1. Importing Libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings("ignore")

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

```
generation_data =
pd.read_csv('../input/solar-power/Plant_2_Generation_Data.csv')

weather_data =
pd.read_csv('../input/solar-power/Plant_2_Weather_Sensor_Data.csv')

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

<pandas.io.formats.style.Styler at 0x7e87b5bf9f10>

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

<pandas.io.formats.style.Styler at 0x7e87b5a08e90>
```

3. Adjust datetime format

```
generation_data['DATE_TIME'] =
pd.to_datetime(generation_data['DATE_TIME'],format = '%Y-%m-%d %H:%M')
weather_data['DATE_TIME'] =
pd.to_datetime(weather_data['DATE_TIME'],format = '%Y-%m-%d %H:%M:%S')
```

4. Merging generation data and weather sensor data

```
df_solar = pd.merge(generation_data.drop(columns = ['PLANT_ID']),
weather_data.drop(columns = ['PLANT_ID', 'SOURCE_KEY']),
on='DATE_TIME')
df_solar.sample(5).style.background_gradient(cmap='cool')
```

```
<pandas.io.formats.style.Styler at 0x7e87b59f21d0>
```

5. Adding separate time and date columns

```
# 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:
%S').dt.hour
df_solar['MINUTES'] = pd.to_datetime(df_solar['TIME'],format='%H:%M:
%S').dt.minute
df_solar['TOTAL MINUTES PASS'] = df_solar['MINUTES'] +
df_solar['HOURS']*60

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

df_solar.head(2)
```

```
   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

   AMBIENT_TEMPERATURE  MODULE_TEMPERATURE  IRRADIATION        DATE
TIME  \
0                27.005              25.061          0.0  2020-05-15
00:00:00
1                27.005              25.061          0.0  2020-05-15
00:00:00

   DAY  MONTH  WEEK HOURS  MINUTES  TOTAL MINUTES PASS DATE_STRING
```

```
0   15       5    20     0        0                    0  2020-05-15
1   15       5    20     0        0                    0  2020-05-15
```

```
df_solar.isnull().sum()
```

```
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

```
df_solar.describe().style.background_gradient(cmap='rainbow')
```

```
<pandas.io.formats.style.Styler at 0x7e87b5a6b190>
```

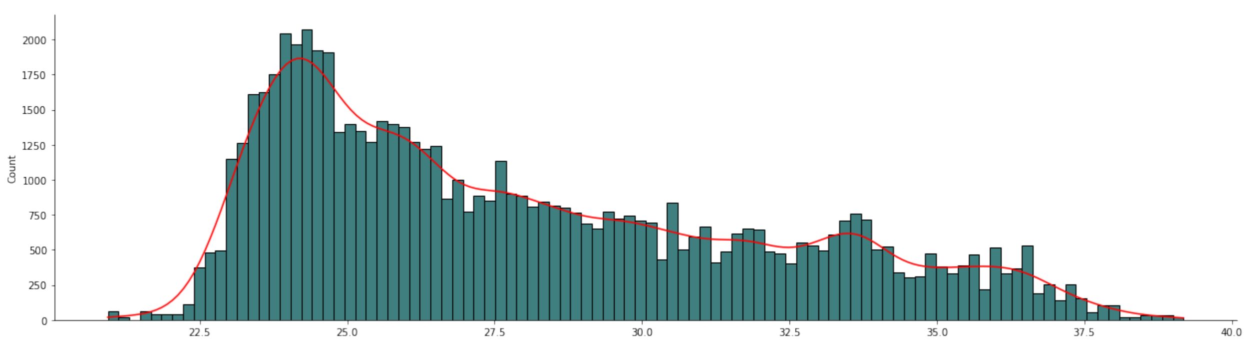
6. Converting 'SOURCE_KEY' from categorical form to numerical form

```
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
df_solar['SOURCE_KEY_NUMBER'] =
encoder.fit_transform(df_solar['SOURCE_KEY'])
df_solar.head()
```

```
   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

   AMBIENT_TEMPERATURE  MODULE_TEMPERATURE  IRRADIATION        DATE
TIME  \
0                 27.005              25.061          0.0  2020-05-15
00:00:00
1                 27.005              25.061          0.0  2020-05-15
00:00:00
2                 27.005              25.061          0.0  2020-05-15
00:00:00
3                 27.005              25.061          0.0  2020-05-15
00:00:00
4                 27.005              25.061          0.0  2020-05-15
00:00:00

   DAY  MONTH  WEEK HOURS  MINUTES  TOTAL MINUTES PASS DATE_STRING  \
0   15      5    20     0        0                   0  2020-05-15
1   15      5    20     0        0                   0  2020-05-15
2   15      5    20     0        0                   0  2020-05-15
3   15      5    20     0        0                   0  2020-05-15
4   15      5    20     0        0                   0  2020-05-15

   SOURCE_KEY_NUMBER
0                  0
1                  1
2                  2
3                  3
4                  4
```

