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SOLAR PANEL DATA CLASSIFICATION

by

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J Component Report submitted to

Prof. PRIYADARSHINI

School of Computer Science and Engineering

In partial fulfilment of the requirements
for the course of
CSE3505 - FOUNDATIONS OF DATA ANALYTICS

in

B.TECH COMPUTER SCIENCE AND ENGINEERING

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BONAFIDE CERTIFICATE

Certified that the project report for the course "**CSE3505 - Foundations of Data Analytics**" entitled "**Solar Panel Data Classification**" is a bonafide work of **PRIYANKA GYANCHANDANI (20BCE1722)** who carried out the Project work under my supervision and guidance.

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I wish to express my sincere thanks and deep sense of gratitude to my project guide, **Prof PRIYADARSHINI**, for her consistent encouragement and valuable guidance offered to me in a pleasant manner throughout the course of the project work.

I am extremely grateful to **Dr. GANESAN R**, Dean of the School of Computer Science and Engineering (SCOPE), Vellore Institute of Technology, Chennai, for extending the facilities of the school towards our project and for her unstinting support.

I take this opportunity to thank all the faculty of the school for their support and wisdom imparted to me throughout the course.

PRIYANKA GYANCHANDANI
(20BCE1722)
B. TECH COMPUTER SCIENCE AND ENGINEERING

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ABSTRACT

Solar energy cost and data analysis examines technology costs, location-specific competitive advantages, policy impacts on system financing, and detailed levelled cost of energy (LCOE) analyses. It also helps to assess the performance and reliability of solar energy facilities, predict energy output, and increase situational awareness for utility system operators.
Analysis plays an important role in soft costs reduction and advancing domestic manufacturing.
Solar power forecasting is the process of gathering and analyzing data in order to predict solar power generation on various time horizons with the goal to mitigate the impact of solar intermittency. Solar power forecasts are used for efficient management of the electric grid and for power trading.

In this project, The analyses is done by keeping the main focus on the below mentioned areas of concern at the solar power plant -

1. Can we predict the power generation for next couple of days? - this allows for better grid management
2. Can we identify the need for panel cleaning/maintenance?
3. Can we identify faulty or suboptimally performing equipment?

INTRODUCTION

The data has been gathered at two solar power plants in India over a 34 day period. It has two pairs of files - each pair has one power generation dataset and one sensor readings dataset. The power generation datasets are gathered at the inverter level - each inverter has multiple lines of solar panels attached to it. The sensor data is gathered at a plant level - single array of sensors optimally placed at the plant. Few areas of concern at the solar power plant are being solved then.

LITERATURE REVIEW

As energy demands is increasing day by day. Most of the techniques and technology is going to improved to fulfill energy needs. Scientist and researchers are in struggle to utilize the Solar Energy. As the energy from sun deliver to earth in one hour is equal to energy consumed by people in one year. So different types of solar Cells are going to introduced, and lot of improvements and modification is going on in this field. Here in this paper we have discus the basics and some Solar Cells.

In this paper a literature review of different Solar Cells have been presented. From the start to now a lot of improvement has been done in the field of SC. Lot of work is need further to make the technology cheap and with high efficiency. Efficiency of 40% has been achieved. The use of rare and expensive material can be replaced with organic / DSSC as best alternate. The environmental friendly revolution can be made by evolution in Photo Voltaic technology.

Electricity plays an important part in our daily life. In today's modern life is being decorated by many devices. Most of our daily routine work is subjected to these devices. These devices need some energy. Usually energy is in the form of natural gas, Electricity and coal etc. These resources are very finite. By using these resources, some side effects have also been considered. Green House effect is one of the prominent draw back. Global Warming, soil & Water pollution are also observed.

As the population of our planet is increasing day by day, the demand of energy (Electricity) is also increasing. To fulfill our Energy demands, we must have to discover/introduce more resources and ways. For this scientists have utilized

Solar Energy and convert it to electricity. The basic principal of this is photoelectric effect. This effect can be explained as follows.

Literature review by Hafiz Tariq Mehmood Electrical Department, CEME, NUST

Novelty:

The project is scheduled in two generation data of solar power plant.

* Cleaning, refining and pre-processing the datasets.
* With the help of Python as a mainly coding language and its libraries such as Pandas, NumPy, Matplotlib, SciPy etc., data analysis will be performed accordingly.
* Inverters are compared on the basis of total_yield using libraries available in google colab.
* Noting down the observation, confusion(interpretations), analysis on prediction using different ML algorithms and so on.
* On the final note, presenting the final review after the exploration of data analysis of the dataset chosen respectively.

Dataset Specification and Illustration :

*** The power generation datasets are gathered at the inverter level - each**

Inverter has multiple lines of solar panels attached to it.

DATE_TIME Date and time for each observation. Observations recorded at 15 minute intervals.
PLANT_ID Plant ID - this will be common for the entire file.
SOURCE_KEY Source key in this file stands for the inverter id
DC_POWER Amount of DC power generated by the inverter (source_key) in

this 15 minute interval. Units - kW. **AC_POWER** Amount of AC power generated by the inverter (source_key) in this 15 minute interval. Units - kW. **DAILY_YIELD** Daily yield is a cumulative sum of power generated on that day, till that point in time. **TOTAL_YIELD** This is the total yield for the inverter till that point in time.

p1_weather

	DATE_TIME	PLANT_ID	SOURCE_KEY	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE	IRRADIATION
0	2020-05-15 00:00:00	4135001	HmiyD2TTLFNqkNe	25.184316	22.857507	0.0
1	2020-05-15 00:15:00	4135001	HmiyD2TTLFNqkNe	25.084589	22.761668	0.0
2	2020-05-15 00:30:00	4135001	HmiyD2TTLFNqkNe	24.935753	22.592306	0.0
3	2020-05-15 00:45:00	4135001	HmiyD2TTLFNqkNe	24.846130	22.360852	0.0
4	2020-05-15 01:00:00	4135001	HmiyD2TTLFNqkNe	24.621525	22.165423	0.0
...	...	...	...	...	...	...
3177	2020-06-17 22:45:00	4135001	HmiyD2TTLFNqkNe	22.150570	21.480377	0.0
3178	2020-06-17 23:00:00	4135001	HmiyD2TTLFNqkNe	22.129816	21.389024	0.0
3179	2020-06-17 23:15:00	4135001	HmiyD2TTLFNqkNe	22.008275	20.709211	0.0
3180	2020-06-17 23:30:00	4135001	HmiyD2TTLFNqkNe	21.969495	20.734963	0.0
3181	2020-06-17 23:45:00	4135001	HmiyD2TTLFNqkNe	21.909288	20.427972	0.0

3182 rows × 6 columns

The sensor data is gathered at a plant level - single array of sensors optimally placed at the plant.

