
DC_POWER               0
AC_POWER               0
DAILY_YIELD            0
TOTAL_YIELD            0
AMBIENT_TEMPERATURE    0
MODULE_TEMPERATURE     0
IRRADIATION            0
DATE                   0
TIME                   0
DAY                    0
MONTH                  0
WEEK                   0
HOURS                  0
MINUTES                0
TOTAL MINUTES PASS     0
DATE_STRING            0
dtype: int64
```

There is no Missing Values in the dataset

In [12]:
```
df_solar.describe().style.background_gradient(cmap='rainbow')
```

Out[12]:

	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD	AMBIENT_TEMPERATURE
count	67698.000	67698.000	67698.000	67698.000	67698.000
mean	246.702	241.278	3294.890	658944788.424	27.987
std	370.570	362.112	2919.448	729667771.073	4.021
min	0.000	0.000	0.000	0.000	20.942
25%	0.000	0.000	272.750	19964944.867	24.570
50%	0.000	0.000	2911.000	282627587.000	26.910
75%	446.592	438.215	5534.000	1348495113.000	30.913
max	1420.933	1385.420	9873.000	2247916295.000	39.182

6. Converting 'SOURCE_KEY' from categorical form to numerical form

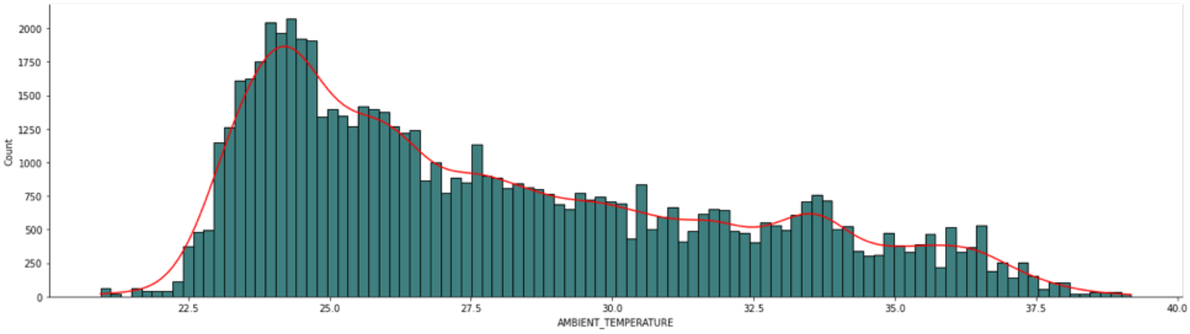
In [13]:
```
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
df_solar['SOURCE_KEY_NUMBER'] = encoder.fit_transform(df_solar['SOU
df_solar.head()
```

Out[13]:

	DATE_TIME	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD
0	2020-05-15	4UPUqMRk7TRMgml	0.0	0.0	9425.000	2.429e+06
1	2020-05-15	81aHJ1q11NBPMrL	0.0	0.0	0.000	1.215e+09
2	2020-05-15	9kRcWv60rDACzjR	0.0	0.0	3075.333	2.248e+09
3	2020-05-15	Et9kgGMDl729KT4	0.0	0.0	269.933	1.704e+06
4	2020-05-15	IQ2d7wF4YD8zU1Q	0.0	0.0	3177.000	1.994e+07

Data Visualization:

In [14]:
```
sns.displot(data=df_solar, x="AMBIENT_TEMPERATURE", kde=True, bins
```



In [15]:
```
df_solar['DATE'].nunique()
```

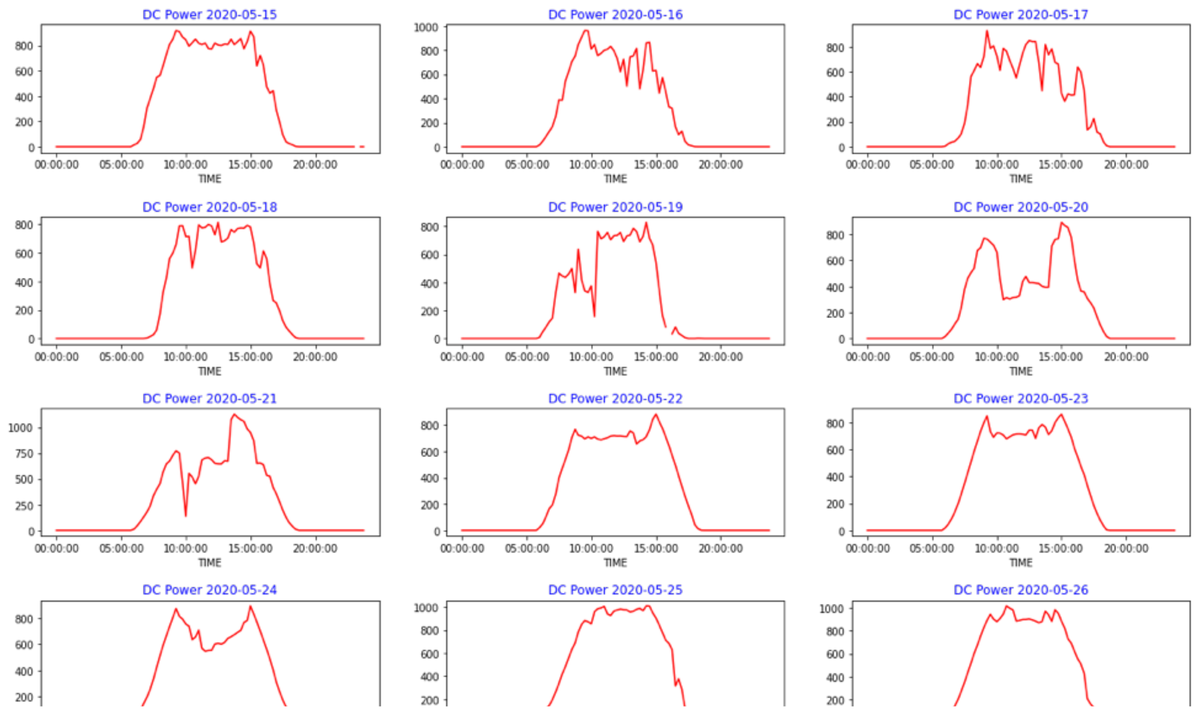
Out[15]: 34

The data of solar power generation is of 34 days

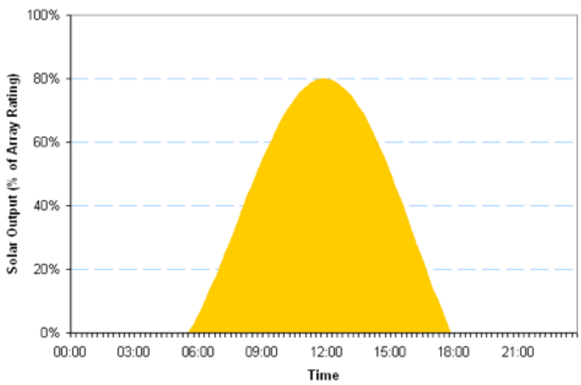
Faults & Abnormalities detection in solar power plant generation

7. Multiple Plotting of DC_POWER generation on per day basis.

In [16]:
```
solar_dc = df_solar.pivot_table(values='DC_POWER', index='TIME', co