```
sns.displot(data=df_solar, x="AMBIENT_TEMPERATURE", kde=True, bins =
100,color = "red", facecolor = "#3F7F7F",height = 5, aspect = 3.5);
```

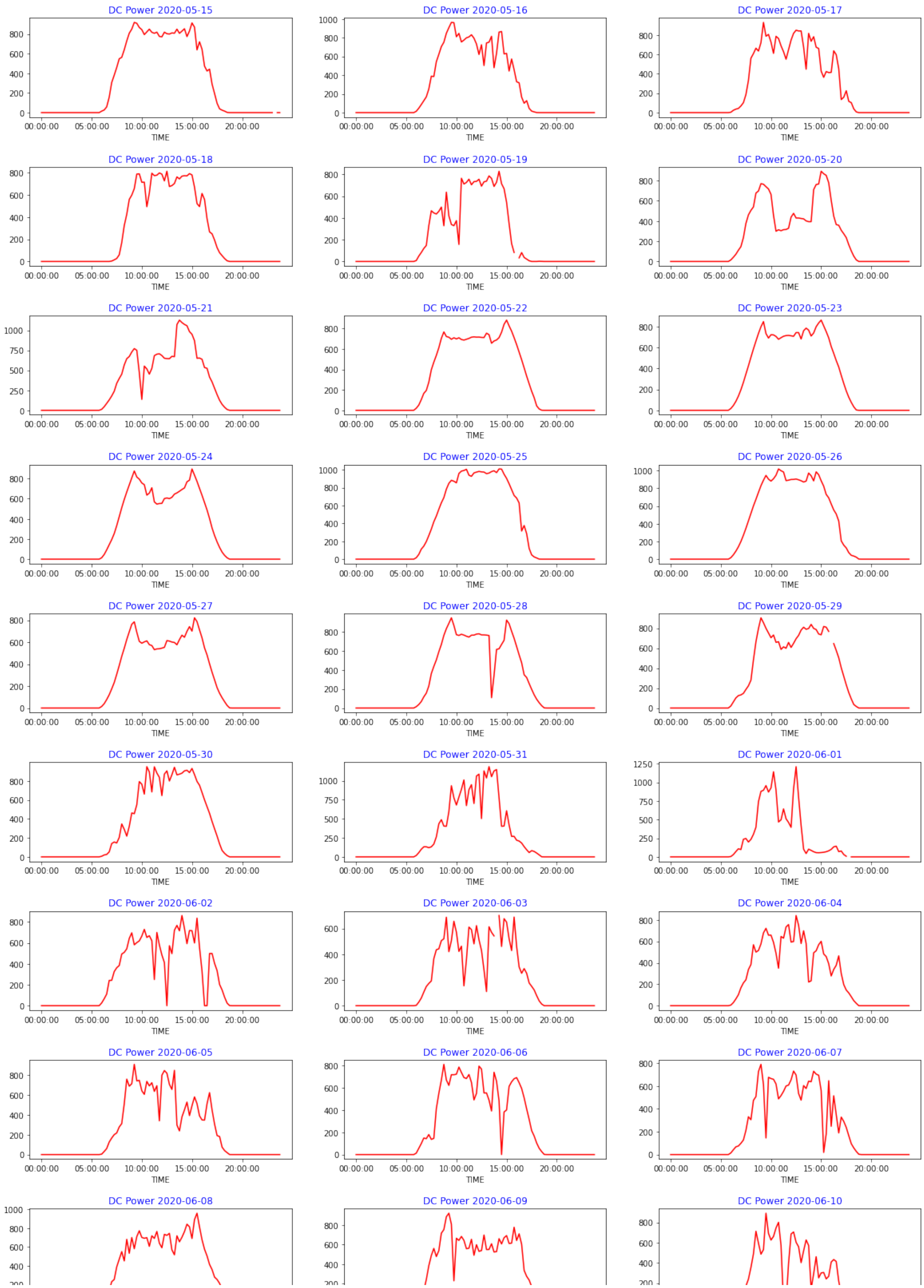



```
df_solar['DATE'].nunique()
```

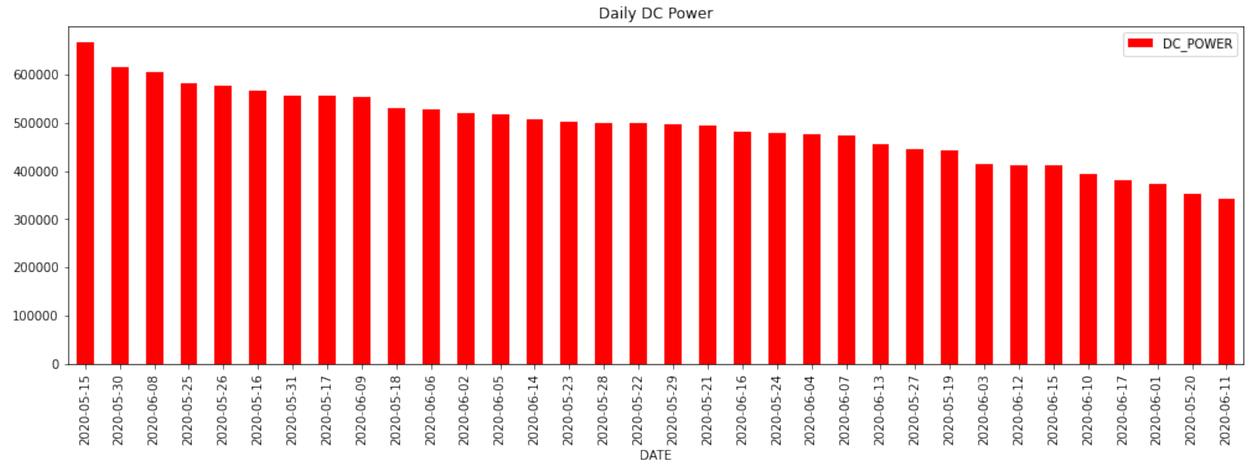
```
34
```

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

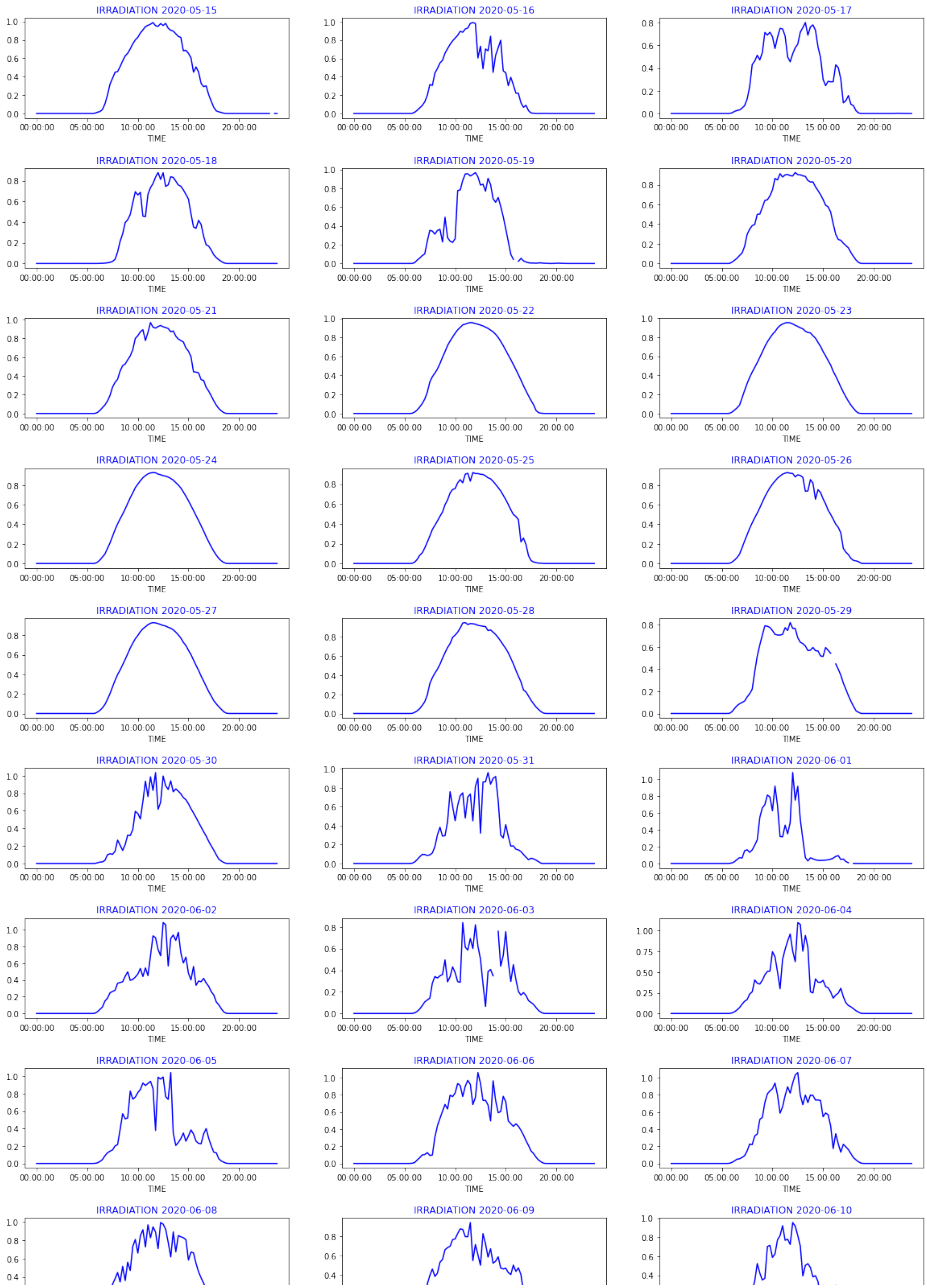
```python
solar_dc = df_solar.pivot_table(values='DC_POWER', index='TIME',
columns='DATE')