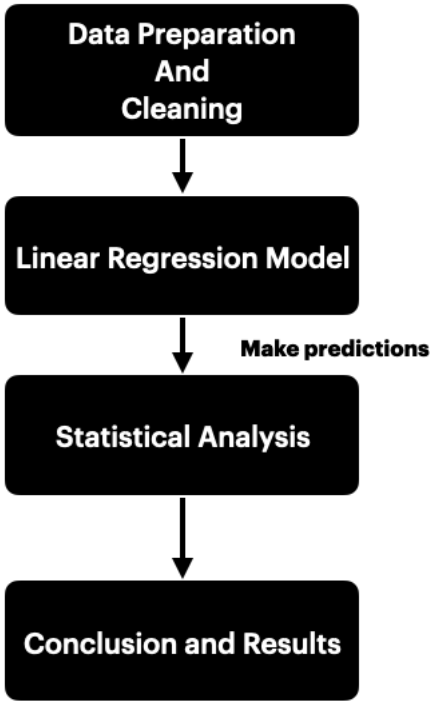
DATE_TIME Date and time for each observation. Observations recorded at 15 minute intervals.
PLANT_ID Plant ID - this will be common for the entire file.
SOURCE_KEY Stands for the sensor panel id. This will be common for the entire file because there's only one sensor panel for the plant.
AMBIENT_TEMPERATURE This is the ambient temperature at the plant.
MODULE_TEMPERATURE There's a module (solar panel) attached to the sensor panel. This is the temperature reading for that module. **IRRADIATION** Amount of irradiation for the 15 minute interval.

p1_generation

	DATE_TIME	PLANT_ID	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD
0	15-05-2020 00:00	4135001	1BY6WEcLGh8j5v7	0.0	0.0	0.000	6259559.0
1	15-05-2020 00:00	4135001	1IF53ai7Xc0U56Y	0.0	0.0	0.000	6183645.0
2	15-05-2020 00:00	4135001	3PZuoBAID5Wc2HD	0.0	0.0	0.000	6987759.0
3	15-05-2020 00:00	4135001	7JYdWkrLSPkdwr4	0.0	0.0	0.000	7602960.0
4	15-05-2020 00:00	4135001	McdE0feGgRqW7Ca	0.0	0.0	0.000	7158964.0
...	...	...	...	...	...	...	...
68773	17-06-2020 23:45	4135001	uHbuxQJl8lW7ozc	0.0	0.0	5967.000	7287002.0
68774	17-06-2020 23:45	4135001	wCURE6d3bPkepu2	0.0	0.0	5147.625	7028601.0
68775	17-06-2020 23:45	4135001	z9Y9gH1T5YWrNuG	0.0	0.0	5819.000	7251204.0
68776	17-06-2020 23:45	4135001	zBIq5rxdHJRwDNY	0.0	0.0	5817.000	6583369.0
68777	17-06-2020 23:45	4135001	zVJPv84UY57bAof	0.0	0.0	5910.000	7363272.0

68778 rows × 7 columns

Design and flow of Model :



IMPLEMENTATION:

* In Jupyter Notebook, import python libraries

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

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

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

* Importing power generation and weather dataset

```
[ ] generation_data = pd.read_csv('/content/Plant_1_Generation_Data.csv')
    weather_data = pd.read_csv('/content/Plant_1_Weather_Sensor_Data.csv')
```

```
generation_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 68778 entries, 0 to 68777
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   DATE_TIME    68778 non-null  object
 1   PLANT_ID     68778 non-null  int64
 2   SOURCE_KEY   68778 non-null  object
 3   DC_POWER     68778 non-null  float64
 4   AC_POWER     68778 non-null  float64
 5   DAILY_YIELD  68778 non-null  float64
 6   TOTAL_YIELD  68778 non-null  float64
dtypes: float64(4), int64(1), object(2)
memory usage: 3.7+ MB
```

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

	DATE_TIME	PLANT_ID	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD
45544	06-06-2020 23:15	4135001	zBIq5rxdHJRwDNY	0.000000	0.000000	0.000000	6506728.000000
55761	11-06-2020 19:30	4135001	YxYtjZvoooNbGkE	0.000000	0.000000	5592.000000	7385279.000000
9804	19-05-2020 20:30	4135001	adLQvlD726eNBSB	0.000000	0.000000	0.000000	6304513.000000
2606	16-05-2020 09:15	4135001	sjndEbLyjtCKgGv	5845.428571	572.800000	1029.571429	7024211.571000
38130	03-06-2020 09:15	4135001	McdE0feGgRqW7Ca	6440.500000	630.887500	977.500000	7301336.500000

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

	DATE_TIME	PLANT_ID	SOURCE_KEY	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE	IRRADIATION
2532	2020-06-11 05:30:00	4135001	HmiyD2TTLFNqkNe	21.764787	20.289380	0.000000
1558	2020-06-01 01:45:00	4135001	HmiyD2TTLFNqkNe	22.151638	20.045486	0.000000
929	2020-05-25 08:15:00	4135001	HmiyD2TTLFNqkNe	24.931500	34.992004	0.444573
911	2020-05-25 03:45:00	4135001	HmiyD2TTLFNqkNe	23.539119	22.201566	0.000000
948	2020-05-25 13:00:00	4135001	HmiyD2TTLFNqkNe	32.788692	60.102559	0.945329

* Adjusting date time format

```
generation_data['DATE'] = pd.to_datetime(generation_data['DATE_TIME']).dt.date
generation_data['TIME'] = pd.to_datetime(generation_data['DATE_TIME']).dt.time
weather_data['DATE'] = pd.to_datetime(weather_data['DATE_TIME']).dt.date
weather_data['TIME'] = pd.to_datetime(weather_data['DATE_TIME']).dt.time
```

```
generation_data.head()
```

	DATE_TIME	PLANT_ID	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD	DATE	TIME
0	15-05-2020 00:00	4135001	1BY6WEcLGh8j5v7	0.0	0.0	0.0	6259559.0	2020-05-15	00:00:00
1	15-05-2020 00:00	4135001	1IF53ai7Xc0U56Y	0.0	0.0	0.0	6183645.0	2020-05-15	00:00:00
2	15-05-2020 00:00	4135001	3PZuoBAID5Wc2HD	0.0	0.0	0.0	6987759.0	2020-05-15	00:00:00
3	15-05-2020 00:00	4135001	7JYdWkrLSPkdwr4	0.0	0.0	0.0	7602960.0	2020-05-15	00:00:00
4	15-05-2020 00:00	4135001	McdE0feGgRqW7Ca	0.0	0.0	0.0	7158964.0	2020-05-15	00:00:00

```
weather_data.head()
```

	DATE_TIME	PLANT_ID	SOURCE_KEY	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE	IRRADIATION	DATE	TIME
0	2020-05-15 00:00:00	4135001	HmiyD2TTLFNqkNe	25.184316	22.857507	0.0	2020-05-15	00:00:00
1	2020-05-15 00:15:00	4135001	HmiyD2TTLFNqkNe	25.084589	22.761668	0.0	2020-05-15	00:15:00
2	2020-05-15 00:30:00	4135001	HmiyD2TTLFNqkNe	24.935753	22.592306	0.0	2020-05-15	00:30:00
3	2020-05-15 00:45:00	4135001	HmiyD2TTLFNqkNe	24.846130	22.360852	0.0	2020-05-15	00:45:00
4	2020-05-15 01:00:00	4135001	HmiyD2TTLFNqkNe	24.621525	22.165423	0.0	2020-05-15	01:00:00

```
del generation_data['DATE_TIME']
del weather_data['DATE_TIME']
```

```
generation_data['DATE_TIME'] = generation_data["DATE"].astype(str) + " " + generation_data["TIME"].astype(str)
```

```
weather_data['DATE_TIME'] = weather_data["DATE"].astype(str) + " " + weather_data["TIME"].astype(str)
```

```
[ ] generation_data['DATE_TIME']
```

```
0        2020-05-15 00:00:00
1        2020-05-15 00:00:00
2        2020-05-15 00:00:00
3        2020-05-15 00:00:00
4        2020-05-15 00:00:00
                ...
68773    2020-06-17 23:45:00
68774    2020-06-17 23:45:00
68775    2020-06-17 23:45:00
68776    2020-06-17 23:45:00
68777    2020-06-17 23:45:00
Name: DATE_TIME, Length: 68778, dtype: object
```

```
gd1=generation_data
del gd1['DATE']
del gd1['TIME']
gd1
```

