DIVE INTO CODE

# MACHINE LEARNING GRADUATION ASSIGNMENT

# PROJECT

# ELECTRICITY POWER CONSUMPTION

THE CODE LINK FOR MY PROJECT

https://github.com/Mosesalieubangura/Github-code-url.git

# SELF INTRODUCTION

| | |
|---|---|
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| DEPARTMENT: | COMPUTER SCIENCE |
| LEVEL: | YEAR 3 |
| COURSE: | DIVE INTO CODE (DIC) |
| PROJECT: | ELECTRICITY POWER CONSUMPTION |

# Electricity Power Consumption

Electricity power consumption has been growing rapidly in spite of serious supply constraints caused by delays in implementing new capacity additions, lower utilization of existing capacity due to maintenance problems, coal and oil availability, and draught conditions (in 1979-80), which simultaneously reduced hydro energy availability and increased agricultural demand for lift irrigation.

# Energy Consumption in Sierra Leone

The most important measure in the energy balance of Sierra Leone is the total consumption of 279.00 m kWh of electric energy per year. Per capita this is an average of **35 kWh**.

Sierra Leone can provide itself completely with self-produced energy. The total production of all electric energy producing facilities is 300 m kWh, also 108% of own requirements. The rest of the self-produced energy is either exported into other countries or unused. Along with pure consumptions the production, imports and exports play an important role. Other energy sources such as natural gas or crude oil are also used.

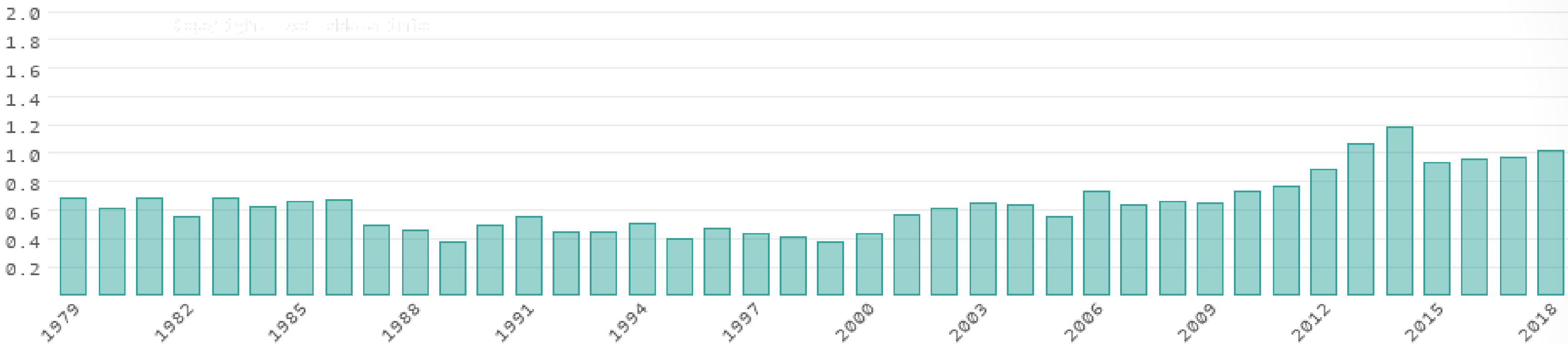
## Energy Balance

| Electricity | total | Sierra Leone per capita | USA per capita |
|---|---|---|---|
| Own consumption | 279.00 m kWh | 34.98 kWh | 11,842.76 kWh |
| Production | 300.00 m kWh | 37.61 kWh | 12,428.52 kWh |

# CARBON FOOTPRINT

| | CO2 emissions in 2018 | Sierra Leone per capita | USA per capita total |
|---|---|---|---|
| Total | 1.02 m t | 0.13 t | 15.12 t |

## Development of CO2 emissions from 1979 to 2018 in million tons




## Production capacities per energy source

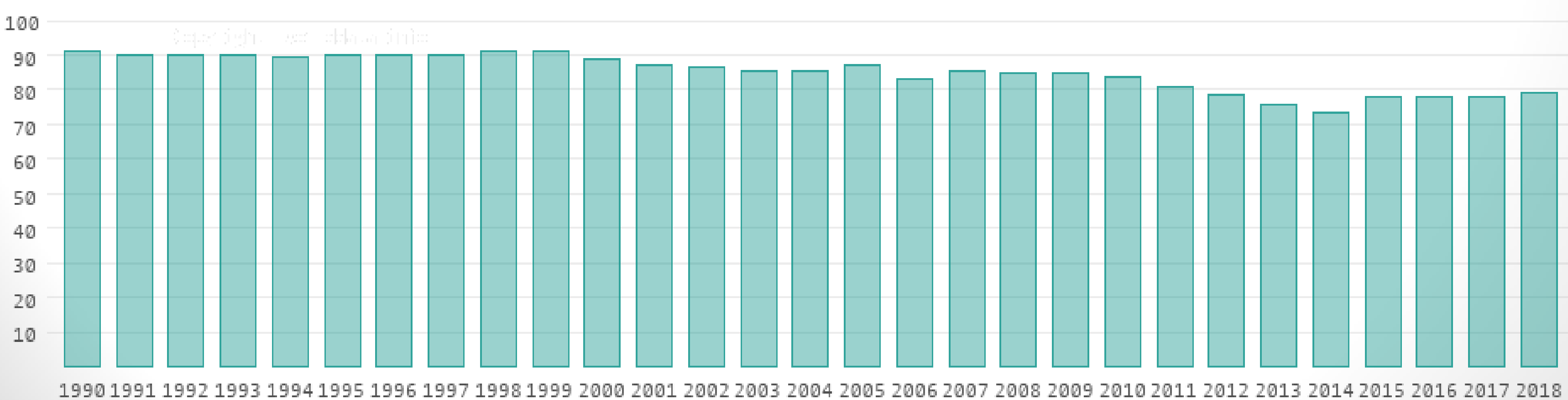
The given production capacities for electric energy have a theoretical value, which could only be obtainable under ideal conditions. They are measuring the generatable amount of energy, that would be reached under permanent and full use of all capacities of all power plants. In practice this isn't possible, because e.g. solar collectors are less efficient unter clouds. Also wind- and water-power plants are not always operating under full load. All these values are only useful in relation to other energy sources or countries.

| Energy source | total in Sierra Leone | percentage in Sierra Leone | percentage USA | per capita in Sierra Leone | per capita USA |
|---|---|---|---|---|---|
| Fossil fuels | 228.28 m kWh | 23,0 % | 70,0 % | 28.62 kWh | 20,230.06 kWh |
| Nuclear power | 0.00 kWh | 0,0 % | 9,0 % | 0.00 kWh | 2,601.01 kWh |
| Water power | 506.18 m kWh | 51,0 % | 7,0 % | 63.45 kWh | 2,023.01 kWh |
| Renewable energy | 258.05 m kWh | 26,0 % | 14,0 % | 32.35 kWh | 4,046.01 kWh |
| Total production capacity | 992.51 m kWh | 100,0 % | 100,0 % | 124.42 kWh | 28,900.09 kWh |
| Actual total production | 300.00 m kWh | 30.2 % | 43.0 % | 37.61 kWh | 12,428.52 kWh |

# Usage of renewable energies

Renewable energies include wind, solar, biomass and geothermal energy sources. This means all energy sources that renew themselves within a short time or are permanently available. Energy from hydropower is only partly a renewable energy. This is certainly the case with river or tidal power plants. Otherwise, numerous dams or reservoirs also produce mixed forms, e.g. by pumping water into their reservoirs at night and recovering energy from them during the day when there is an increased demand for electricity. Since it is not possible to clearly determine the amount of generated energy, all energies from hydropower are displayed separately.