def Daywise_plot(data= None, row = None, col = None, title='DC Powe
    cols = data.columns # take all column
    gp = plt.figure(figsize=(20,40))

    gp.subplots_adjust(wspace=0.2, hspace=0.5)
    for i in range(1, len(cols)+1):
        ax = gp.add_subplot(row,col, i)
        data[cols[i-1]].plot(ax=ax, color='red')
        ax.set_title('{} {}'.format(title, cols[i-1]),color='blue')

Daywise_plot(data=solar_dc, row=12, col=3)
```



Ideal Graph of Solar Power Generation 📊📈



Abnormalities in DC_POWER Generation

Form the per day DC_POWER generation graph we can find that, most of the days there is a some fluctuation in the power generation.

Less Fluctuation in DC_POWER generation is observed in these days.

> 1. 2020-05-15
> 2. 2020-05-18
> 3. 2020-05-22
> 4. 2020-05-23
> 5. 2020-05-24
> 6. 2020-05-25
> 7. 2020-05-26

High Fluctuation in DC_POWER generation is observed in these days.

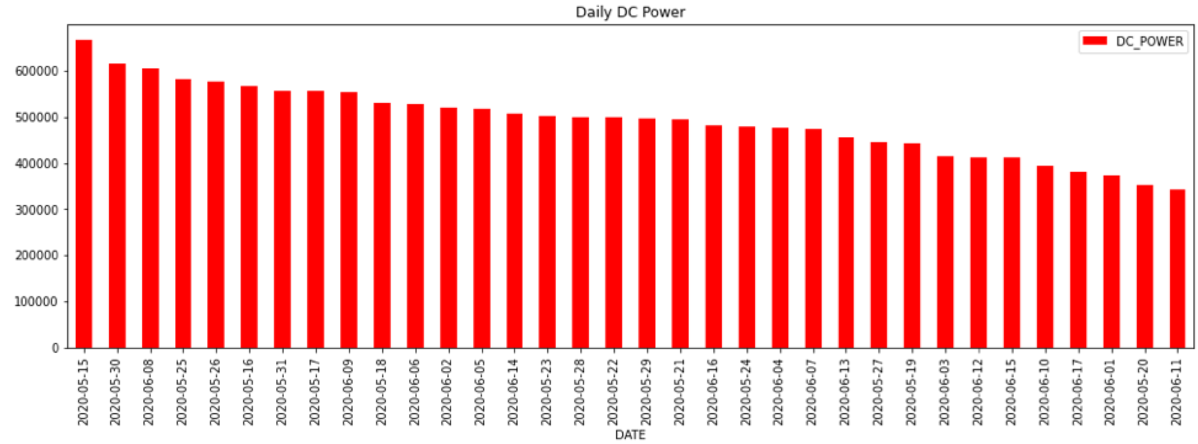
> 1. 2020-05-19
> 2. 2020-05-28
> 3. 2020-05-29
> 4. 2020-06-02
> 5. 2020-06-03
> 6. 2020-06-04
> 7. 2020-06-13
> 8. 2020-06-14
> 9. 2020-06-17

Very High Fluctuation & Reduction in DC_POWER generation is observed in these days.

> 1. 2020-06-03
> 2. 2020-06-11
> 3. 2020-06-12
> 4. 2020-06-15

Note: Reason for very high Fluctuation & Reduction in DC_POWER generation is due to fault in the system or may be fluctuation in weather or due to clouds etc. which need to be analyse further

In [17]:
```
daily_dc = df_solar.groupby('DATE')['DC_POWER'].agg('sum')