def Daywise_plot(data= None, row = None, col = None, title='DC
Power'):
    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)
```


DC Power 2020-05-15
DC Power 2020-05-16
DC Power 2020-05-17
DC Power 2020-05-18
DC Power 2020-05-19
DC Power 2020-05-20
DC Power 2020-05-21
DC Power 2020-05-22
DC Power 2020-05-23
DC Power 2020-05-24
DC Power 2020-05-25
DC Power 2020-05-26
DC Power 2020-05-27
DC Power 2020-05-28
DC Power 2020-05-29
DC Power 2020-05-30
DC Power 2020-05-31
DC Power 2020-06-01
DC Power 2020-06-02
DC Power 2020-06-03
DC Power 2020-06-04
DC Power 2020-06-05
DC Power 2020-06-06
DC Power 2020-06-07
DC Power 2020-06-08
DC Power 2020-06-09
DC Power 2020-06-10
TIME
00:00:00
05:00:00
10:00:00
15:00:00
20:00:00

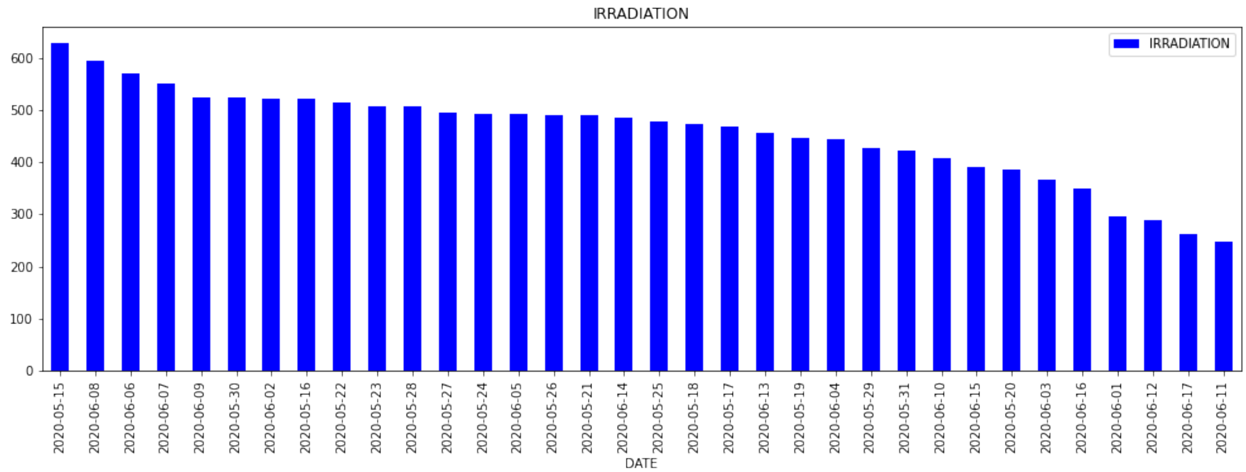
```
daily_dc = df_solar.groupby('DATE')['DC_POWER'].agg('sum')