	PLANT_ID	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD	DATE_TIME
0	4135001	1BY6WEcLGh8j5v7	0.0	0.0	0.000	6259559.0	2020-05-15 00:00:00
1	4135001	1IF53ai7Xc0U56Y	0.0	0.0	0.000	6183645.0	2020-05-15 00:00:00
2	4135001	3PZuoBAID5Wc2HD	0.0	0.0	0.000	6987759.0	2020-05-15 00:00:00
3	4135001	7JYdWkrLSPkdwr4	0.0	0.0	0.000	7602960.0	2020-05-15 00:00:00
4	4135001	McdE0feGgRqW7Ca	0.0	0.0	0.000	7158964.0	2020-05-15 00:00:00
...	...	...	...	...	...	...	...
68773	4135001	uHbuxQJl8lW7ozc	0.0	0.0	5967.000	7287002.0	2020-06-17 23:45:00
68774	4135001	wCURE6d3bPkepu2	0.0	0.0	5147.625	7028601.0	2020-06-17 23:45:00
68775	4135001	z9Y9gH1T5YWrNuG	0.0	0.0	5819.000	7251204.0	2020-06-17 23:45:00
68776	4135001	zBIq5rxdHJRwDNY	0.0	0.0	5817.000	6583369.0	2020-06-17 23:45:00
68777	4135001	zVJPv84UY57bAof	0.0	0.0	5910.000	7363272.0	2020-06-17 23:45:00

68778 rows × 7 columns

```
[ ] gd1['DATE_TIME'] =  pd.to_datetime(gd1['DATE_TIME'], format='%Y-%m-%d')
```

```
[ ] gd1['DATE_TIME'] =  pd.to_datetime(gd1['DATE_TIME'], format='%Y-%m-%d')
```

```
[ ] gd1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 68778 entries, 0 to 68777
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PLANT_ID     68778 non-null  int64
 1   SOURCE_KEY   68778 non-null  object
 2   DC_POWER     68778 non-null  float64
 3   AC_POWER     68778 non-null  float64
 4   DAILY_YIELD  68778 non-null  float64
 5   TOTAL_YIELD  68778 non-null  float64
 6   DATE_TIME    68778 non-null  datetime64[ns]
dtypes: datetime64[ns](1), float64(4), int64(1), object(1)
memory usage: 3.7+ MB
```

```
wd1=weather_data
del wd1['DATE']
del wd1['TIME']
wd1
```

	PLANT_ID	SOURCE_KEY	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE	IRRADIATION	DATE_TIME
0	4135001	HmiyD2TTLFNqkNe	25.184316	22.857507	0.0	2020-05-15 00:00:00
1	4135001	HmiyD2TTLFNqkNe	25.084589	22.761668	0.0	2020-05-15 00:15:00
2	4135001	HmiyD2TTLFNqkNe	24.935753	22.592306	0.0	2020-05-15 00:30:00
3	4135001	HmiyD2TTLFNqkNe	24.846130	22.360852	0.0	2020-05-15 00:45:00
4	4135001	HmiyD2TTLFNqkNe	24.621525	22.165423	0.0	2020-05-15 01:00:00
...	...	...	...	...	...	...
3177	4135001	HmiyD2TTLFNqkNe	22.150570	21.480377	0.0	2020-06-17 22:45:00
3178	4135001	HmiyD2TTLFNqkNe	22.129816	21.389024	0.0	2020-06-17 23:00:00
3179	4135001	HmiyD2TTLFNqkNe	22.008275	20.709211	0.0	2020-06-17 23:15:00
3180	4135001	HmiyD2TTLFNqkNe	21.969495	20.734963	0.0	2020-06-17 23:30:00
3181	4135001	HmiyD2TTLFNqkNe	21.909288	20.427972	0.0	2020-06-17 23:45:00

3182 rows × 6 columns

Converting object date_time into daytime stamping

```
[ ] wd1['DATE_TIME'] =  pd.to_datetime(wd1['DATE_TIME'], format='%Y-%m-%d')
```

```
[ ] wd1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3182 entries, 0 to 3181
Data columns (total 6 columns):
 #   Column               Non-Null Count  Dtype         
---  ------               --------------  -----         
 0   PLANT_ID             3182 non-null   int64         
 1   SOURCE_KEY           3182 non-null   object        
 2   AMBIENT_TEMPERATURE  3182 non-null   float64       
 3   MODULE_TEMPERATURE   3182 non-null   float64       
 4   IRRADIATION          3182 non-null   float64       
 5   DATE_TIME            3182 non-null   datetime64[ns]
dtypes: datetime64[ns](1), float64(3), int64(1), object(1)
memory usage: 149.3+ KB
```

Merging generation data and weather sensor data¶

```
df_solar = pd.merge(gd1.drop(columns = ['PLANT_ID']), wd1.drop(columns = ['PLANT_ID', 'SOURCE_KEY']), on='DATE_TIME')
df_solar.sample(5).style.background_gradient(cmap='cool')
```

	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD	DATE_TIME	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE	IRRADIATION
14446	WRmjgnKYAwPKWDb	10018.285710	979.557143	6141.714286	7083499.714000	2020-05-22 14:45:00	32.801117	56.020087	0.779872
37109	ZoEaEvLYb1n2sOq	0.000000	0.000000	8378.000000	7315763.000000	2020-06-13 22:00:00	22.700739	20.306745	0.000000
15423	bvBOhCH3iADSZry	0.000000	0.000000	0.000000	6368908.000000	2020-05-23 02:45:00	21.891612	20.528487	0.000000
38734	WRmjgnKYAwPKWDb	2845.428571	279.342857	7175.714286	7254354.714000	2020-06-14 16:30:00	26.423556	32.757710	0.199226
1025	bvBOhCH3iADSZry	8394.428571	821.228571	2185.142857	6318988.143000	2020-05-15 11:45:00	30.811049	47.836383	0.467987

Adding separate time and date columns¶

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)
```

	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD	DATE_TIME	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE	IRRADIATION	DATE	TIME	DAY	MONTH	WEE
0	1BY6WEcLGh8j5v7	0.0	0.0	0.0	6259559.0	2020-05-15	25.184316	22.857507	0.0	2020-05-15	00:00:00	15	5	2
1	1IF53ai7Xc0U56Y	0.0	0.0	0.0	6183645.0	2020-05-15	25.184316	22.857507	0.0	2020-05-15	00:00:00	15	5	2

```
df_solar.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 45680 entries, 0 to 45679
Data columns (total 18 columns):
 #   Column               Non-Null Count  Dtype         
---  ------               --------------  -----         
 0   SOURCE_KEY           45680 non-null  object        
 1   DC_POWER             45680 non-null  float64       
 2   AC_POWER             45680 non-null  float64       
 3   DAILY_YIELD          45680 non-null  float64       
 4   TOTAL_YIELD          45680 non-null  float64       
 5   DATE_TIME            45680 non-null  datetime64[ns]
 6   AMBIENT_TEMPERATURE  45680 non-null  float64       
 7   MODULE_TEMPERATURE   45680 non-null  float64       
 8   IRRADIATION          45680 non-null  float64       
 9   DATE                 45680 non-null  object        
 10  TIME                 45680 non-null  object        
 11  DAY                  45680 non-null  int64         
 12  MONTH                45680 non-null  int64         
 13  WEEK                 45680 non-null  int64         
 14  HOURS                45680 non-null  object        
 15  MINUTES              45680 non-null  int64         
 16  TOTAL MINUTES PASS   45680 non-null  int64         
 17  DATE_STRING          45680 non-null  object        
dtypes: datetime64[ns](1), float64(7), int64(5), object(5)
memory usage: 6.6+ MB
```

finding null values

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