In 2018, renewable energies accounted for around 79.6 percent of actual total consumption in Sierra Leone. The following chart shows the percentage share from 1990 to 2018:



# Power Consumption in Sierra Leone

Sierra Leone consumed **13,386,542,000 BTU** (0.01 quadrillion BTU) of energy in 2017.
This represents **0.00%** of global energy consumption.
Sierra Leone **produced 1,234,542,000 BTU** (0.00 quadrillion BTU) of energy, covering **9%** of its annual energy consumption needs.

NON RENEWABLE (FOSSIL FUELS)
Power Consumption
**94%**
**12,576,000,000BTU**

**Oil: 12,576,000,000 BTU (94%)**
Oil Reserves,Years left,Production,Consumption,Imports/Exports

**Gas: 0 BTU (0%)**
Natural Gas Reserves,Years left,Production,Consumption,Imports/Exports

**Coal: 0 BTU (0%)**
-Reserves,Years left,Production,Consumption,Imports/Exports

RENEWABLE AND NUCLEAR
Power Consumption
**6%**
**1,234,542,000**

# Energy Situation / Statistics

Energy statistics are difficult to obtain in Sierra Leone, especially for renewable energy. Although the conventional thermal energy production and consumption patterns have been reported, no consolidated set of statistics exists for the total Energy situation of Sierra Leone.

This is also reflected in international reports, such as the "Renewable Energy Statistics 2017" report by IRENA, where the solar power capacity for Sierra Leone is claimed to be 0MW.

# Overall Energy Use

- 80% Biomass (mainly for cooking): Wood and Charcoal
- 13% Petroleum products (mainly for transport, lighting and private energy generation, all petroleum is imported)
- Grid connected energy accounts for the remaining energy
- Most of the energy is used in households

| | Biomass | | | | |
|---|---|---|---|---|---|
| Sector | Fuelwood | Charcoal | Petroleum Products | Electricity (Grid Connected) (Thermal, Hydro etc.) | Total % |
| Agriculture, Forestry, Fishing | 1% | - | 5% | 2% | 2% |
| Mining | - | - | 9% | 1% | 2.5% |
| Industry/Commercial | 3% | 10% | 12% | 60% | 21% |
| Transport | - | - | 49% | - | 12% |
| Household/Residents | 96% | 90% | 25% | 37% | 62.5% |
| Total | 100% | 100% | 100% | 100% | 100% |

Source: Ministry of Agriculture and Food Security (2012), PMU (2012), MEWR and NPA-BKPS (2012).

# RENEWABLE ENERGY

The country possesses vast potential in renewable energy in the form of biomass from agricultural wastes, hydro and solar power, which remain virtually untapped.”[2]
According to the“Renewable Energy Statistics 2017” report by IRENAis a total capacity of 88 MW of Renewable Energy in the country, of which 56 MW are Hydro Power and 33 MW Bioenergy. However, as lined out above, data are incomplete. For example, Solar Energy is not included in the statistics.
According to the Ministry of Energy, the share of Renewables was 78,4% in 2013.

# HYDRO POWER

In Sierra Leone, hydropower is a major energy source, holding great promise for a country which possesses several rivers that could be exploited for electricity.
According to the German Bundesministerium für Wirtschaft und Energie, there is potential for 2.000MW of hydro power. Faktsheet Republik Sierra Leone. According to the German Bundesministerium für Wirtschaft und Energie, there is potential for 2.000MW of hydro power.Faktsheet Republik Sierra Leoneoptimistic studies are the Power Sector Master Plan (1996), identifiying 27 potential hydropower sites with a total capacity of 1,513 MW. And a study conducted by UNIDO (Hydropower Potentials in Sierra Leone, UNIDO, 2013) that estimates hydropower potentials to about 5,000 MW covering 300 sites nationwide.

# SOLAR ENERGY

In February 2017 Sierra Leone was the first African country to sign the "Energy Africa Policy Compact" with the Government of the UK. As part of the compact, the Energy Revolution initiative was launched, committing to reach 250.000 households with modern energy solutions by 2018. A task force was established and within government and private sector the focus shifted notably to renewable energy, especially solar energy.

# BIOMASS

Energy consumption in Sierra Leone is dominated by biomass, which accounts for over 80% of energy used. The largest source of biomass energy is wood fuel followed by charcoal[5], while the use of agricultural crop residues and bagasse in the sugar industry remains limited. In addition, there is considerable potential (without impacting on food production) to produce bio-fuels from energy crops such as maize and cassava, and processing of charcoal into biochar.

## WIND ENERGY

Sierra Leone's best wind velocities indicate a country-wide average of between 3 m/s and 5 m/s, increasing to approximately 8 m/s in some mountainous areas (Metrological Statistics, 2012). There is some indication that wind speeds of 12 m/s are possible in parts of the country, implying that wind energy could be a viable option in selected locations. Wind farms are for instance possible at certain locations such as along the coast line, at sea near the coast line and at some locations in the country.

With the low wind speed turbines now available in the market, there is a strong potential for the use of these systems in the rural areas especially in the north of the country. There is a known wind energy system of 5kw in Sierra Leone, located in the Bonthe District, along the south coastline area.