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



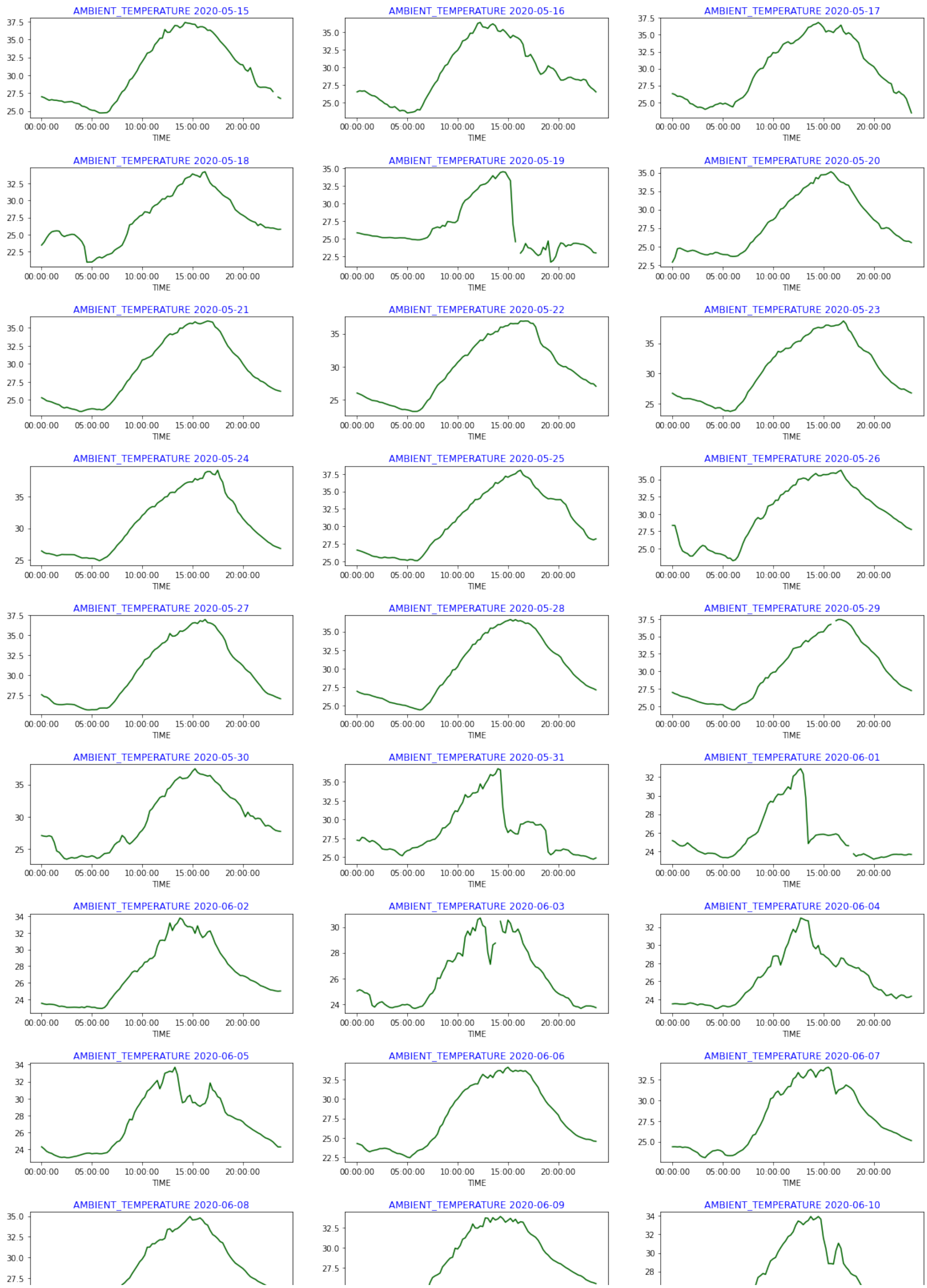

```
solar_irradiation = df_solar.pivot_table(values='IRRADIATION',
index='TIME', columns='DATE')

def Daywise_plot(data= None, row = None, col = None,
title='IRRADIATION'):
    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 2020-05-15
IRRADIATION 2020-05-16
IRRADIATION 2020-05-17
IRRADIATION 2020-05-18
IRRADIATION 2020-05-19
IRRADIATION 2020-05-20
IRRADIATION 2020-05-21
IRRADIATION 2020-05-22
IRRADIATION 2020-05-23
IRRADIATION 2020-05-24
IRRADIATION 2020-05-25
IRRADIATION 2020-05-26
IRRADIATION 2020-05-27
IRRADIATION 2020-05-28
IRRADIATION 2020-05-29
IRRADIATION 2020-05-30
IRRADIATION 2020-05-31
IRRADIATION 2020-06-01
IRRADIATION 2020-06-02
IRRADIATION 2020-06-03
IRRADIATION 2020-06-04
IRRADIATION 2020-06-05
IRRADIATION 2020-06-06
IRRADIATION 2020-06-07
IRRADIATION 2020-06-08
IRRADIATION 2020-06-09
IRRADIATION 2020-06-10
TIME
00:00:00
05:00:00
10:00:00
15:00:00
20:00:00

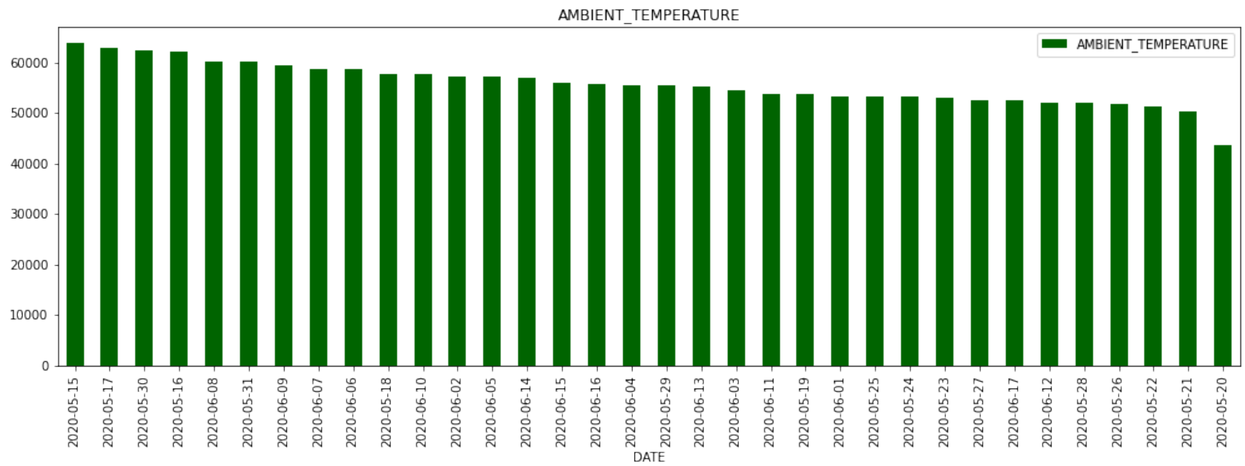
```python
daily_irradiation = df_solar.groupby('DATE')['IRRADIATION'].agg('sum')

daily_irradiation.sort_values(ascending=False).plot.bar(figsize=(17,5)
, legend=True,color='blue')
plt.title('IRRADIATION')
plt.show()
```