ax = daily_dc.sort_values(ascending=False).plot.bar(figsize=(17,5),
plt.title('Daily DC Power')
plt.show()
```



Form the per day DC_POWER generation graph we can find the average power generation per day.

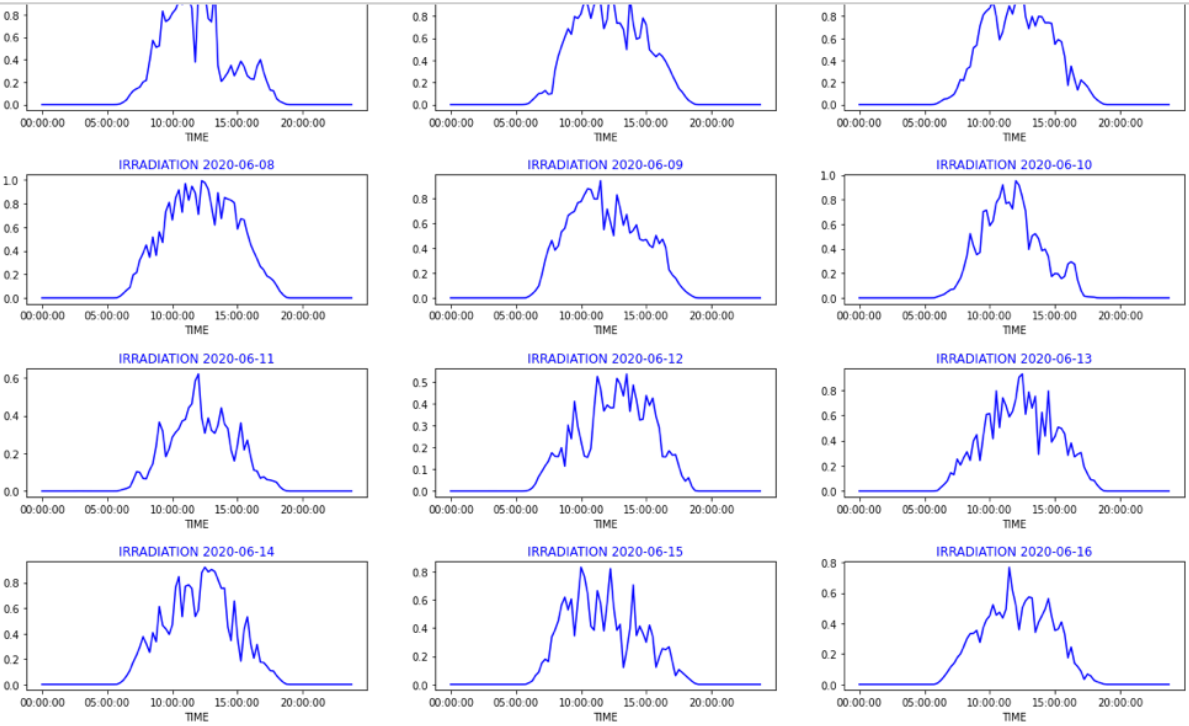
> *Highest average DC_POWER Generation is on*: **2020-05-15**

> *Lowest average DC_POWER Generation is on* : **2020-06-11**

NOTE: This Large variation in the DC_POWER generation is due to the fault in the system or due to weather change, which needs to study further. But from this bar plot we find the day on which there is highest DC_POWER is generated and the day with the lowest DC_POWER generated.

8. Multiple Plotting of IRRADIATION generation on per day basis.

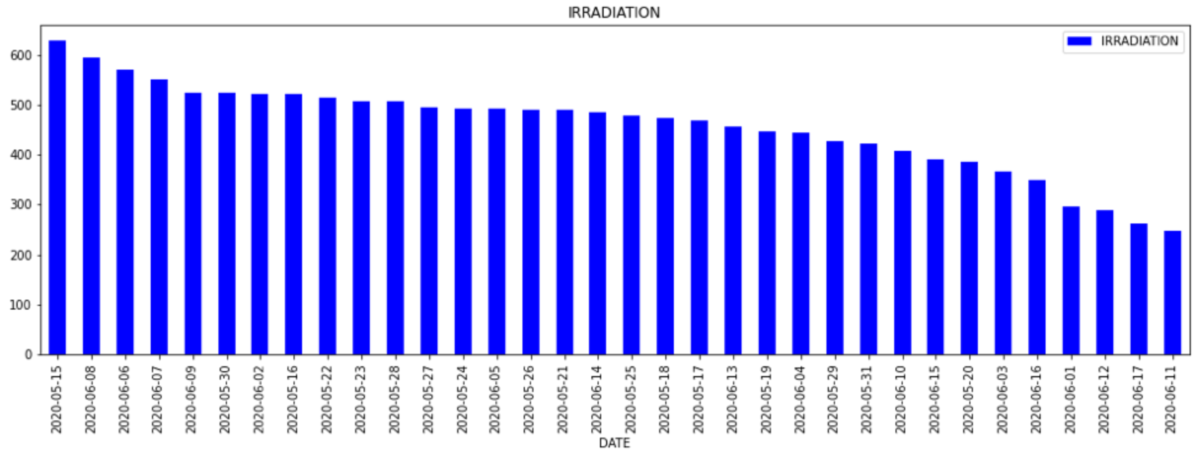
In [18]:
```
solar_irradiation = df_solar.pivot_table(values='IRRADIATION', inde

def Daywise_plot(data= None, row = None, col = None, title='IRRADIA
    cols = data.columns # take all column
    gp = plt.figure(figsize=(20,40))

    gp.subplots_adjust(wspace=0.2, hspace=0.5)
    for i in range(1, len(cols)+1):
        ax = gp.add_subplot(row,col, i)
        data[cols[i-1]].plot(ax=ax, color='blue')
        ax.set_title('{} {}'.format(title, cols[i-1]),color='blue')