## POLICY FRAMEWORK, LAWS AND REGULATIONS

The main recently ratified laws, regulations and compacts, concerning the Energy Sector, with a focus on Renewables at a glimpse are:

- The„National Electricity Act 2011"one of the biggest recent changes in the Electricity Sector in Sierra Leone, unbundling the vertically integrated National Power Authority, that was created by an Act of Parliament in 1982, into two entities, the Electricity Generation and Transmission Company (EGTC) and the Electricity Distribution and Supply Authority (EDSA). Furthermore, trough the Electricity and Water Regulatory Act 2011, a regulatory body, the Energy and Water Regulatory Commission was established.
- The Sustainable Energy for All (SE4ALL) Action Agenda for Sierra Leone. The Action Agenda was part of an 2014 agreement of ECOWAS member states, that agreed on the development of National Renewable Energy Action Plans (NREAPs) and SE4ALL Agendas. In its agendas, Sierra Leone outlined goals, such as the electrification of all district headquarter towns, increased installed power capacity, 1.229MW in 2030, increased access to Renewable off-grid solutions, but also objectives such as increased access to improved cooking technologies or improved charcoal production. The goals are outlined for 2020 and 2030 respectively.
- TheEnergy Africa Policy Compact. In February 2016, Sierra Leone was the first African country to sign the Energy Africa Policy Compact with the Government of the UK. As a result, the Government of Sierra Leone launched the Energy Revolution, a government-led initiative to promote the solar home system market with activities in the areas of Demand Creation, Technical Assistance for Businesses, Policy Reform and Access to Finance. The initiative is committing to reach 250,000 households with modern solar solutions by 2018 and achieve 'Power for All' by 2025. A DFID financedPower for All Campaignlaunched and a "Energy Task Force Meeting" established.
- TheFinance Act, 2017.pdf 2017 Finance ActDuty Waivers for imported solar products that fulfill IEC Standards. In practice, it is difficult for private companies to impose the measures, due to unclear administrative processes and long delays.
- TheEnergy policy of SL_FINAL for Print.pdf Renewable Energy Policy of Sierra LeonetheEnergy Efficiency Policy of Sierra Leone, ratified by the Parliament in 2016 and launched in 2018, outlining the status of Renewable Energy in the country and objectives and measurements in the sector.
- In August 2017 the Millenium Challenge Coordinating Unit (MCCU), together with the Ministry of Energy, launched the "Electricity Sector Reform Roadmap 2017-2030)", with a vision for the Electricity Sector up to 2030.
- TheNational Energy Policy 2009reviewed but still needs ratification, as of beginning of 2018.

# INSTITUTIONAL SET UP IN THE ENERGY SECTOR

Some observations on the institutional set up of the (Renewable) Energy Sector in Sierra Leone are:

- The power sector has been unbundled into distinct actors for generation and transmission and for distribution and retail: The„National Electricity Act 2011"the vertically integrated National Power Authority into the Electricity Generation and Transmission Company (EGTC) and the Electricity Distribution and Supply Authority (EDSA). Furthermore, trough the Electricity and Water Regulatory Act 2011, a regulatory body, the Energy and Water Regulatory Commission was established.
- There is no separate Rural Electrification Agency. The Ministry of Energy has a Renewable Energy Department and works closely with the President's Recovery Priorities team. One of the priority sectors isEnergy, with the key objectives to double acesss to electricity from 125.000 to 250.000 households and double the operational power generation capacity from 75MW to 150MW.
- Following the launch of the Energy Revolution, the private sector associationRenewable Energy Association of Sierra Leone (REASL)founded, comprising of aprox. 30 members in the beginning of 2018.
- There are three Government Learning Institutions that offer courses in Renewable Energy, the Government Technical Institute in Freetown, Kissy Dockyards, the Government Technical Institute in Magburaka and the Eastern Polytechnic in Kenema.

# KEY PROBLEMS OF THE ENERGY SECTOR

- **Financing/Investment:**lack of private investments, lack of economic incentives, support and implementation for PAYGO availability necessary, microfinance should be available for solar businesses, no fully functioning mobile money platform exists
- **Enabling Legal Framework:**Need for clear regulations of private sector participation in electricity generation, need for mini-grid licensing and concessions, need for standardized Power Purchase Agreements (PPAs), need for less bureaucratic process of receiving tax / duty waivers for private companies importing certified solar products, no Rural Electrification Agency exists
- **Infrastructure and Services:**Transmission and distribution infrastructure need to be improved, most parts of the country have no access to any grid, many distribution lines were destroyed during the civil war, old equipment is in place and needs to be replaced, poor energy efficiency, the existing network is very old and there are immense power losses in the generation, transmission and distribution,(40% transmission losses), generation capacity does not cover the demand, especially in the industry many companies are forced to rely on diesel generators , service standards of EDSA are poor, use of inefficient cook stoves / 3-stone-fires and kerosene lights/battery torches
- **Lack of accurate data:**lack of data collection in the energy sector, absence of detailed research
- **Lack of awareness:**Missing awareness on quality standards for solar, especially PicoPV products, missing awareness on Improved Cook Stoves , missing awareness on environmental benefits (climate change, health etc.) of solar and improved cook stoves, recycling programme for old batteries necessary

# AM TRYING TO PREDICT THE DATASET OF ELECTRICITY POWER CONSUMPTION IN SIERRA LEONE

In 1

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
        for filename in filenames:
                print(os.path.join(dirname, filename))
```

```
/kaggle/input/electricity-consumption/train.csv
/kaggle/input/electricity-consumption/test.csv
```

In 2

```
!pip install DataScienceHelper
```

```
Collecting DataScienceHelper
      Downloading datasciencehelper-1.5.2.tar.gz (6.4 kB)
Building wheels for collected packages: DataScienceHelper
   Building wheel for DataScienceHelper (setup.py) ... done
   Created wheel for DataScienceHelper: filename=datasciencehelper-1.5.2-py3-none-any.whl size=5727
sha256=6aaeddf275658cdbca7b7f0564ea1b409583a584d2286b32b46d052c0b3399ae
   Stored in directory: /root/.cache/pip/wheels/49/5e/d2/84a664218a270ce173c1d02086f556367a00002afe0
aae6409
Successfully built DataScienceHelper
Installing collected packages: DataScienceHelper
Successfully installed DataScienceHelper-1.5.2
```

In 3

```
!pip install --upgrade pip
```

```
Collecting pip
  Downloading pip-20.2.2-py2.py3-none-any.whl (1.5 MB)
     |████████████████████████████████| 1.5 MB 402 kB/s eta 0:00:01
Installing collected packages: pip
  Attempting uninstall: pip
    Found existing installation: pip 20.2.1
    Uninstalling pip-20.2.1:
      Successfully uninstalled pip-20.2.1
Successfully installed pip-20.2.2
```

In 4

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import DataScienceHelper as dsh
Import plotly.express as px
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

%matplotlib inline
```

In 5

```
import time
from datetime import datetime
import re
from math import *
```

In 6

```python
data = pd.read_csv("/kaggle/input/electricity-consumption/train.csv")
data.head()
```

Out 6

| ID | datetime | temperature | var1 | pressure | windspeed | var2 | electricity_consumption | |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 2013-07-01 00:00:00 | -11.4 | -17.1 | 1003.0 | 571.910 | A | 216.0 |
| 1 | 1 | 2013-07-01 01:00:00 | -12.1 | -19.3 | 996.0 | 575.040 | A | 210.0 |
| 2 | 2 | 2013-07-01 02:00:00 | -12.9 | -20.0 | 1000.0 | 578.435 | A | 225.0 |
| 3 | 3 | 2013-07-01 03:00:00 | -11.4 | -17.1 | 995.0 | 582.580 | A | 216.0 |
| 4 | 4 | 2013-07-01 04:00:00 | -11.4 | -19.3 | 1005.0 | 586.600 | A | 222.0 |