```python
solar_ambiant_temp =
df_solar.pivot_table(values='AMBIENT_TEMPERATURE', index='TIME',
columns='DATE')

def Daywise_plot(data= None, row = None, col = None,
title='AMBIENT_TEMPERATURE'):
    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)
```


AMBIENT_TEMPERATURE 2020-05-15
TIME
AMBIENT_TEMPERATURE 2020-05-16
TIME
AMBIENT_TEMPERATURE 2020-05-17
TIME
AMBIENT_TEMPERATURE 2020-05-18
TIME
AMBIENT_TEMPERATURE 2020-05-19
TIME
AMBIENT_TEMPERATURE 2020-05-20
TIME
AMBIENT_TEMPERATURE 2020-05-21
TIME
AMBIENT_TEMPERATURE 2020-05-22
TIME
AMBIENT_TEMPERATURE 2020-05-23
TIME
AMBIENT_TEMPERATURE 2020-05-24
TIME
AMBIENT_TEMPERATURE 2020-05-25
TIME
AMBIENT_TEMPERATURE 2020-05-26
TIME
AMBIENT_TEMPERATURE 2020-05-27
TIME
AMBIENT_TEMPERATURE 2020-05-28
TIME
AMBIENT_TEMPERATURE 2020-05-29
TIME
AMBIENT_TEMPERATURE 2020-05-30
TIME
AMBIENT_TEMPERATURE 2020-05-31
TIME
AMBIENT_TEMPERATURE 2020-06-01
TIME
AMBIENT_TEMPERATURE 2020-06-02
TIME
AMBIENT_TEMPERATURE 2020-06-03
TIME
AMBIENT_TEMPERATURE 2020-06-04
TIME
AMBIENT_TEMPERATURE 2020-06-05
TIME
AMBIENT_TEMPERATURE 2020-06-06
TIME
AMBIENT_TEMPERATURE 2020-06-07
TIME
AMBIENT_TEMPERATURE 2020-06-08
AMBIENT_TEMPERATURE 2020-06-09
AMBIENT_TEMPERATURE 2020-06-10

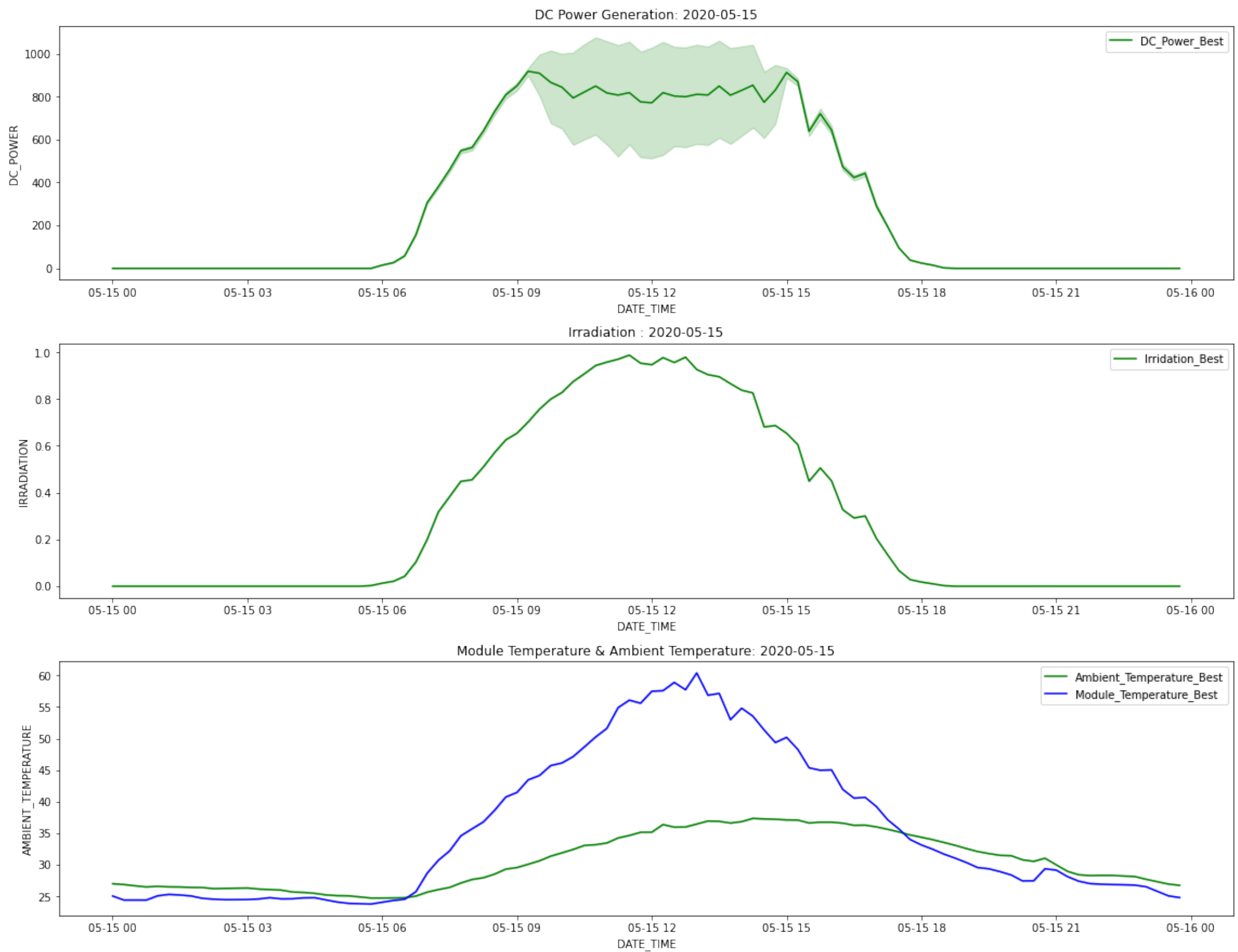
```
daily_ambient_temp = df_solar.groupby('DATE')
['AMBIENT_TEMPERATURE'].agg('sum')

daily_ambient_temp.sort_values(ascending=False).plot.bar(figsize=(17,5
), legend=True,color='darkgreen')
plt.title('AMBIENT_TEMPERATURE')
plt.show()
```



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