Daywise_plot(data=solar_irradiation, row=12, col=3)
```



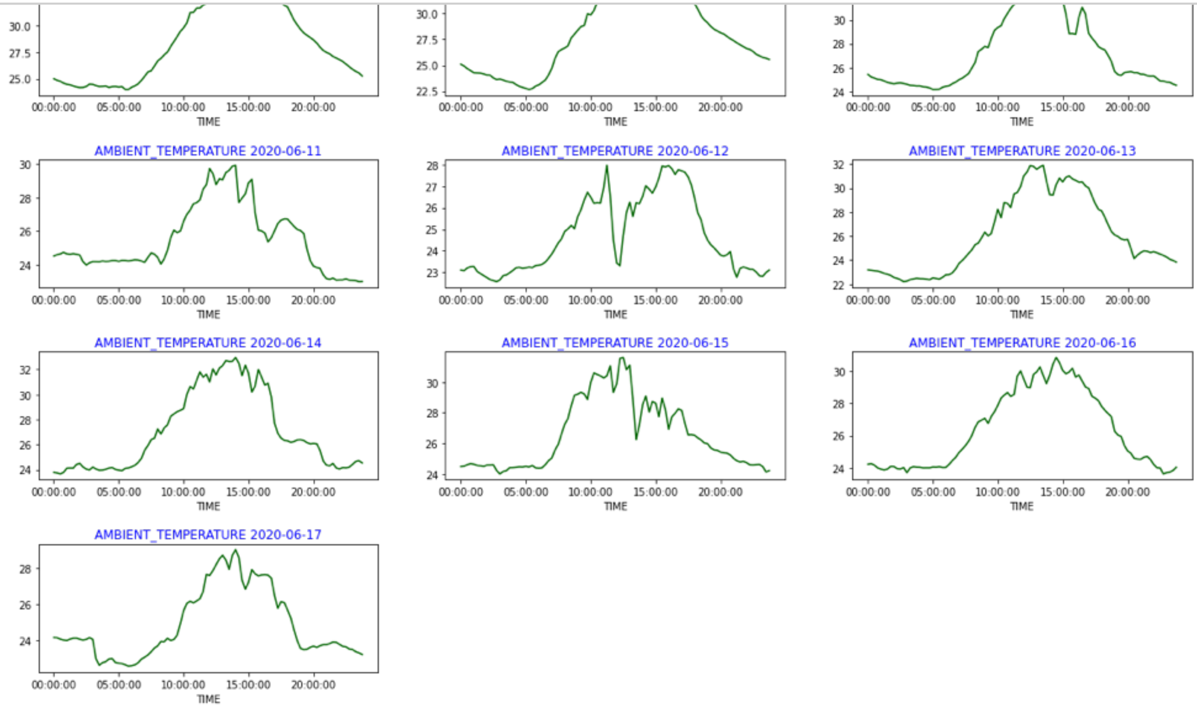
IRRADIATION graph pattern is looking very similar to the corresponding DC_POWER generation on per day basis.

- In solar power plant DC_POWER or Output power is mostly depends on IRRADIATION .Or it is not wrong to say that it’s directly proportional.

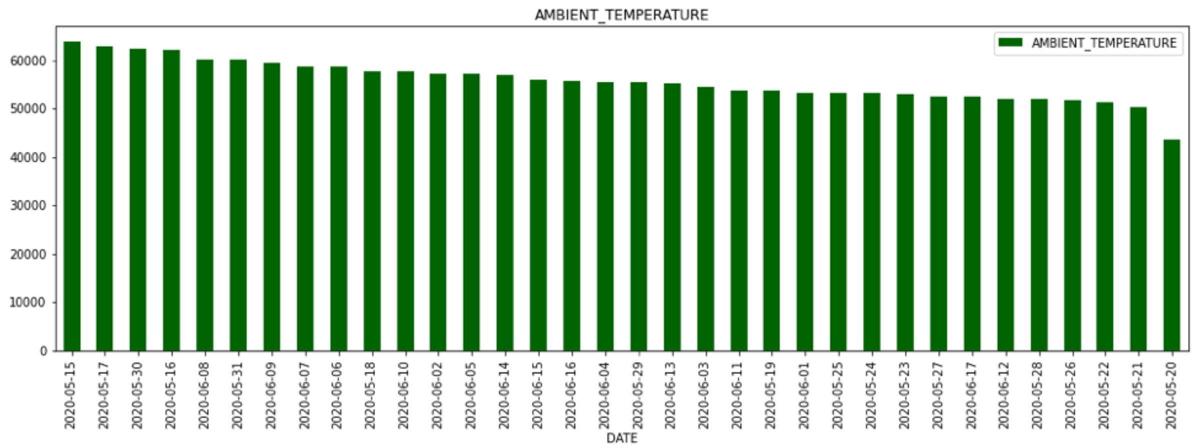
In [19]:
```
daily_irradiation = df_solar.groupby('DATE')['IRRADIATION'].agg('su

daily_irradiation.sort_values(ascending=False).plot.bar(figsize=(17
plt.title('IRRADIATION')
plt.show()
```



In [20]:
```
solar_ambiant_temp = df_solar.pivot_table(values='AMBIENT_TEMPERATU

def Daywise_plot(data= None, row = None, col = None, title='AMBIENT_
    cols = data.columns # take all column
    gp = plt.figure(figsize=(20,40))

    gp.subplots_adjust(wspace=0.2, hspace=0.5)
    for i in range(1, len(cols)+1):
        ax = gp.add_subplot(row,col, i)
        data[cols[i-1]].plot(ax=ax, color='darkgreen')
        ax.set_title('{} {}'.format(title, cols[i-1]),color='blue')

Daywise_plot(data=solar_ambiant_temp, row=12, col=3)
```



In [21]:
```
daily_ambient_temp = df_solar.groupby('DATE')['AMBIENT_TEMPERATURE'