In 7 `data.tail()`

Out 7

| ID | datetime | temperature | var1 | pressure | windspeed | var2 | electricity_consumption | |
|---|---|---|---|---|---|---|---|---|
| 26491 | 34891 | 2017-06-23 19:00:00 | -0.7 | -15.0 | 1009.0 | 51.685 | A | 225.0 |
| 26492 | 34892 | 2017-06-23 20:00:00 | -2.9 | -11.4 | 1005.0 | 56.105 | A | 213.0 |
| 26493 | 34893 | 2017-06-23 21:00:00 | -1.4 | -12.9 | 995.0 | 61.275 | A | 213.0 |
| 26494 | 34894 | 2017-06-23 22:00:00 | -2.9 | -11.4 | 996.0 | 67.210 | A | 210.0 |
| 26495 | 34895 | 2017-06-23 23:00:00 | -2.1 | -11.4 | 1009.0 | 71.880 | A | 210.0 |

In 8 `data.isnull().sum()`

Out 8

```
ID                          0
Datetime                    0
temperature                 0
var1                        0
pressure                    0
windspeed                   0
var2                        0
electricity_consumption     0
dtype: int64
```

In 9 data.describe()

Out 9

| ID | temperature | var1 | pressure | windspeed | electricity_co nsumption | |
|---|---|---|---|---|---|---|
| count | 26496.000000 | 26496.000000 | 26496.000000 | 26496.000000 | 26496.000000 | 26496.000000 |
| mean | 17455.500000 | 5.098989 | -1.916233 | 986.450615 | 23.959956 | 298.359601 |
| std | 10122.873673 | 8.682860 | 10.424860 | 12.002647 | 48.280321 | 108.020555 |
| min | 0.000000 | -17.100000 | -32.900000 | 953.000000 | 1.075000 | 174.000000 |
| 25% | 8717.750000 | -2.900000 | -10.700000 | 978.000000 | 3.155000 | 219.000000 |
| 50% | 17435.500000 | 6.400000 | -1.400000 | 986.000000 | 6.545000 | 267.000000 |
| 75% | 26177.250000 | 12.100000 | 7.900000 | 995.000000 | 22.260000 | 342.000000 |
| max | 34895.000000 | 23.600000 | 18.600000 | 1024.000000 | 586.600000 | 1386.000000 |

In 10 data.count()

Out 10

```
ID 26496 datetime                26496
temperature                      26496
var1                             26496
pressure                         26496
windspeed                        26496
var2                             26496
electricity_consumption          26496
dtype: int64
```

In 11 data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26496 entries, 0 to 26495
Data columns (total 8 columns):
 #    Column                    Non-Null Count    Dtype
---   ------ ---               -------------- ------   ---------
0     ID                        26496 non-null    int64
1     datetime                  26496 non-null    object
2     temperature               26496 non-null    float64
3     var1                      26496 non-null    float64
4     pressure                  26496 non-null    float64
5     windspeed                 26496 non-null    float64
6     var2                      26496 non-null    object
7   electricity_consumption   26496 non-null    float64
dtypes: float64(5), int64(1), object(2)
memory usage: 1.6+ MB
```

In 12 `data.memory_usage()`

Out 12

```
Index                        128
ID                        211968
datetime                  211968
temperature               211968
var1                      211968
pressure                  211968
windspeed                 211968
var2                      211968
electricity_consumption   211968
dtype: int64
```

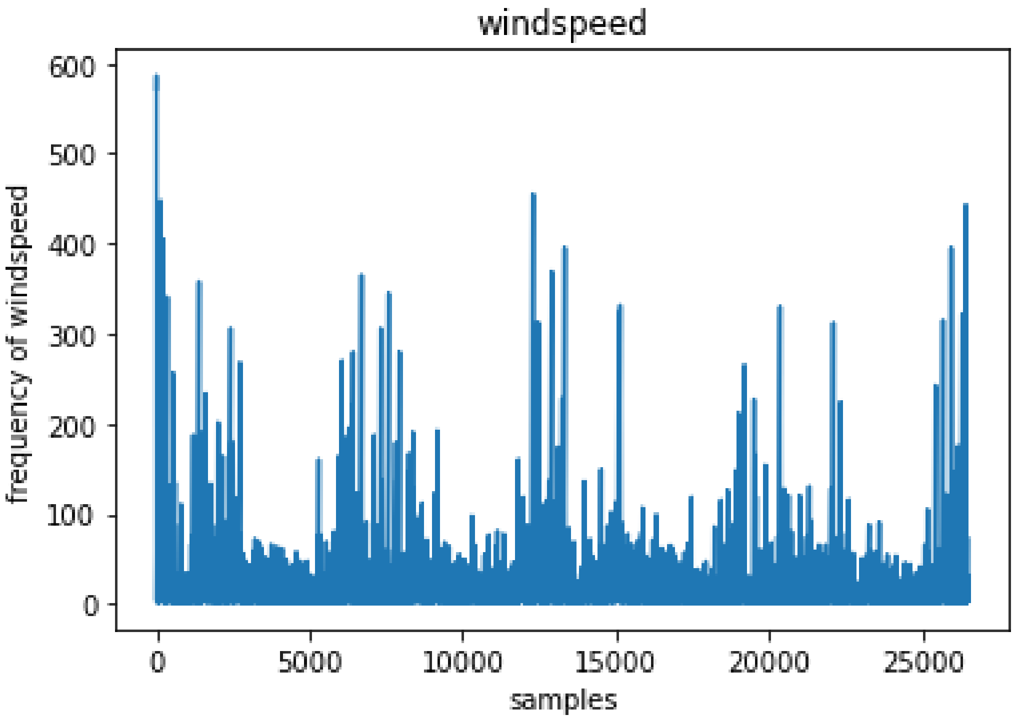
In 13 `data.windspeed.value_counts()`

Out 13