```
plt.figure(figsize=(16,16))

date=["2020-05-15"]

plt.subplot(411)
sns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME,
df_solar[df_solar["DATE_STRING"].isin(date)].DC_POWER,
label="DC_Power_Best",color='green');
plt.title("DC Power Generation: {}" .format(date[0]))

plt.subplot(412)
sns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME,
df_solar[df_solar["DATE_STRING"].isin(date)].IRRADIATION,
label="Irridation_Best",color='green');
plt.title("Irradiation : {}" .format(date[0]))

plt.subplot(413)
sns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME,
df_solar[df_solar["DATE_STRING"].isin(date)].AMBIENT_TEMPERATURE,
label="Ambient_Temperature_Best",color='green');
sns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME,
df_solar[df_solar["DATE_STRING"].isin(date)].MODULE_TEMPERATURE,
label="Module_Temperature_Best",color='blue');
plt.title("Module Temperature & Ambient Temperature:
```

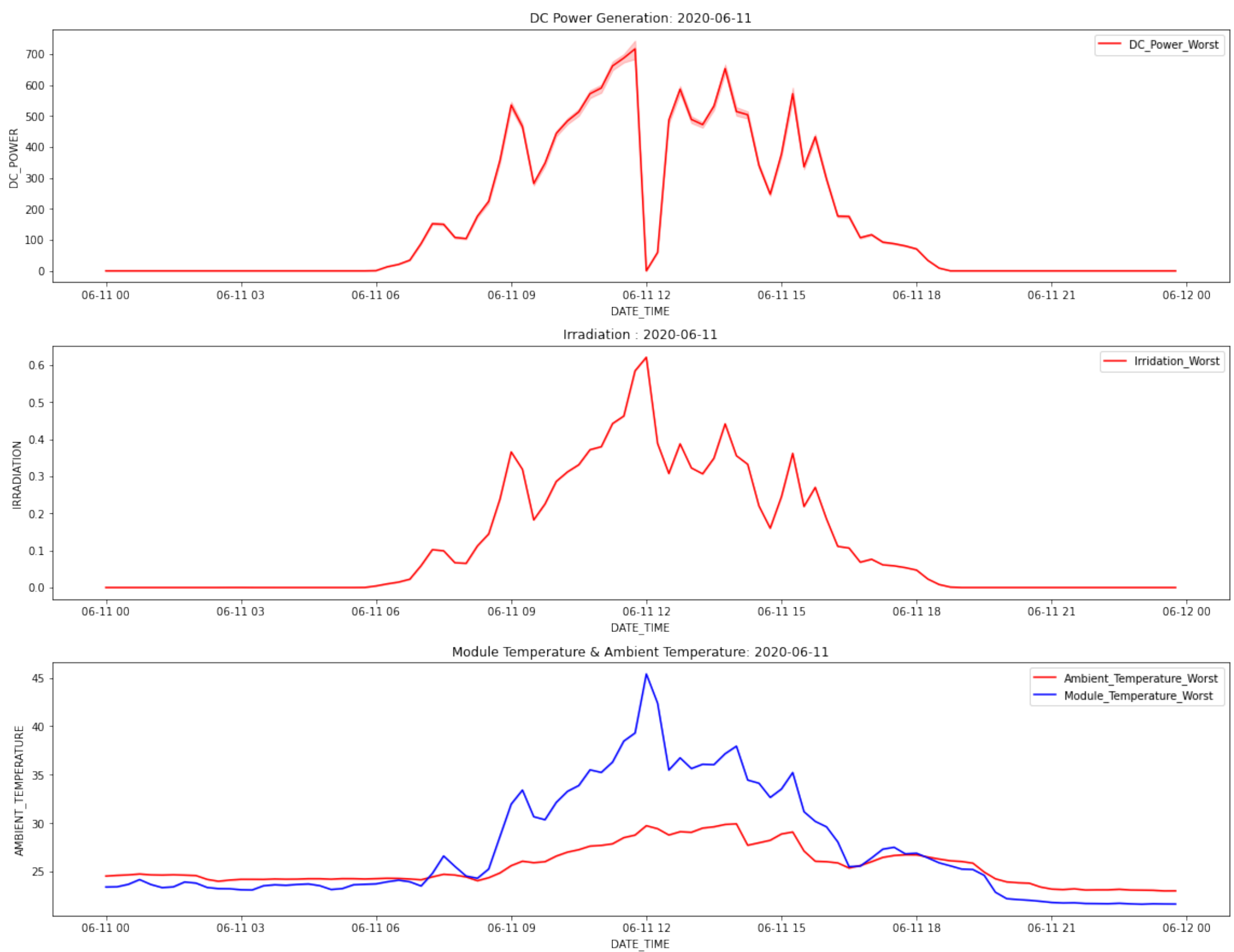
```
{}" .format(date[0]));

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



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

```
date=["2020-06-11"]
plt.figure(figsize=(16,16))

plt.subplot(411)
sns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME,
df_solar[df_solar["DATE_STRING"].isin(date)].DC_POWER,
label="DC_Power_Worst",color='red');
plt.title("DC Power Generation: {}" .format(date[0]))

plt.subplot(412)
sns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME,
df_solar[df_solar["DATE_STRING"].isin(date)].IRRADIATION,
```

```
label="Irridation_Worst",color='red');
plt.title("Irradiation : {}" .format(date[0]))

plt.subplot(413)
sns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME,
df_solar[df_solar["DATE_STRING"].isin(date)].AMBIENT_TEMPERATURE,
label="Ambient_Temperature_Worst",color='red');
sns.lineplot(df_solar[df_solar["DATE_STRING"].isin(date)].DATE_TIME,
df_solar[df_solar["DATE_STRING"].isin(date)].MODULE_TEMPERATURE,
label="Module_Temperature_Worst",color='blue');
plt.title("Module Temperature & Ambient Temperature:
{}" .format(date[0]));

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