daily_ambient_temp.sort_values(ascending=False).plot.bar(figsize=(1
plt.title('AMBIENT_TEMPERATURE')
plt.show()
```



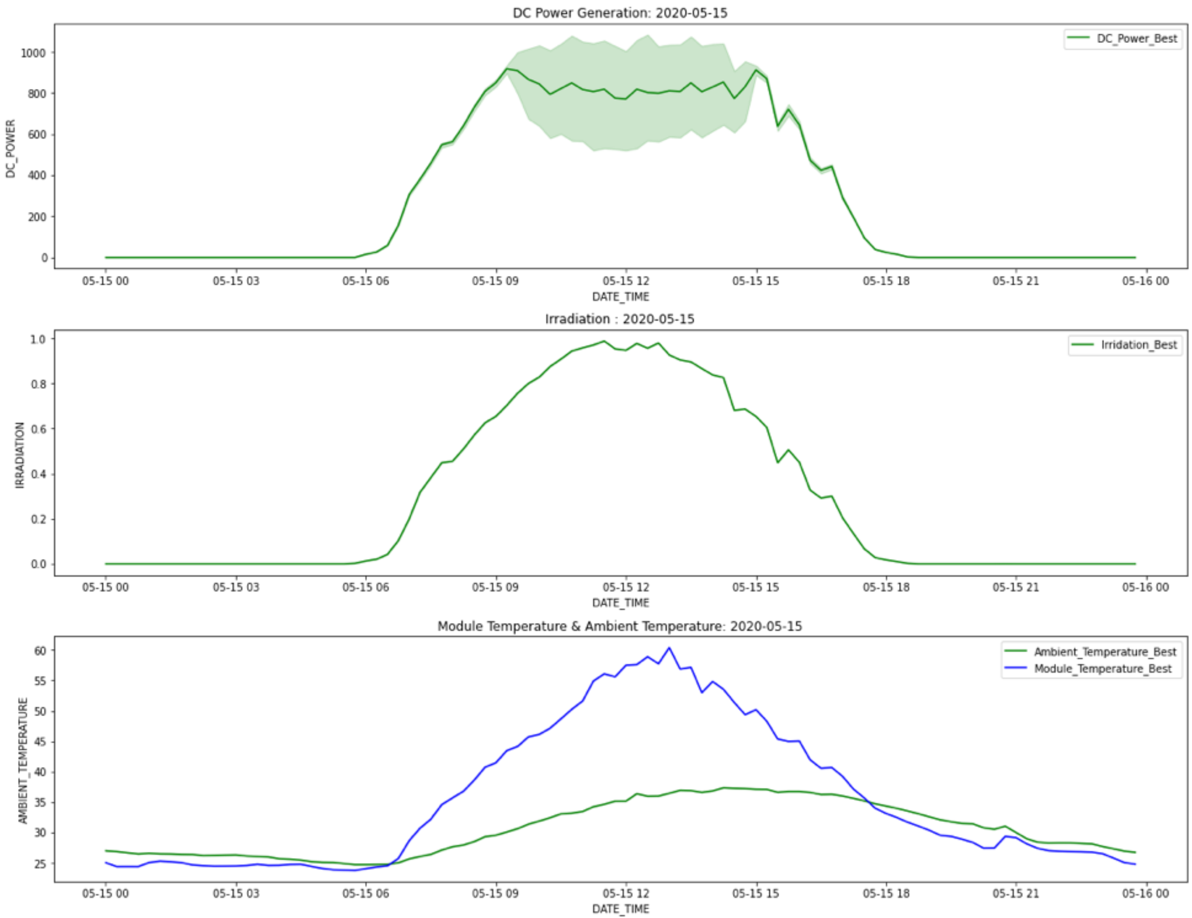
Best and Worst Power generation comparision:

Major Environmental Factors affecting the of sola

1. The thickness of clouds is also a factor in how much sunlight your solar panels can soak up. We may see thicker clouds in winter too and this is something else to look out for. It's hard for sunlight to travel through thick clouds, which will affect your solar power system's output.
2. While we've looked at the sun's positioning and how it can affect output, there's another factor to consider when your system may not be performing at its maximum… even at midday.
3. Solar panel temperature is the number one reason behind your solar power system not achieving peak performance
4. Solar power generation is directly depends on Irradiation comming from the sun.

9. Highest average DC_POWER is generated on "2020-05-15"

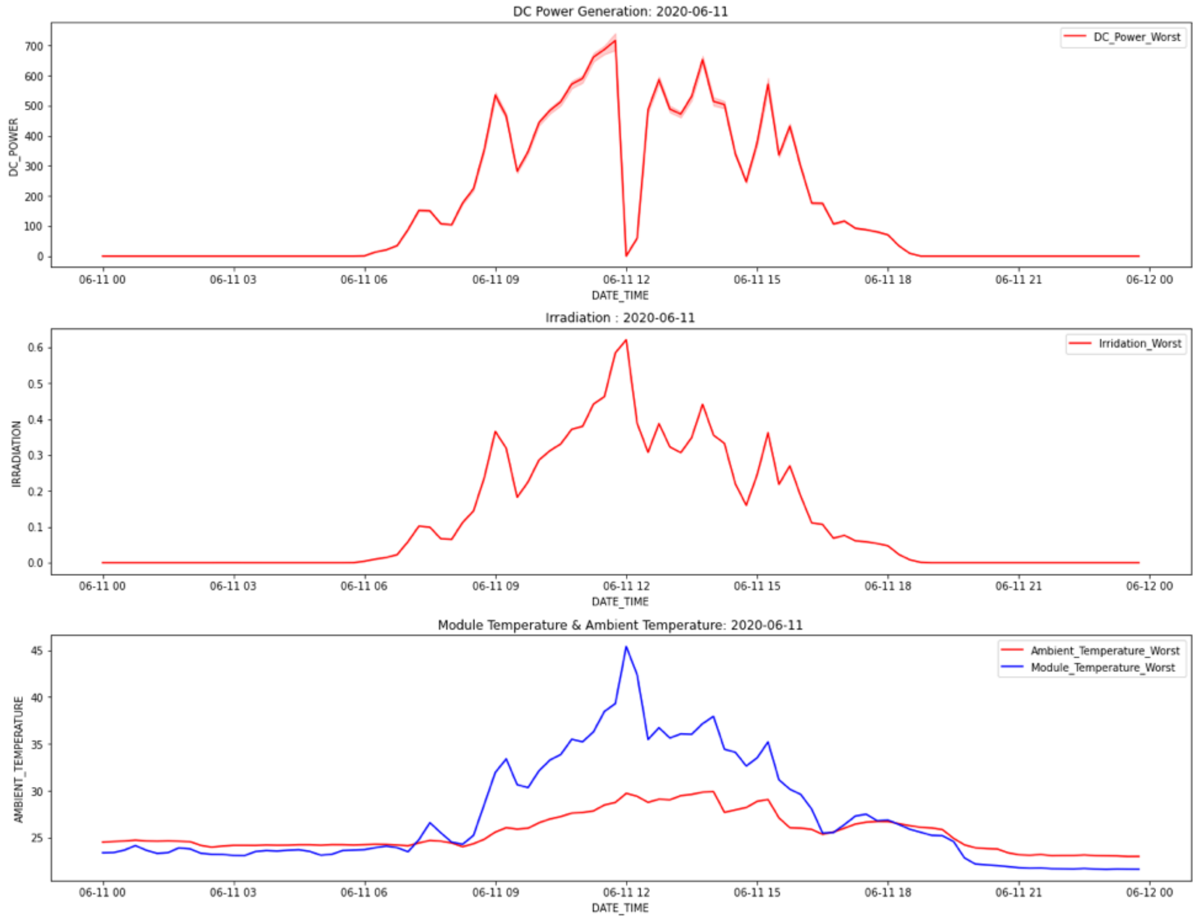
In [22]:
```
plt.figure(figsize=(16,16))