```
2.265      380
1.890      369
2.015      359
2.390      354
2.140      347
           ...
318.210      1
123.435      1
282.485      1
160.465      1
27.825       1
Name: windspeed, Length: 5603, dtype: int64
```

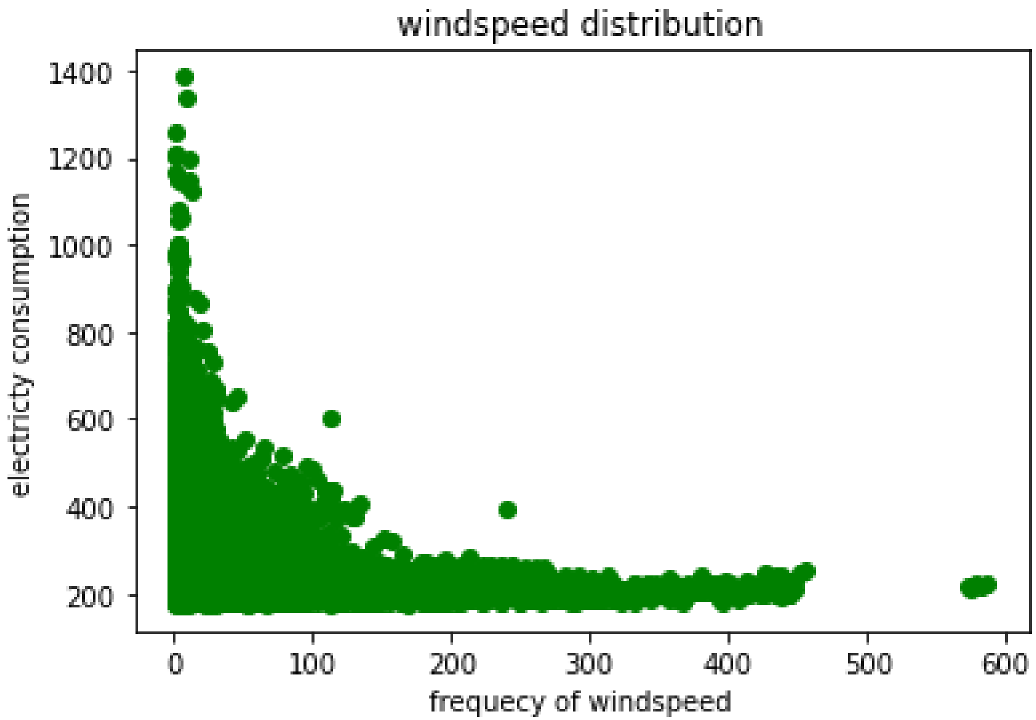
In 14

```
plott = data.windspeed
plt.plot(plott)
plt.xlabel("samples")
plt.ylabel("frequency of windspeed")
plt.title("windspeed")
plt.show()
```



In 15

```
plt.scatter(data.windspeed,data.electricity_consumption,c='green')
plt.xlabel("frequecy of windspeed")
plt.ylabel("electricty consumption")
plt.title("windspeed distribution")
plt.show()
```



In16

```python
average = round(data.windspeed.mean(),3)
max_windspeed = round(max(data.windspeed),3)
min_windspeed = round(min(data.windspeed),3)
print(f'The average windspeed is : {average} ')
print(f'The maximum windspeed is : {max_windspeed}')
print(f'The minimum windspeed is : {min_windspeed}')
```

```
The average windspeed is : 23.96
The maximum windspeed is : 586.6
The minimum windspeed is : 1.075
```

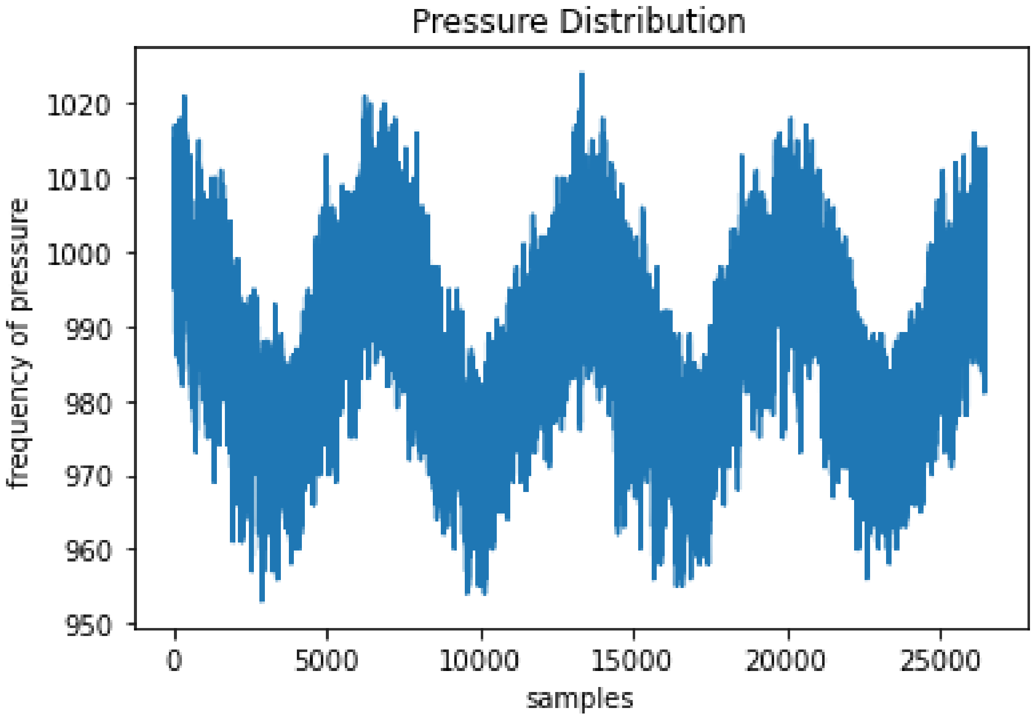
In17

```python
avg_pressure = round(data.pressure.mean(),3)
max_pressure = round(data.pressure.max(),3)
min_pressure = round(data.pressure.min(),3)
print(f'The average pressure is : {avg_pressure}')
print(f'The maximum pressure is : {max_pressure}')
print(f'The minimum pressure is : {min_pressure}')
```

```
The average pressure is : 986.451
The maximum pressure is : 1024.0
The minimum pressure is : 953.0
```

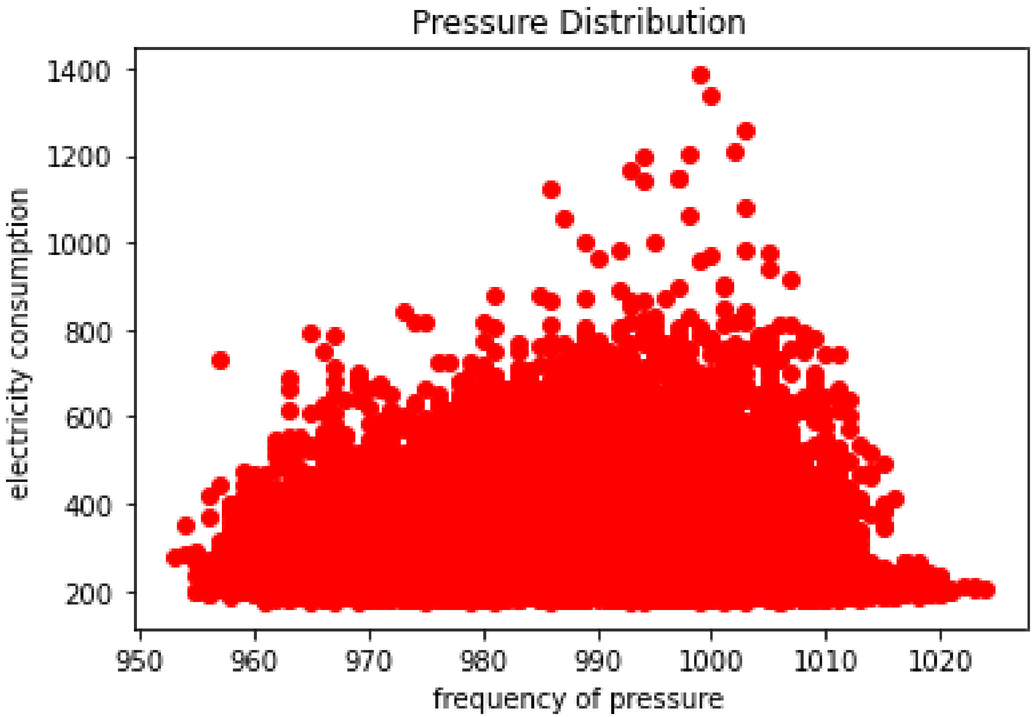
In18