```
SOURCE_KEY              0
DC_POWER                0
AC_POWER                0
DAILY_YIELD             0
TOTAL_YIELD             0
DATE_TIME               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')
```

	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE	IRRADIATION	DAY	MONTH	WEEK	MINUTES	TOTAL MINUTES PASS
count	45680.000000	45680.000000	45680.000000	45680.000000	45680.000000	45680.000000	45680.000000	45680.000000	45680.000000	45680.000000	45680.000000	45680.000000
mean	3197.175971	312.652679	3313.146538	6957007.021147	25.917168	31.877975	0.236834	20.414317	5.275131	22.090543	22.484895	719.701182
std	4080.448523	398.668968	3156.100252	417238.643557	3.556550	12.638448	0.306316	6.258661	0.446585	1.568935	16.777147	410.155042
min	0.000000	0.000000	0.000000	6183645.000000	20.398505	18.140415	0.000000	6.000000	5.000000	20.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	6512357.875000	22.930031	21.406390	0.000000	16.000000	5.000000	21.000000	0.000000	375.000000
50%	464.196429	44.912500	2653.633928	7115710.714000	24.993020	25.379072	0.035266	20.000000	5.000000	22.000000	15.000000	720.000000
75%	6478.424107	634.481250	6318.000000	7244521.410750	28.379008	42.757119	0.459503	26.000000	6.000000	23.000000	30.000000	1065.000000
max	14471.125000	1410.950000	9163.000000	7846821.000000	35.252486	65.545714	1.221652	31.000000	6.000000	25.000000	45.000000	1425.000000

Converting 'SOURCE_KEY' from categorical form to numerical form

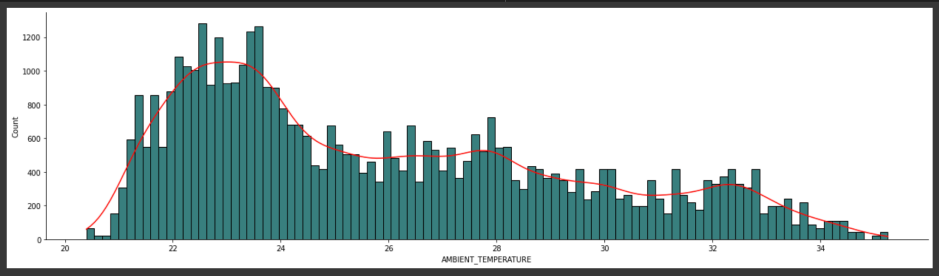
```
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
df_solar['SOURCE_KEY_NUMBER'] = encoder.fit_transform(df_solar['SOURCE_KEY'])
df_solar.head()
```

[ ]

	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD	DATE_TIME	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE	IRRADIATION	DATE	TIME	DAY	MONTH	WEEK	HOURS	MINUTES	TOTAL MINUTES PASS	DATE_STRING	SOU
0	1BY6WEcLGh8j5v7	0.0	0.0	0.0	6259559.0	2020-05-15	25.184316	22.857507	0.0	2020-05-15	00:00:00	15	5	20	0	0	0	2020-05-15	
1	1IF53ai7Xc0U56Y	0.0	0.0	0.0	6183645.0	2020-05-15	25.184316	22.857507	0.0	2020-05-15	00:00:00	15	5	20	0	0	0	2020-05-15	
2	3PZuoBAID5Wc2HD	0.0	0.0	0.0	6987759.0	2020-05-15	25.184316	22.857507	0.0	2020-05-15	00:00:00	15	5	20	0	0	0	2020-05-15	
3	7JYdWkrLSPkdwr4	0.0	0.0	0.0	7602960.0	2020-05-15	25.184316	22.857507	0.0	2020-05-15	00:00:00	15	5	20	0	0	0	2020-05-15	
4	McdE0feGgRqW7Ca	0.0	0.0	0.0	7158964.0	2020-05-15	25.184316	22.857507	0.0	2020-05-15	00:00:00	15	5	20	0	0	0	2020-05-15	

Data Visualization¶

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

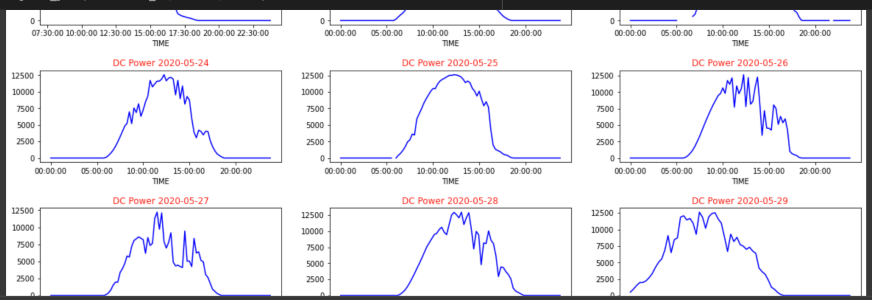


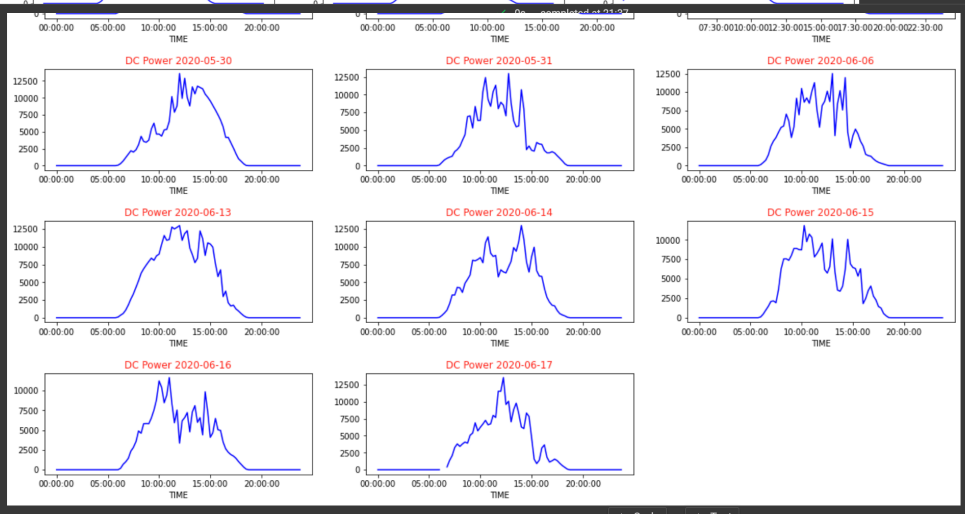

```
[ ] df_solar['DATE'].nunique()
```

```
23
```

The data of solar power generation is of 23 days Faults & Abnormalities detection in solar power plant generation Multiple Plotting of DC_POWER generation on per day basis.

```
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='blue')
        ax.set_title('{} {}'.format(title, cols[i-1]),color='red')

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





+ Code + Text

above per day DC_POWER generation graph shows that there is a some fluctuation in the Solar power generation.

Less Fluctuation in DC_POWER generation is observed in the below mentioned days.

above per day DC_POWER generation graph shows that there is a some fluctuation in the Solar power generation.

Less Fluctuation in DC_POWER generation is observed in the below mentioned days.

```
2020-05-15
2020-05-18
2020-05-22
2020-05-23
2020-05-24
2020-05-25
2020-05-26
```

High Fluctuation in DC_POWER generation is observed in the below mentioned days.