```
solar_dc_power = df_solar[df_solar['DC_POWER'] > 0]['DC_POWER'].values
solar_ac_power = df_solar[df_solar['AC_POWER'] > 0]['AC_POWER'].values
```

```
solar_plant_eff = (np.max(solar_ac_power)/np.max(solar_dc_power ))*100
print(f"Power ratio AC/DC (Efficiency) of Solar Power Plant:
{solar_plant_eff:0.3f} %")

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

11. What does inverter efficiency mean?

```
df2 = df_solar.copy()
X =
df2[['DAILY_YIELD','TOTAL_YIELD','AMBIENT_TEMPERATURE','MODULE_TEMPERA
TURE','IRRADIATION']]
y = df2['AC_POWER']

X.head()

   DAILY_YIELD  TOTAL_YIELD  AMBIENT_TEMPERATURE
MODULE_TEMPERATURE  \
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


   IRRADIATION
0          0.0
1          0.0
2          0.0
3          0.0
4          0.0

y.head()

0    0.0
1    0.0
2    0.0
3    0.0
4    0.0
Name: AC_POWER, dtype: float64

from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test =
train_test_split(X,y,test_size=.2,random_state=21)
```

1. LinearRegression

```python
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error
import numpy as np
lr_clf = LinearRegression()
lr_clf.fit(X_train, y_train)

# Make predictions on the test set
y_pred = lr_clf.predict(X_test)

# Calculate R² score
score_lr = 100 * lr_clf.score(X_test, y_test)
print(f'LR Model R² Score = {score_lr:.4f}%')

# Calculate Mean Squared Error (MSE)
mse = mean_squared_error(y_test, y_pred)
print(f'Mean Squared Error (MSE) = {mse:.4f}')

# Calculate Root Mean Squared Error (RMSE)
rmse = np.sqrt(mse)
print(f'Root Mean Squared Error (RMSE) = {rmse:.4f}')
```

```
LR Model R² Score = 61.3383%
Mean Squared Error (MSE) = 50252.2816
Root Mean Squared Error (RMSE) = 224.1702
```

2. RandomForestRegressor

```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score, mean_squared_error
import numpy as np

# Assuming X_train, X_test, y_train, y_test are already defined and
preprocessed

# Initialize and train the Random Forest Regressor
rfr = RandomForestRegressor()
rfr.fit(X_train, y_train)

# Make predictions on the test set
y_pred_rfr = rfr.predict(X_test)

# Calculate R² score
r2_score_rfr = round(r2_score(y_test, y_pred_rfr) * 100, 2)
print("R² Score: ", r2_score_rfr, "%")

# Calculate Mean Squared Error (MSE)
mse_rfr = mean_squared_error(y_test, y_pred_rfr)
print("Mean Squared Error (MSE): ", round(mse_rfr, 4))

# Calculate Root Mean Squared Error (RMSE)
```

```
rmse_rfr = np.sqrt(mse_rfr)
print("Root Mean Squared Error (RMSE): ", round(rmse_rfr, 4))
```

```
R² Score:  93.85 %
Mean Squared Error (MSE):  7994.0654
Root Mean Squared Error (RMSE):  89.4095
```

3. DecisionTreeRegressor

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import r2_score, mean_squared_error
import numpy as np

# Initialize and train the Decision Tree Regressor
dtr = DecisionTreeRegressor()
dtr.fit(X_train, y_train)

# Make predictions on the test set
y_pred_dtr = dtr.predict(X_test)

# Calculate R² score
r2_score_dtr = round(r2_score(y_test, y_pred_dtr) * 100, 2)
print("R² Score: ", r2_score_dtr, "%")

# Calculate Mean Squared Error (MSE)
mse_dtr = mean_squared_error(y_test, y_pred_dtr)
print("Mean Squared Error (MSE): ", round(mse_dtr, 4))

# Calculate Root Mean Squared Error (RMSE)
rmse_dtr = np.sqrt(mse_dtr)
print("Root Mean Squared Error (RMSE): ", round(rmse_dtr, 4))
```

```
R² Score:  88.9 %
Mean Squared Error (MSE):  14428.436
Root Mean Squared Error (RMSE):  120.1184
```

```
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor, StackingRegressor
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
import numpy as np

# Assuming df2 is already defined and cleaned
X = df2[['DAILY_YIELD', 'TOTAL_YIELD', 'AMBIENT_TEMPERATURE',
'MODULE_TEMPERATURE', 'IRRADIATION']]
y = df2['AC_POWER']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
```

```
test_size=0.2, random_state=21)

# Initialize base models (Linear Regression, Random Forest, Gradient
Boosting)
base_learners = [
    ('lr', LinearRegression()),
    ('rfr', RandomForestRegressor(n_estimators=100, random_state=42)),
    ('gbr', GradientBoostingRegressor(n_estimators=100,
random_state=42))
]

# Initialize the Stacking Regressor (meta-model)
stacking_model = StackingRegressor(
    estimators=base_learners,
    final_estimator=LinearRegression()  # Meta-model could also be
RandomForestRegressor or another model
)

# Train the stacking model
stacking_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_stacking = stacking_model.predict(X_test)

# Calculate MSE and RMSE for the stacking model
mse_stacking = mean_squared_error(y_test, y_pred_stacking)
rmse_stacking = np.sqrt(mse_stacking)

# Calculate R² score
r2_stacking = stacking_model.score(X_test, y_test) * 100

# Print the results for the stacking model
print(f"Stacking Model (LR Meta-Model) - MSE: {mse_stacking:.4f},
RMSE: {rmse_stacking:.4f}, R²: {r2_stacking:.4f}%")
```

```
Stacking Model (LR Meta-Model) - MSE: 7945.5703, RMSE: 89.1379, R²:
93.8871%
```