```
plt.plot(data.pressure)
plt.xlabel("samples")
plt.ylabel("frequency of pressure")
plt.title("Pressure Distribution")
plt.show()
```



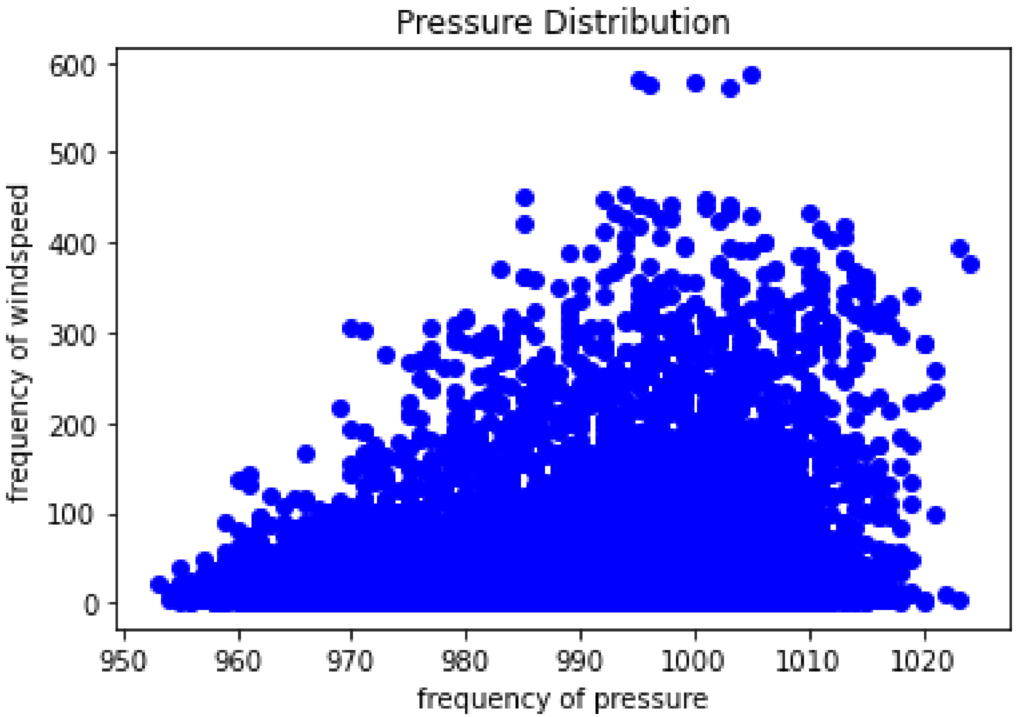
In19

```
plt.scatter(data.pressure,data.electricity_consumption,c='red')
plt.xlabel("frequency of pressure")
plt.ylabel("electricity consumption")
plt.title("Pressure Distribution")
plt.show()
```



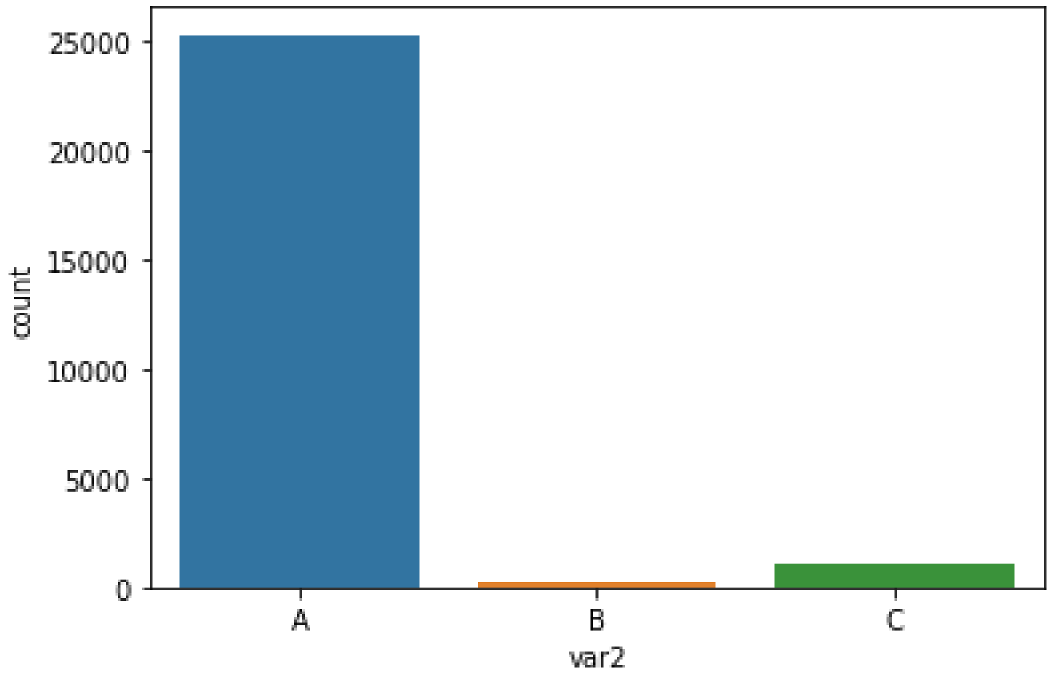
In20