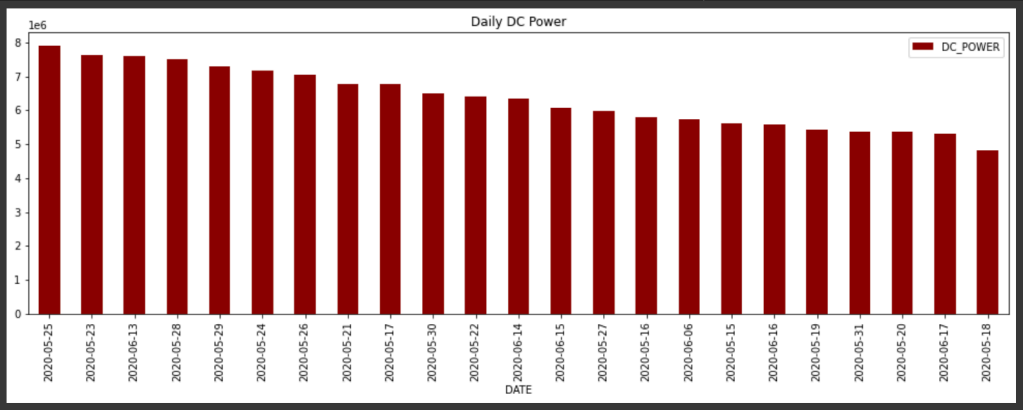
```
2020-05-19
2020-05-28
2020-05-29
2020-06-02
2020-06-03
2020-06-04
2020-06-13
2020-06-14
2020-06-17
```

Very High Fluctuation & Reduction in DC_POWER generation is observed in in the below mentioned days.

```
2020-06-03
2020-06-11
2020-06-12
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

```
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='darkred')
plt.title('Daily DC Power')
plt.show()
```



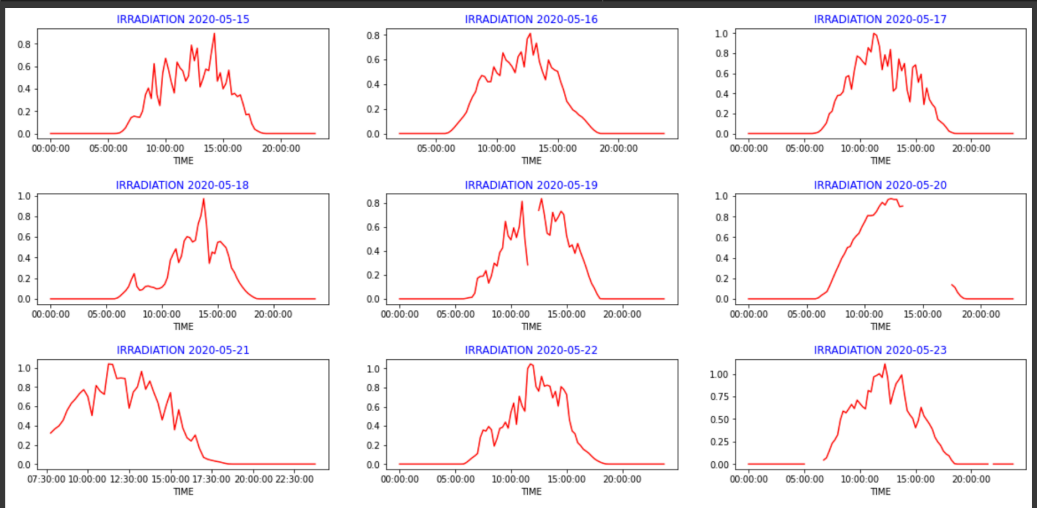
Form the per day DC_POWER generation graph we can find the average power generation per day

Highest average DC_POWER Generation is on: 2020-05-25

Lowest average DC_POWER Generation is on : 2020-05-18

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. Multiple Plotting of IRRADIATION generation on per day basis.

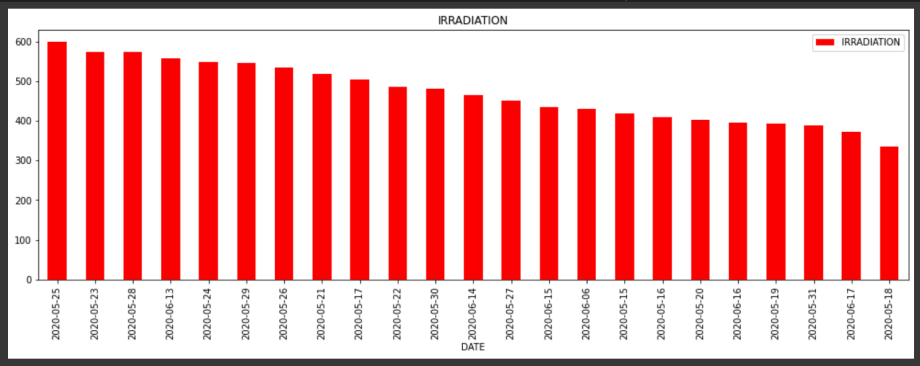
```
solar_irradiation = df_solar.pivot_table(values='IRRADIATION', index='TIME', columns='DATE')

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='red')
        ax.set_title('{} {}'.format(title, cols[i-1]),color='blue')

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



— for full analysis of graphs refer references —

In solar power plant DC_POWER or Output power mostly depends on the IRRADIATION received from the sun .Or it is not wrong to say that generation is directly proportional to IRRADIATION.

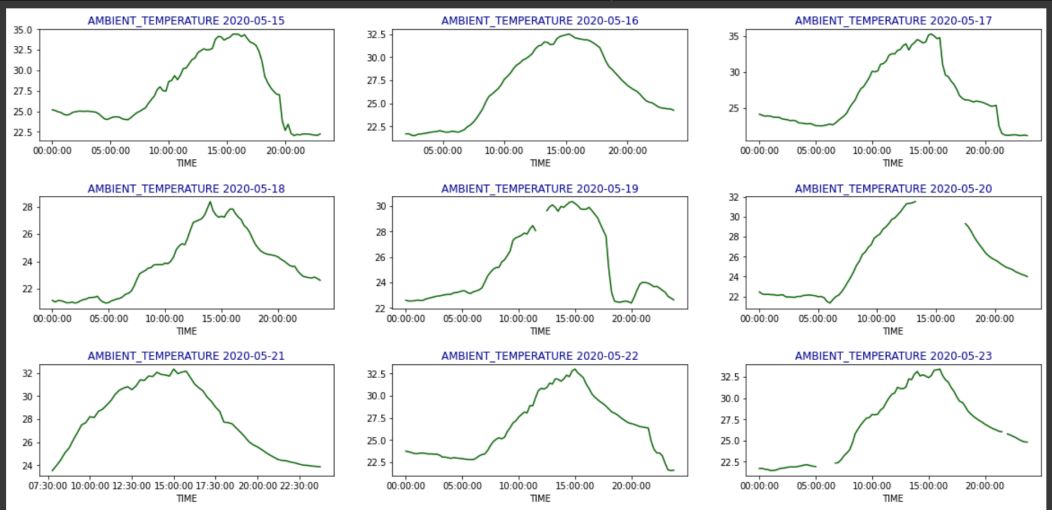
```
daily_irradiation = df_solar.groupby('DATE')['IRRADIATION'].agg('sum')

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



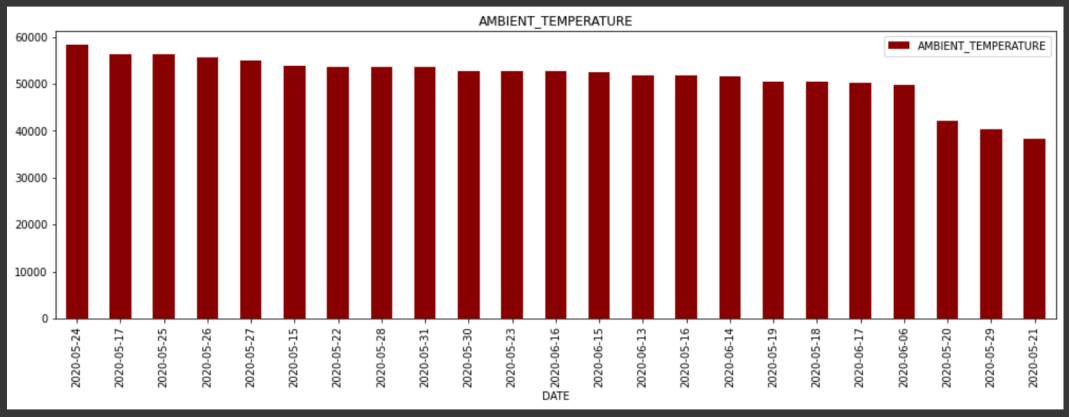
Form the per day IRRADIATION graph we can find the average IRREDIATION per day. Highest average IRRADIATION is on: 2020-05-25

Lowest average IRRADIATION is on : 2020-05-18