date=["2020-05-15"]

plt.subplot(411)
sns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME
plt.title("DC Power Generation: {}" .format(date[0]))

plt.subplot(412)
sns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME
plt.title("Irradiation : {}" .format(date[0]))

plt.subplot(413)
sns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME
sns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME
plt.title("Module Temperature & Ambient Temperature: {}" .format(da

plt.tight_layout()
plt.show()
```



NOTE: Both DC_POWER graph and IRRADIATION graph is almost looking like an ideal graph which is explained earlier. Weather is also looking good, and there is no cloud is in the sky because there is very less variation in IRRADIATION and temperature of the solar panel and ambient temperature.

10. Lowest average DC_POWER is generated on "2020-06-11"

In [23]:
```
ate=["2020-06-11"]
lt.figure(figsize=(16,16))

lt.subplot(411)
ns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME,
lt.title("DC Power Generation: {}" .format(date[0]))

lt.subplot(412)
ns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME,
lt.title("Irradiation : {}" .format(date[0]))

lt.subplot(413)
ns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME,
ns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME,
lt.title("Module Temperature & Ambient Temperature: {}" .format(date

lt.tight_layout()
lt.show()
```



NOTE: There are very large fluctuations in both DC_POWER graph and IRRADIATION graph

Possible Reasons for these large fluctuation in the DC_POWER, IRRADIATION, Ambient temperature, Module temperature:

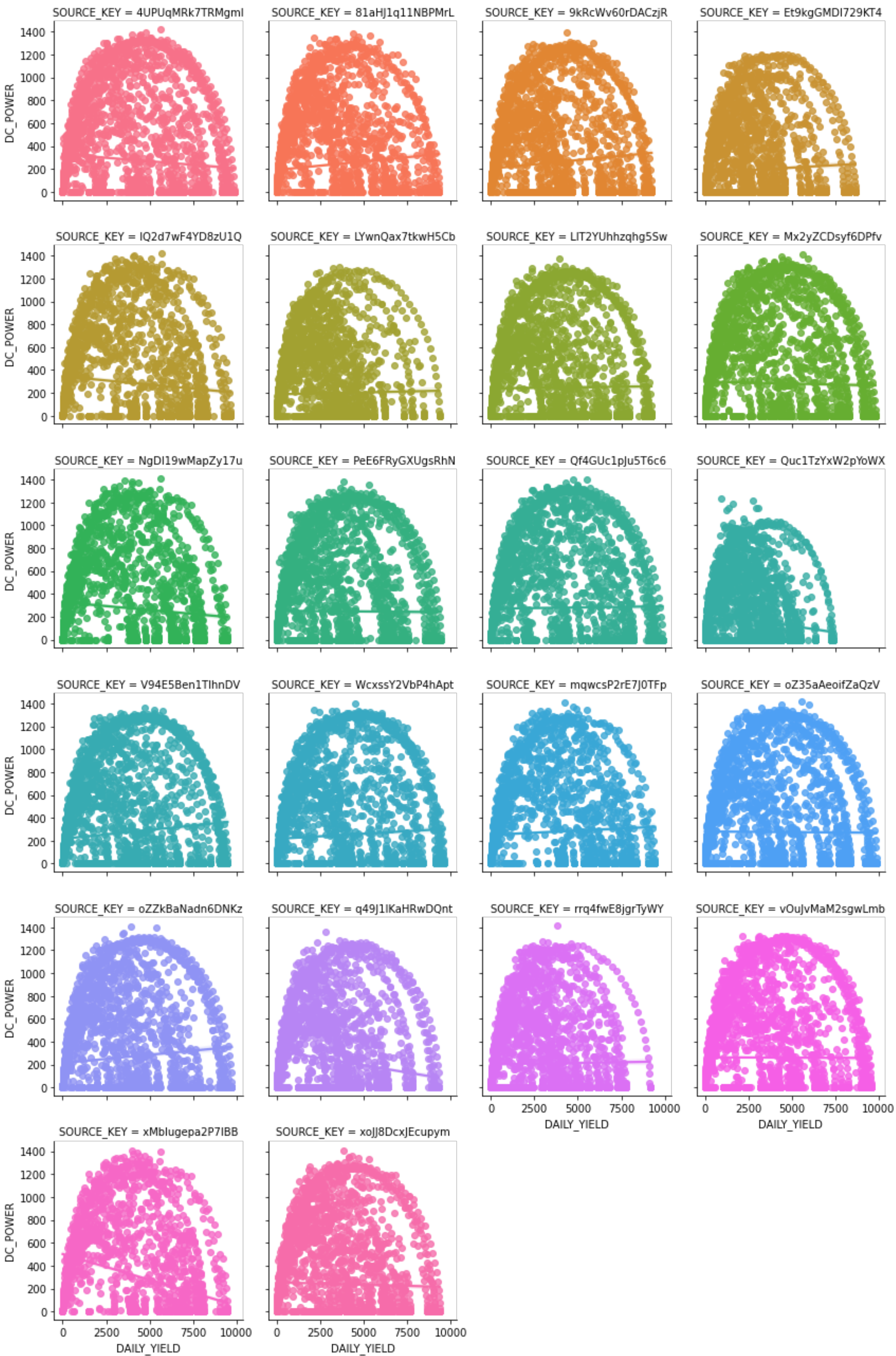
> At about 12 O’clock there is a sharp decline in the DC_POWER generation from 700 to almost 20 KWatt.

> And at the same time IRRADIATION fall from 0.6 to 0.3 almost half.

> Ambient temperature and Module temperature also fall drastically. Module temperature from 45 C to 35 C & Ambient temperature is also reduced.