```
plt.scatter(data.pressure,data.windspeed,c='blue')
plt.xlabel("frequency of pressure")
plt.ylabel("frequency of windspeed")
plt.title("Pressure Distribution")
plt.show()
```



In 21 sns.countplot(x='var2',data = data)

Out 21 <matplotlib.axes._subplots.AxesSubplot at 0x7f66e65e2f90>

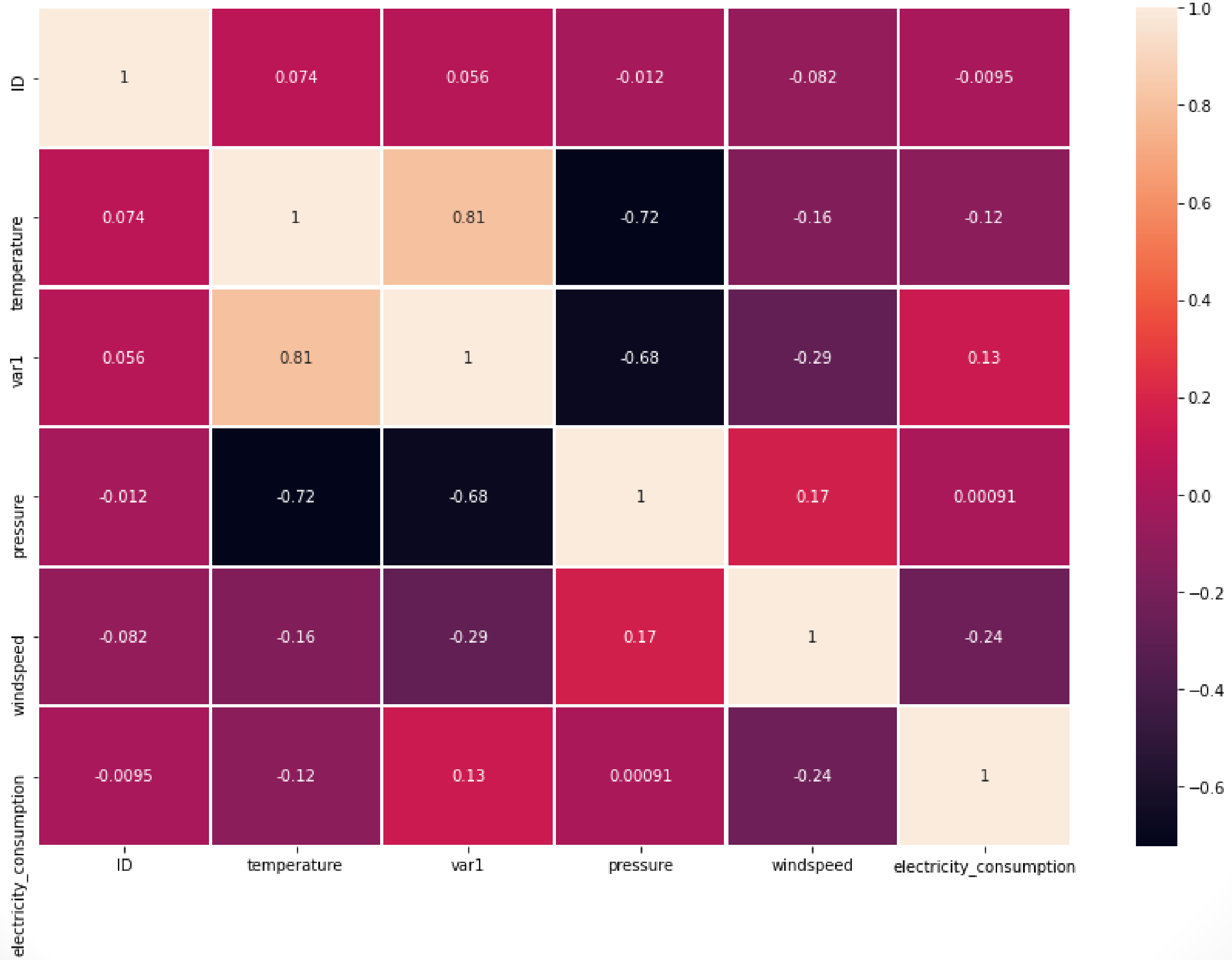


In 43

```
fig,ax = plt.subplots(figsize = (15,10))
corr = data.corr()
sns.heatmap(corr,xticklabels = corr.columns,annot = True,yticklabels = corr.columns,linewidth =1.2)
```

Out 43

<matplotlib.axes._subplots.AxesSubplot at 0x7f66e6c07e50>



In 23

```
corr[abs(corr['electricity_consumption']) > 0.1]['electricity_consumption']
```

Out 23

```
temperature                  -0.117254
var1                          0.133914
windspeed                    -0.238883
electricity_consumption       1.000000
Name: electricity_consumption, dtype: float64
```

In 24

```
data.var1.value_counts()
```

Out 24

```
10.0     836
8.6      809
10.7     797
7.9      779
9.3      770
         ...
-29.3    3
17.9     2
-32.9    1
18.6     1
-32.1    1
Name: var1, Length: 71, dtype: int64
```

In 25 data.var2.value_counts()

Out 25

| | |
|---|---|
| A | 25239 |
| C | 1040 |
| B | 217 |

Name: var2, dtype: int64

# MODEL

## My Funtions

In [2}

```
Def  datetounix(df):
    # Initialising unixtime list
    unixtime = []

    # Running a loop to convert Date to seconds
    for date in df['datetime']:
        unixtime.append(time.mktime(date.timetuple()))
    # Replacing Date with unixtime list
    df['datetime'] = unixtime
    return(df)
```

## Import Libraries

In [3}

```
# import libs
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from datetime import datetime
import time
from sklearn.ensemble import ExtraTreesClassifier
import operator
from sklearn.preprocessing import StandardScaler
import keras
from keras.models import Sequential
from keras.layers import Dense

# read train dataframe
# file_path = os.path.join(os.path.abspath(''), 'train.csv')
df_train = pd.read_csv("../input/train.csv", encoding='ISO-8859-1', engine='c')

# read test dataframe
# file_path = os.path.join(os.path.abspath(''), 'test.csv')
df_test = pd.read_csv("../input/test.csv", encoding='ISO-8859-1', engine='c')
df_train.info()
```

```
Using TensorFlow backend.

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26496 entries, 0 to 26495
Data columns (total 8 columns):
ID                         26496 non-null int64
datetime                   26496 non-null object
temperature                26496 non-null float64
var1                       26496 non-null float64
pressure                   26496 non-null float64
windspeed                  26496 non-null float64
var2                       26496 non-null object
electricity_consumption    26496 non-null float64
dtypes: float64(5), int64(1), object(2)
memory usage: 1.6+ MB
```

**Data Cleaning**

Uploading and cleaning of data.

In [4}

```
# Converting to datetime
df_train['datetime'] = pd.to_datetime(df_train['datetime'])
df_test['datetime'] = pd.to_datetime(df_test['datetime'])
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8568 entries, 0 to 8567
Data columns (total 7 columns):
ID              8568 non-null int64
datetime        8568 non-null datetime64[ns]
temperature     8568 non-null float64
var1            8568 non-null float64
pressure        8568 non-null float64
windspeed       8568 non-null float64
var2            8568 non-null object
dtypes: datetime64[ns](1), float64(4), int64(1), object(1)
memory usage: 468.6+ KB
```

In [5}