```
from sklearn.model_selection import RandomizedSearchCV
import numpy as np
import xgboost as xgb
import lightgbm as lgb
import catboost as cb
from sklearn.svm import SVR
from sklearn.ensemble import GradientBoostingRegressor,
StackingRegressor
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

```python
# Define hyperparameter grids for each model
xgb_param_grid = {
    'n_estimators': [100, 200, 300, 400, 500],
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'max_depth': [3, 4, 5, 6, 7],
    'subsample': [0.8, 0.9, 1.0],
    'colsample_bytree': [0.7, 0.8, 0.9, 1.0]
}

lgb_param_grid = {
    'n_estimators': [100, 200, 300, 400, 500],
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'max_depth': [3, 4, 5, 6, 7],
    'num_leaves': [31, 50, 70, 90],
    'subsample': [0.8, 0.9, 1.0]
}

cat_param_grid = {
    'iterations': [100, 200, 300, 400, 500],
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'depth': [6, 7, 8, 9, 10],
    'l2_leaf_reg': [1, 3, 5, 7]
}

svr_param_grid = {
    'C': [0.1, 1, 10, 100],
    'gamma': ['scale', 'auto'],
    'kernel': ['linear', 'rbf', 'poly']
}

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split data
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
test_size=0.2, random_state=21)

# Initialize models
xgb_model = xgb.XGBRegressor(random_state=42)
lgb_model = lgb.LGBMRegressor(random_state=42)
cat_model = cb.CatBoostRegressor(verbose=0, random_seed=42)
svr_model = SVR()

# Hyperparameter tuning using RandomizedSearchCV
xgb_search = RandomizedSearchCV(xgb_model, xgb_param_grid, n_iter=10,
cv=3, verbose=1, random_state=42, n_jobs=-1)
lgb_search = RandomizedSearchCV(lgb_model, lgb_param_grid, n_iter=10,
cv=3, verbose=1, random_state=42, n_jobs=-1)
cat_search = RandomizedSearchCV(cat_model, cat_param_grid, n_iter=10,
```

```
cv=3, verbose=1, random_state=42, n_jobs=-1)
svr_search = RandomizedSearchCV(svr_model, svr_param_grid, n_iter=10,
cv=3, verbose=1, random_state=42, n_jobs=-1)

# Fit the models
xgb_search.fit(X_train, y_train)
lgb_search.fit(X_train, y_train)
cat_search.fit(X_train, y_train)
svr_search.fit(X_train, y_train)

# Print best parameters for each model
print("Best XGBoost Parameters: ", xgb_search.best_params_)
print("Best LightGBM Parameters: ", lgb_search.best_params_)
print("Best CatBoost Parameters: ", cat_search.best_params_)
print("Best SVR Parameters: ", svr_search.best_params_)

# Use the best models from the search
xgb_best = xgb_search.best_estimator_
lgb_best = lgb_search.best_estimator_
cat_best = cat_search.best_estimator_
svr_best = svr_search.best_estimator_

# Define meta-model (GradientBoostingRegressor)
meta_model = GradientBoostingRegressor(n_estimators=200,
learning_rate=0.05, max_depth=6, random_state=42)

# Stacking Model: Combine Base Models and Meta-Model
ensemble_stacking_model = StackingRegressor(
    estimators=[('xgb', xgb_best), ('lgb', lgb_best), ('cat',
cat_best), ('svr', svr_best)],
    final_estimator=meta_model
)

# Fit Ensemble Stacking Model
ensemble_stacking_model.fit(X_train, y_train)

# Predictions and Evaluation
y_pred_ensemble_stacking = ensemble_stacking_model.predict(X_test)

# Calculate MSE and RMSE for the ensemble stacking model
mse_ensemble_stacking = mean_squared_error(y_test,
y_pred_ensemble_stacking)
rmse_ensemble = np.sqrt(mse_ensemble_stacking)

# Calculate R² for the ensemble stacking model
r2_ensemble = ensemble_stacking_model.score(X_test, y_test) * 100

# Print the results for the ensemble stacking model
print(f"Ensemble Stacking Model - MSE: {mse_ensemble_stacking:.4f},
RMSE: {rmse_ensemble:.4f}, R²: {r2_ensemble:.4f}%")
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
Fitting 3 folds for each of 10 candidates, totalling 30 fits
Fitting 3 folds for each of 10 candidates, totalling 30 fits
Fitting 3 folds for each of 10 candidates, totalling 30 fits
Best XGBoost Parameters:  {'subsample': 0.9, 'n_estimators': 500,
'max_depth': 7, 'learning_rate': 0.1, 'colsample_bytree': 1.0}
Best LightGBM Parameters:  {'subsample': 1.0, 'num_leaves': 31,
'n_estimators': 500, 'max_depth': 6, 'learning_rate': 0.2}
Best CatBoost Parameters:  {'learning_rate': 0.1, 'l2_leaf_reg': 1,
'iterations': 400, 'depth': 8}
Best SVR Parameters:  {'kernel': 'rbf', 'gamma': 'auto', 'C': 10}
Ensemble Stacking Model - MSE: 6274.4520, RMSE: 79.2114, R²: 95.1727%
```

```
import matplotlib.pyplot as plt
import numpy as np

# Store RMSE and R² values for the models
models = ['Linear Regression', 'Decision Tree', 'Random Forest',
'Stacking (Base)', 'Ensemble Stacking (Tuned)']
rmse_values = [rmse, rmse_dtr, rmse_rfr,rmse_stacking,rmse_ensemble]
# RMSE for each model
r2_values = [score_lr, r2_score_dtr, r2_score_rfr, r2_stacking,
r2_ensemble]  # R² for each model

# Define the positions for the bars
x = np.arange(len(models))

# Set up the figure and axis
fig, ax1 = plt.subplots(figsize=(10, 6))

# Create bar plot for RMSE
bar_rmse = ax1.bar(x - 0.2, rmse_values, 0.4, label='RMSE',
color='lightblue')

# Create secondary axis for R² (percentage)
ax2 = ax1.twinx()
bar_r2 = ax2.bar(x + 0.2, r2_values, 0.4, label='R²', color='salmon')

# Set the labels for the x-axis, y-axis, and title
ax1.set_xlabel('Models')
ax1.set_ylabel('RMSE', color='blue')
ax2.set_ylabel('R² (%)', color='red')
ax1.set_xticks(x)
ax1.set_xticklabels(models)
ax1.set_title('Comparison of RMSE and R² for Different Models')

# Add legend
ax1.legend(loc='upper left')
ax2.legend(loc='upper right')
```

```python
# Show the plot
plt.tight_layout()
plt.show()
```