```
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='darkblue')

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



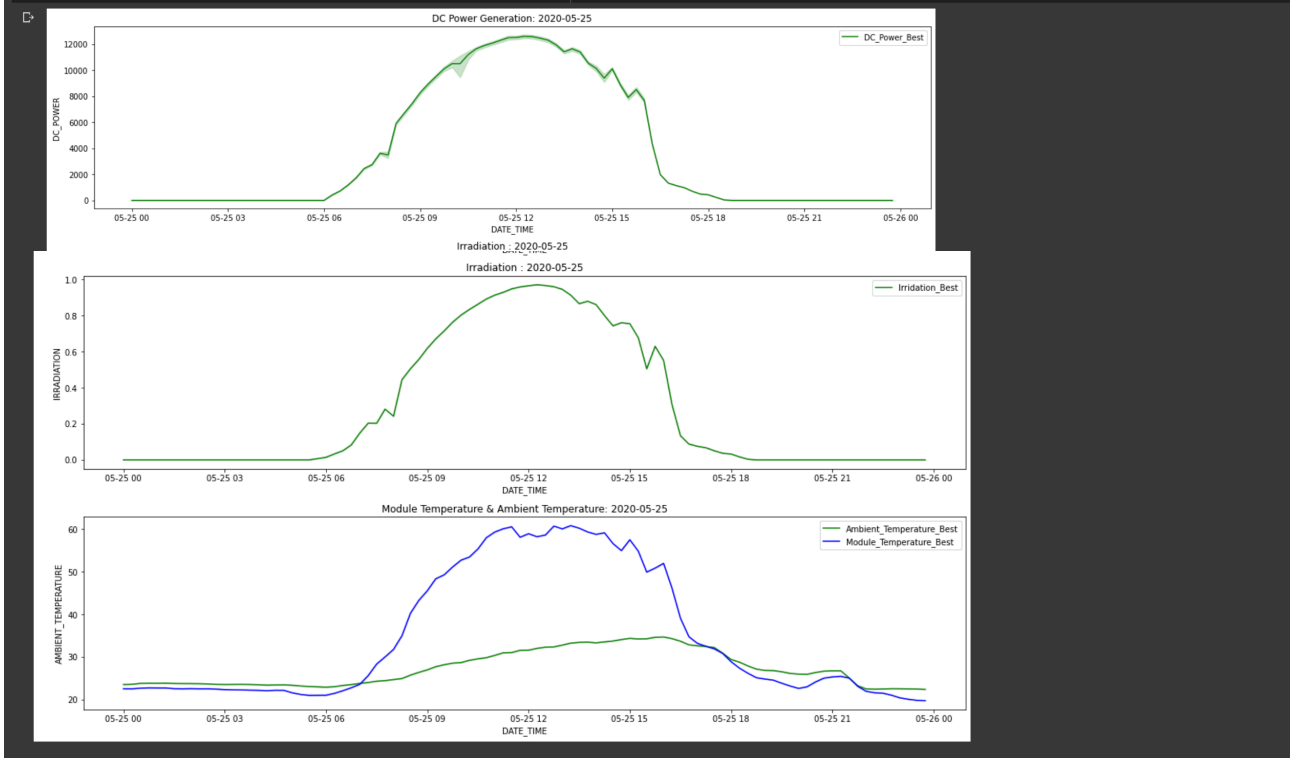

```
daily_ambient_temp = df_solar.groupby('DATE')['AMBIENT_TEMPERATURE'].agg('sum')

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



Comparision between Best and Worst Power generation¶

Highest average DC_POWER is generated on "2020-05-25"

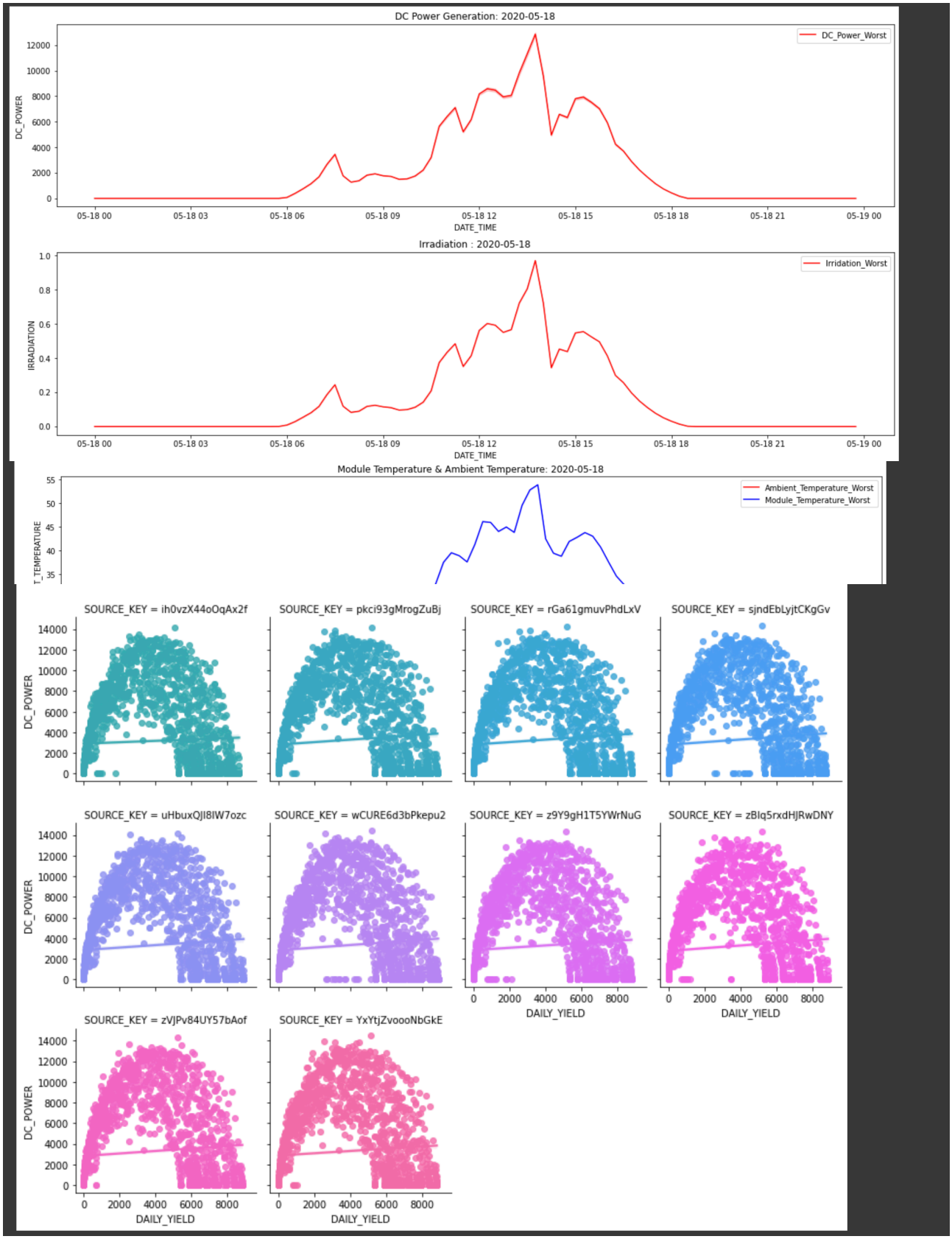
```
plt.figure(figsize=(16,16))