```
# Creating features from DateTime for train data

df_test['Weekday'] = [datetime.weekday(date) for date in df_test.datetime]
df_test['Year'] = [date.year for date in df_test.datetime]
df_test['Month'] = [date.month for date in df_test.datetime]
df_test['Day'] = [date.day for date in df_test.datetime]
df_test['Time'] = [((date.hour*60+(date.minute))*60)+date.second for date in df_test.datetime]
df_test['Week'] = [date.week for date in df_test.datetime]
df_test['Quarter'] = [date.quarter for date in df_test.datetime]

# Creating features from DateTime for test data

df_train['Weekday'] = [datetime.weekday(date) for date in df_train.datetime]
df_train['Year'] = [date.year for date in df_train.datetime]
df_train['Month'] = [date.month for date in df_train.datetime]
df_train['Day'] = [date.day for date in df_train.datetime]
df_train['Time'] = [((date.hour*60+(date.minute))*60)+date.second for date in df_train.datetime]
df_train['Week'] = [date.week for date in df_train.datetime]
df_train['Quarter'] = [date.quarter for date in df_train.datetime]
```

In [6} **Data Preparation**

```
# Create Dummy Variables for Train set
df_train.loc[df_train.var2 == 'A', 'var2A'] = 1
df_train.loc[df_train.var2 == 'B', 'var2B'] = 1

df_train['var2A'].fillna(0, inplace=True)
df_train['var2B'].fillna(0, inplace=True)

df_train.drop(['var2'], axis=1, inplace=True)

# Create Dummy Variables for Test set
df_test.loc[df_test.var2 == 'A', 'var2A'] = 1
df_test.loc[df_test.var2 == 'B', 'var2B'] = 1

df_test['var2A'].fillna(0, inplace=True)
df_test['var2B'].fillna(0, inplace=True)

df_test.drop(['var2'], axis=1, inplace=True)

# Creating X_test
X_test = datetounix(df_test).drop(['ID'], axis=1).values

# Remove target column from the df
df_train_features = df_train.drop(['electricity_consumption', 'ID'], axis=1)

# Convet timestamp to seconds
df_train_features = datetounix(df_train_features)

# store features in X array
X = df_train_features.values
y = df_train['electricity_consumption'].values
```

In [9]:
```
# Initialising the ANN
classifier = Sequential()

# Adding the input layer and the first hidden layer
classifier.add(Dense(units = 10, kernel_initializer = 'uniform', activation = 'relu', input_dim = 14))

# Adding the second hidden layer
classifier.add(Dense(units = 5, kernel_initializer = 'uniform', activation = 'relu'))

# Adding the output layer
classifier.add(Dense(units = 1, kernel_initializer = 'uniform', activation = 'sigmoid'))

# Compiling the ANN
classifier.compile(optimizer = 'adam', loss = 'mean_squared_error', metrics = ['mae'])

# Fitting the ANN to the training set
classifier.fit(X, y_norm, batch_size = 10, epochs = 100)

# Part 3 - Making the predictions and evaluating the model

# Predicting the Test set results
y_pred = classifier.predict(X_test)
y_pred = (y_pred * (max(y) - min(y))) + min(y)

predictions = [int(elem) for elem in y_pred]

df_solution = pd.DataFrame()
df_solution['ID'] = df_test.ID

# Prepare Solution dataframe
df_solution['electricity_consumption'] = predictions
df_solution['electricity_consumption'].unique()

df_solution
```

```
Epoch 1/100
26496/26496 [==============================] - 4s 159us/step - loss: 0.0142 - mean_absolute_error: 0.0762
Epoch 2/100
26496/26496 [==============================] - 4s 155us/step - loss: 0.0048 - mean_absolute_error: 0.0492
Epoch 3/100
26496/26496 [==============================] - 4s 158us/step - loss: 0.0046 - mean_absolute_error: 0.0481
Epoch 4/100
26496/26496 [==============================] - 4s 157us/step - loss: 0.0045 - mean_absolute_error: 0.0472
Epoch 5/100
26496/26496 [==============================] - 4s 157us/step - loss: 0.0044 - mean_absolute_error: 0.0465
Epoch 6/100
26496/26496 [==============================] - 4s 156us/step - loss: 0.0043 - mean_absolute_error: 0.0459
Epoch 7/100
26496/26496 [==============================] - 4s 156us/step - loss: 0.0042 - mean_absolute_error: 0.0455
Epoch 8/100
26496/26496 [==============================] - 4s 154us/step - loss: 0.0042 - mean_absolute_error: 0.0452
Epoch 9/100
26496/26496 [==============================] - 4s 155us/step - loss: 0.0041 - mean_absolute_error: 0.0451
Epoch 10/100
26496/26496 [==============================] - 4s 155us/step - loss: 0.0041 - mean_absolute_error: 0.0450
Epoch 11/100
26496/26496 [==============================] - 4s 158us/step - loss: 0.0041 - mean_absolute_error: 0.0449
Epoch 12/100
26496/26496 [==============================] - 4s 154us/step - loss: 0.0041 - mean_absolute_error: 0.0448
Epoch 13/100
26496/26496 [==============================] - 4s 154us/step - loss: 0.0041 - mean_absolute_error: 0.0447
Epoch 14/100
26496/26496 [==============================] - 4s 153us/step - loss: 0.0041 - mean_absolute_error: 0.0448
Epoch 15/100
26496/26496 [==============================] - 4s 153us/step - loss: 0.0041 - mean_absolute_error: 0.0447
Epoch 16/100
26496/26496 [==============================] - 4s 156us/step - loss: 0.0041 - mean_absolute_error: 0.0446
Epoch 17/100
26496/26496 [==============================] - 4s 154us/step - loss: 0.0041 - mean_absolute_error: 0.0445
Epoch 18/100
26496/26496 [==============================] - 4s 153us/step - loss: 0.0041 - mean_absolute_error: 0.0445
Epoch 19/100
26496/26496 [==============================] - 4s 155us/step - loss: 0.0040 - mean_absolute_error: 0.0444
```

This first part shows how the codes show the in classifier as a sequential way, and also the second part is about adding adding the input layer and the first hidden layer. Am also adding the second hidden layer to show some examples, adding the output layer to show the output of the result. Compiling the ANN is also important to gathered some information about everything, Fitting the ANN to the training set comes after the compiling of the ANN.
After all that i used the Prepare Solution data frame to make it more unique and also predict about the electricity consumption, and this model shows everything above as you can see.

# REFERENCE

This is what i have gathered so far for my Graduation Assignment project title ELECTRICITY POWER CONSUMPTION, also gathered some assistance material on KAGGLE to add some important materials on my project. Although there are many codes, i just collected few just to show some examples.

DIVE INTO CODE

# MACHINE LEARNING GRADUATION ASSIGNMENT

## END OF SESSION