```
 The possible reason for this reduction is due to may be heavy
rain and heavily clouded sky and bad weather. There is almost very
less possibility of any fault in the system
```

In [24]:
```
sns.lmplot(y="DC_POWER",x="DAILY_YIELD",hue="SOURCE_KEY",col="SOURC
```



Solar Power Plant Inverter Efficiency Calculation

In [25]:
```
solar_dc_power = df_solar[df_solar['DC_POWER'] > 0]['DC_POWER'].val
solar_ac_power = df_solar[df_solar['AC_POWER'] > 0]['AC_POWER'].val
```

In [26]:
```
solar_plant_eff = (np.max(solar_ac_power)/np.max(solar_dc_power ))*
print(f"Power ratio AC/DC (Efficiency) of Solar Power Plant:  {sola
```

```
Power ratio AC/DC (Efficiency) of Solar Power Plant:  97.501 %
```

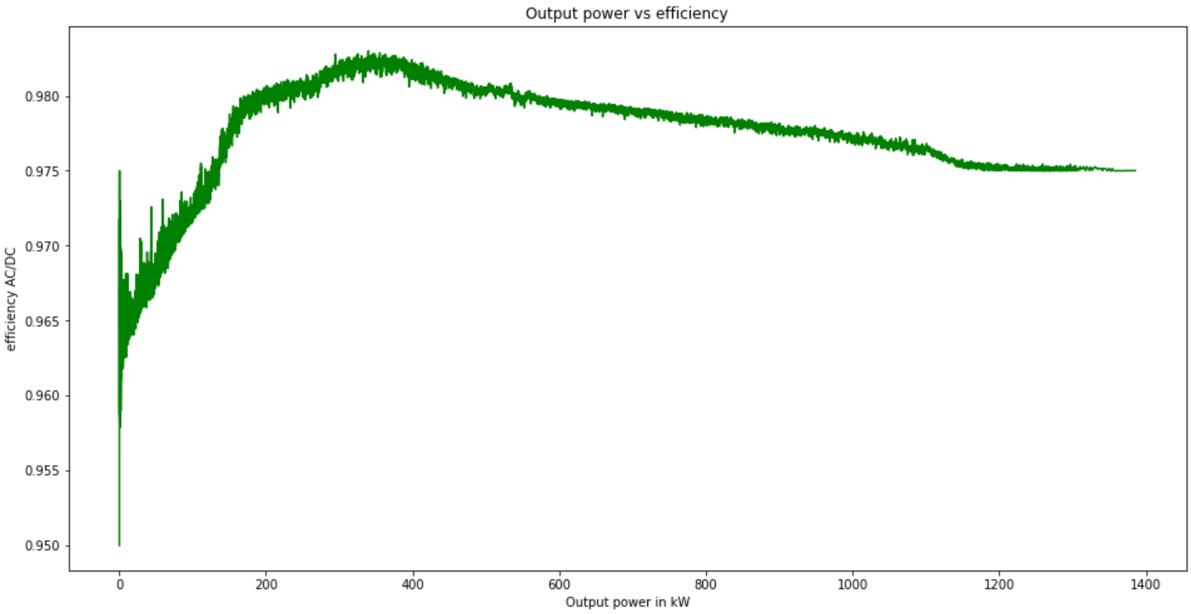
In [27]:
```
AC_list=[]
for i in df_solar['AC_POWER']:
    if i>0:
        AC_list.append(i)
AC_list
#AC_list.sort()
#AC_list.reverse()
len(AC_list)
```

Out[27]:
```
32036
```

In [28]:
```
#Here we take all nonzero DC values and plot them on histogram
DC_list=[]
for i in df_solar['DC_POWER']:
    if i>0:
        DC_list.append(i)
DC_list
DC_list.sort()
DC_list.reverse()
len(DC_list)
```

Out[28]:
```
32036
```

In [29]:
```
plt.figure(figsize=(16,8))
AC_list.sort()
DC_list.sort()
#print(DC_list)
#DC_list.sort
#res = [i / 10 for i in AC_list]
eff = [i/j for i,j in zip(AC_list,DC_list)]