date=["2020-05-25"]

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()
```



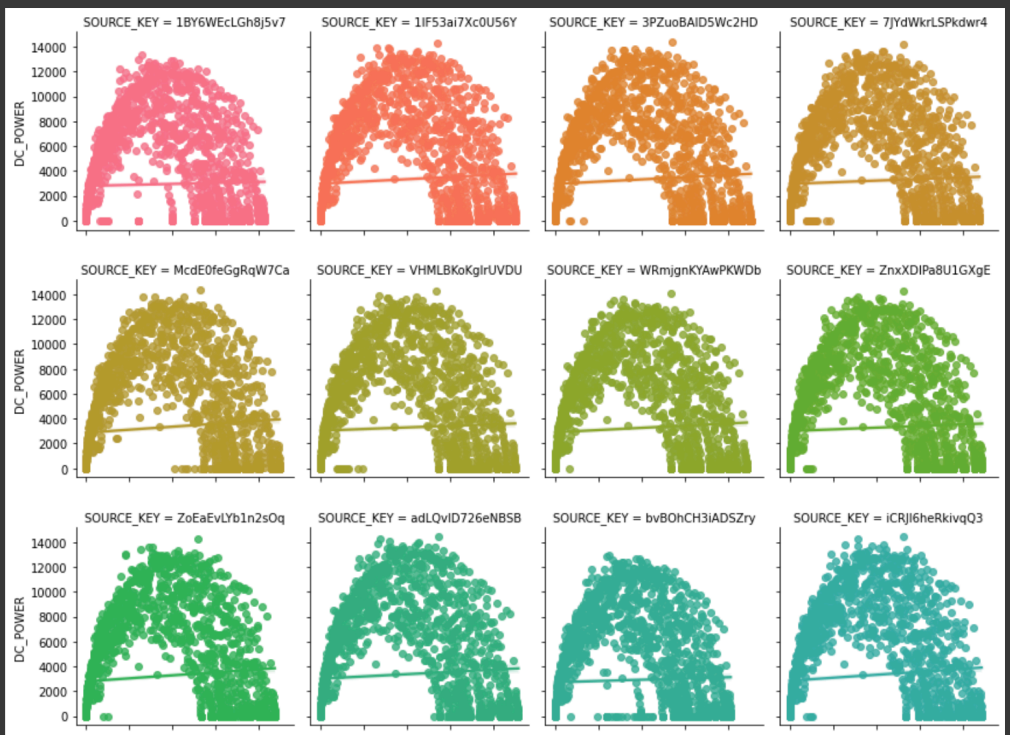
Both DC_POWER graph and IRRADIATION graph is almost looking like an ideal graph. Weather is also looking good, and there is no cloud is in the sky because there is very less variation in IRRADIATION and temperature of the solar panel and ambient temperature.

Lowest average DC_POWER is generated on "2020-06-18"

```
date=["2020-05-18"]
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()
```


DC Power Generation: 2020-05-18
DC_Power_Worst
DC_POWER
DATE_TIME
Irradiation : 2020-05-18
Irridation_Worst
IRRADIATION
DATE_TIME
Module Temperature & Ambient Temperature: 2020-05-18
Ambient_Temperature_Worst
Module_Temperature_Worst
T_TEMPERATURE
SOURCE_KEY = ih0vzX44oOqAx2f
SOURCE_KEY = pkci93gMrogZuBj
SOURCE_KEY = rGa61gmuvPhdLxV
SOURCE_KEY = sjndEbLyjtCKgGv
SOURCE_KEY = uHbuxQJl8lW7ozc
SOURCE_KEY = wCURE6d3bPkepu2
SOURCE_KEY = z9Y9gH1T5YWrNuG
SOURCE_KEY = zBIq5rxdHJRwDNY
SOURCE_KEY = zVJPv84UY57bAof
SOURCE_KEY = YxYtjZvoooNbGkE
DC_POWER
DAILY_YIELD

```
sns.lmplot(y="DC_POWER",x="DAILY_YIELD",hue="SOURCE_KEY",col="SOURCE_KEY",height=3,col_wrap=4,data=df_solar,fit_reg=True);
```



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.

Solar Power Plant Inverter Efficiency Calculation

```
[ ] 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_dc_power.max()
```

```
14471.125
```

```
[ ] solar_ac_power.max()
```

```
1410.95
```

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

```
Power conversion Efficiency ratio AC/DC of Solar Power Plant:  9.750 %
```

Power conversion Efficiency ratio AC/DC of Solar Power Plant: 9.750 %

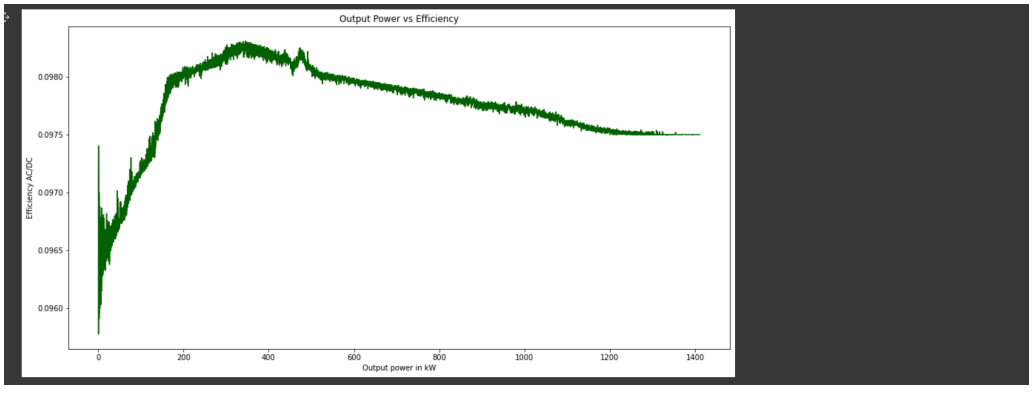
```
AC_list=[]
for i in df_solar['AC_POWER']:
    if i>0:
        AC_list.append(i)
AC_list
#AC_list.sort()
#AC_list.reverse()
len(AC_list)
```

```
24620
```

```
[ ] #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)
```

```
24620
```

```
plt.figure(figsize=(16,8))
AC_list.sort()
DC_list.sort()
eff = [i/j for i,j in zip(AC_list,DC_list)]

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



Solar Power

Prediction using different ML Techniques:

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

if required we can check the values in X and y by passing the command X.head() and y.head()

```
[ ] 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. Linear Regression

```
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%
```

```
[ ] 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. Random Forest Regressor

```
[ ] from sklearn.ensemble import RandomForestRegressor
    rfr = RandomForestRegressor()
    rfr.fit(X_train,y_train)
    y_pred_rfr = lr.predict(X_test)
    R2_Score_rfr = r                    ore(y_pred_rfr,y_test) * 100, 2)

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

Add code cell
⌘/Ctrl+M B

```
R2 Score :  100.0 %
```

3. Decision Tree Regressor

```
[ ] 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 %
```

Accuracy and Results:

```
[ ] forecast_prediction = rfr.predict(X_test)
    print(forecast_prediction)
```

```
[  0.         186.26655357 970.50189286 ...   0.           0.
 363.04508929]
```

```
[ ] cross_check = pd.DataFrame({'Actual' : y_test , 'Predicted' : forecast_prediction})
    cross_check.head()
```

	Actual	Predicted
39704	0.000000	0.000000
16578	186.325000	186.266554
38467	971.014286	970.501893
19471	0.000000	0.000000
21836	0.000000	0.000000

```
cross_check['Error'] = cross_check['Actual'] - cross_check['Predicted']
cross_check.head()
```

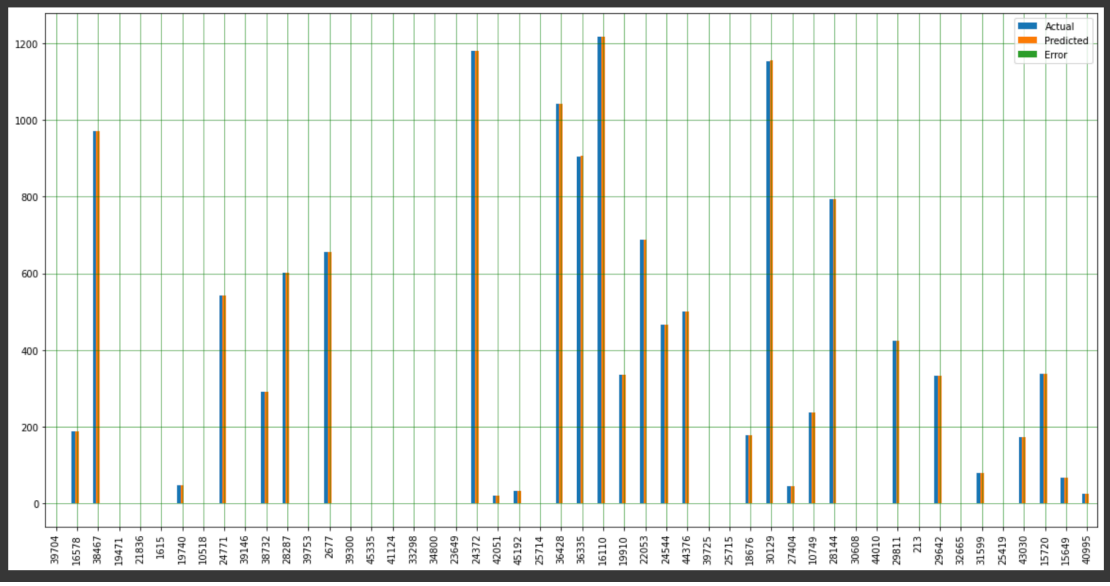
	Actual	Predicted	Error
39704	0.000000	0.000000	0.000000
16578	186.325000	186.266554	0.058446
38467	971.014286	970.501893	0.512393
19471	0.000000	0.000000	0.000000
21836	0.000000	0.000000	0.000000

```
cross_check_final  = cross_check[cross_check['Error'] <= 20]
cross_check_final.sample(25).style.background_gradient(
        cmap='coolwarm').set_properties(**{
            'font-family': 'Times',
            'color': 'LigntGreen',
            'font-size': '13px'
        })
```

	Actual	Predicted	Error
25850	0.000000	0.000000	0.000000
21825	0.000000	0.000000	0.000000
35288	0.000000	0.000000	0.000000
20403	1148.857143	1149.553625	-0.696482
859	517.050000	518.177071	-1.127071
2260	0.000000	0.000000	0.000000
15286	0.000000	0.000000	0.000000
44033	0.000000	0.000000	0.000000
6663	341.957143	341.993089	-0.035946
18472	626.971429	627.057232	-0.085804
41428	0.000000	0.000000	0.000000
14340	1086.675000	1086.906714	-0.231714
26456	1221.814286	1222.019054	-0.204768
36121	977.325000	977.493839	-0.168839
19155	0.000000	0.000000	0.000000
31527	0.000000	0.000000	0.000000
1814	0.000000	0.000000	0.000000
20149	1132.400000	1132.102768	0.297232
42474	1032.750000	1031.683304	1.066696
40175	752.457143	752.375286	0.081857
27098	0.000000	0.000000	0.000000
7918	0.000000	0.000000	0.000000
3027	662.228571	661.956339	0.272232
1964	0.000000	0.000000	0.000000
8383	0.000000	0.000000	0.000000

```
# Visualizing the differences between actual prices and predicted values
plt.scatter(y_test,forecast_prediction)
plt.xlabel("Prices")
plt.ylabel("Predicted prices")
plt.title("Prices vs Predicted prices")
plt.show()
```

```
df3 = cross_check.head(50)
df3.plot(kind='bar',figsize=(20,10))
plt.grid(which='major', linestyle='-', linewidth='0.5',color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5',color='black')
plt.show()
```



Conclusion:

The reason for the reduction in Ambient temperature worst 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

Power conversion Efficiency ratio AC/DC of Solar Power Plant: 9.750 %

With different ML Algorithms, solar power prediction is done where in R2 score came as 100%.
In actual and predicted results, max error is 1.066 which makes our solar panel data classification and forecast analysis a success project.

Future Scope:

The project is useful and is demanding to analyse the Generation of solar energy which has tremendous scope in India. The geographical location of the country stands to its benefit for generating solar energy. The reason being India is a tropical country and it receives solar radiation almost throughout the year, which amounts to 3,000 hours of sunshine. This is equal to

more than 5,000 trillion kWh. Almost, all parts of India receive 4-7 kWh of solar radiation per sq metres. This is equivalent to 2,300–3,200 sunshine hours per year. States like Andhra Pradesh, Bihar, Gujarat, Haryana, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, and West Bengal have great potential for tapping solar energy due to their location. Since majority of the population live in rural areas, there is much scope for solar energy being promoted in these areas. Use of solar energy can reduce the use of firewood and dung cakes by rural household. Many large projects have been proposed in India, some of them are: i).Thar Desert of India has best solar power projects, estimated to generate 700 to 2,100 GW, ii). The Jawaharlal Nehru National Solar Mission (JNNSM) launched by the Centre is targeting 20,000 MW of solar energy power by 2022, iii).Gujarat's pioneering solar power policy aims at 1,000 MW of solar energy generation, and Rs. 130 billion solar power plan was unveiled in July 2009, which projected to produce 20 GW of solar power by 2020. Apart from above, about 66 MW is installed for various applications in the rural area, amounting to be used in solar lanterns, street lighting systems and solar water pumps, etc. Thus, India has massive plan for Solar Energy generation that may not only fulfill the deficit of power generation but also contribute largely in Green Energy Production to help to reduce the Climatic Changes globally.

References:

https://www.kaggle.com/datasets/anikannal/solar-power-generation-data

https://www.researchgate.net/publication/270476484_Literature_Review_Article_for_Solar_Cell

Publicity:

(Github link)

https://github.com/priyanka-gyan/Solar-Panel-Data-Classification.git