plt.plot(AC_list,eff,color='green')
plt.xlabel('Output power in kW')
plt.ylabel('efficiency AC/DC')
plt.title('Output power vs efficiency');
```

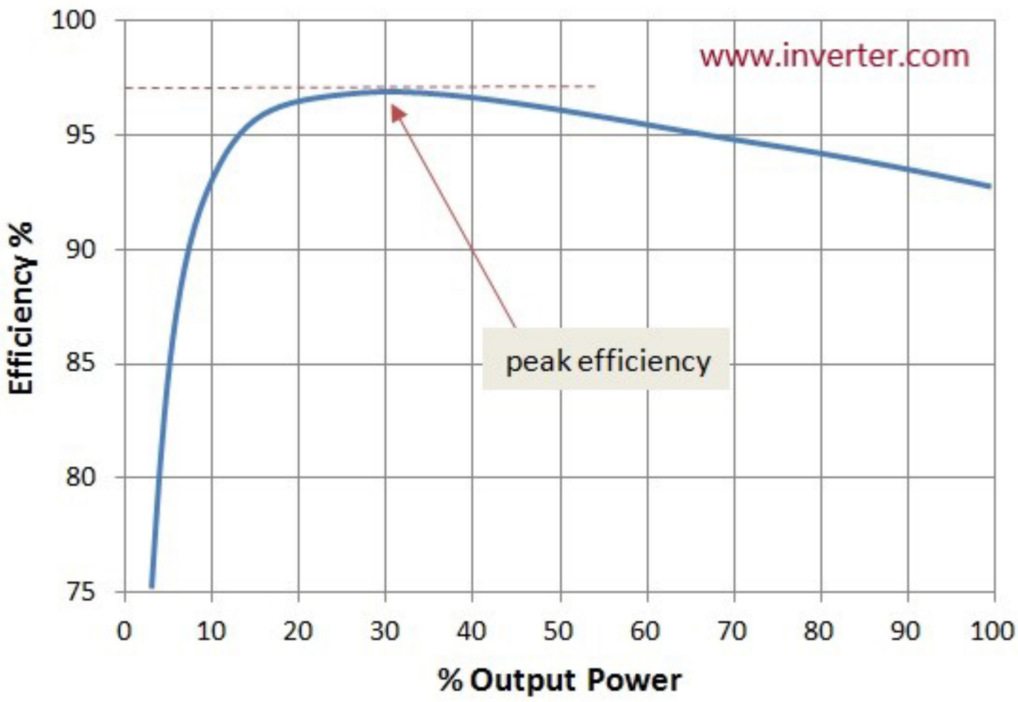


11. What does inverter efficiency mean?

- In fact, we shall discuss here the general power inverter efficiency whether it's solar inverter or pure sine wave inverter or even modified sine wave inverter.
- The inverter efficiency refers to how much dc power will be converted to ac power, as some of power will be lost during this transition in two forms:

Heat loss.

- Stand-by power which consumed just to keep the inverter in power mode. Also, we can refer to it as inverter power consumption at no load condition.
- Hence, inverter efficiency = pac/pdc where pac refers to ac output power in watt and pdc refers to dc input power in watts.



> For the two basic inverters types in the market, the typical efficiency of high-quality pure sine wave inverter varied from 90% to 95% and for low quality modified sine wave inverter, it varied from 75% to 85%.

> This power inverter efficiency value depends on inverter load power capacity variation, as the efficiency increases and may reach to its max value at higher load power capacity in compare to lower loading power capacity, and in condition that not going above inverter output power capacity limit. Generally, below 15% inverter loading, the efficiency will be quite low. Consequently, good matching between inverter capacity and its load capacity will enable us harvest larger efficiency, which means larger inverter ac output power for the same dc input power.

[REFERENCE: (https://www.inverter.com/what-is-inverter-efficiency)](https://www.inverter.com/what-is-inverter-efficiency)

Solar Power Prediction

In [30]:
```
df2 = df_solar.copy()
X = df2[['DAILY_YIELD','TOTAL_YIELD','AMBIENT_TEMPERATURE','MODULE_
y = df2['AC_POWER']
```

In [31]:
```
X.head()
```

Out[31]:

	DAILY_YIELD	TOTAL_YIELD	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE	IRRAD
0	9425.000	2.429e+06	27.005	25.061	
1	0.000	1.215e+09	27.005	25.061	
2	3075.333	2.248e+09	27.005	25.061	
3	269.933	1.704e+06	27.005	25.061	
4	3177.000	1.994e+07	27.005	25.061	

In [32]:
```
y.head()
```

Out[32]:
```
0    0.0
1    0.0
2    0.0
3    0.0
4    0.0
Name: AC_POWER, dtype: float64
```

In [33]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=.2,r
```

1. LinearRegression

In [34]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

lr_clf = LinearRegression()
lr_clf.fit(X_train,y_train)
score_lr = 100*lr_clf.score(X_test,y_test)
print(f'LR Model score = {score_lr:4.4f}%')
```

```
LR Model score = 99.9994%
```

In [35]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

lr = LinearRegression()
lr.fit(X_train,y_train)
y_pred_lr = lr.predict(X_test)
R2_Score_lr = round(r2_score(y_pred_lr,y_test) * 100, 2)

print("R2 Score : ",R2_Score_lr,"%")
```

```
R2 Score :  100.0 %
```

2. RandomForestRegressor

In [36]:
```
from sklearn.ensemble import RandomForestRegressor
rfr = RandomForestRegressor()
rfr.fit(X_train,y_train)
y_pred_rfr = lr.predict(X_test)
R2_Score_rfr = round(r2_score(y_pred_rfr,y_test) * 100, 2)

print("R2 Score : ",R2_Score_rfr,"%")
```

```
R2 Score :  100.0 %
```

3. DecisionTreeRegressor

In [37]:
```
from sklearn.tree import DecisionTreeRegressor
dtr = DecisionTreeRegressor()
dtr.fit(X_train,y_train)

y_pred_dtr = lr.predict(X_test)
R2_Score_dtr = round(r2_score(y_pred_dtr,y_test) * 100, 2)

print("R2 Score : ",R2_Score_dtr,"%")
```

```
R2 Score :  100.0 %
```

12. Result Prediction

In [38]:
```
prediction = rfr.predict(X_test)
print(prediction)
```

```
[   0.            0.          684.72575238 ...    0.          1007.
14018095
    0.        ]
```

In [39]:
```
cross_checking = pd.DataFrame({'Actual' : y_test , 'Predicted' : pr
cross_checking.head()
```

Out[39]:

	Actual	Predicted
40426	0.000	0.000
50974	0.000	0.000
53919	684.913	684.726
2384	0.000	0.000
22014	0.000	0.000

In [40]:
```
cross_checking['Error'] = cross_checking['Actual'] - cross_checking
cross_checking.head()
```

Out[40]:

	Actual	Predicted	Error
40426	0.000	0.000	0.000
50974	0.000	0.000	0.000
53919	684.913	684.726	0.188
2384	0.000	0.000	0.000
22014	0.000	0.000	0.000

In [41]:
```
cross_checking_final  = cross_checking[cross_checking['Error'] <= 2
cross_checking_final.sample(25).style.background_gradient(
        cmap='coolwarm').set_properties(**{
            'font-family': 'Lucida Calligraphy',
            'color': 'LigntGreen',
            'font-size': '15px'
        })
```

Out[41]:

	Actual	Predicted	Error
19681	971.633	971.031	0.602
35768	0.000	0.000	0.000
54605	0.000	0.000	0.000
46146	0.000	0.000	0.000
13644	0.000	0.000	0.000
25546	0.000	0.000	0.000
38669	4.560	4.544	0.016
59634	0.000	0.000	0.000
2115	0.000	0.000	0.000
41306	1349.307	1348.696	0.612
55652	128.693	128.536	0.158
13834	0.000	0.000	0.000
5901	0.000	0.000	0.000
14884	545.493	545.422	0.071
29073	539.421	538.428	0.994
6525	0.000	0.000	0.000
39972	0.000	0.000	0.000
12091	0.000	0.000	0.000
8928	0.000	0.000	0.000
50482	0.000	0.000	0.000
3235	0.000	0.000	0.000
27837	0.000	0.000	0.000
54341	294.140	294.002	0.138
41500	460.821	460.500	0.321
40833	61.753	61.741	0.013