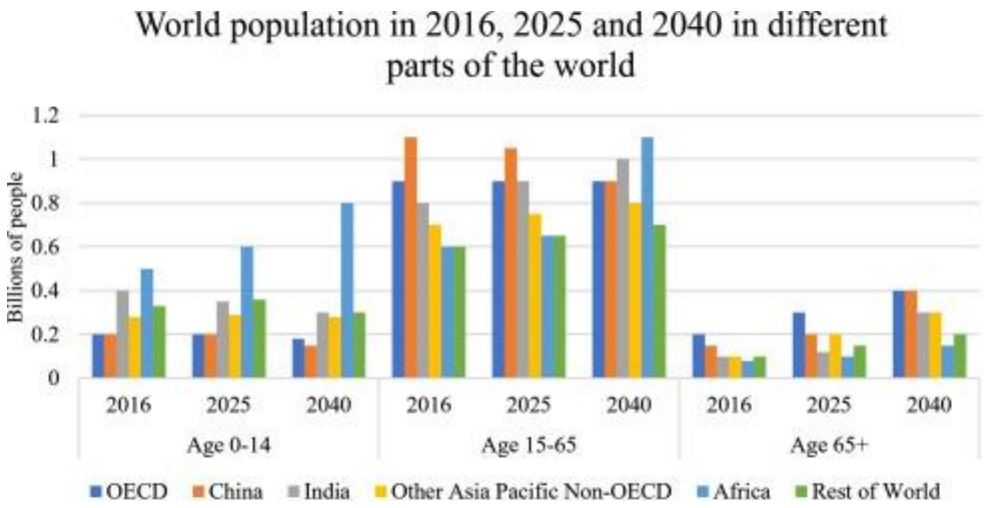
MEASURE ENERGY CONSUMPTION

ABSTRACT:

Energy consumption, product water costs and technology reliability are key parameters that determine the viability of a process. Both cost and energy for desalination, especially seawater RO, have fallen dramatically since the 1970s due to the development of higher permeability and higher performance membranes, lower operating pressure, use of energy recovery devices, more efficient pumps and well-established RO feed water treatment practices. In addition, membrane plants have proven reliable in the field with longer life and lower plant maintenance costs. Engineering analyses of typical commercialised and well-established membrane processes used for desalination and municipal and industrial water treatment are discussed as well as relevant data on energy consumption and water costs presented with special focus on seawater and brackish water desalination

INTRODUCTION:

Energy consumption is influenced by many social and economic factors and drivers. Especially in the less developed countries, the tremendous increase of the population as well as the expected significant increase of domestic GDP may result in a significant increase in energy consumption. As reported by ExxonMobil (2018), the world's population is expected to reach 9.2 billion people by 2040, compared to nearly 7.4 billion today. Most of the new population will be in Africa and Asia.



About this data set:

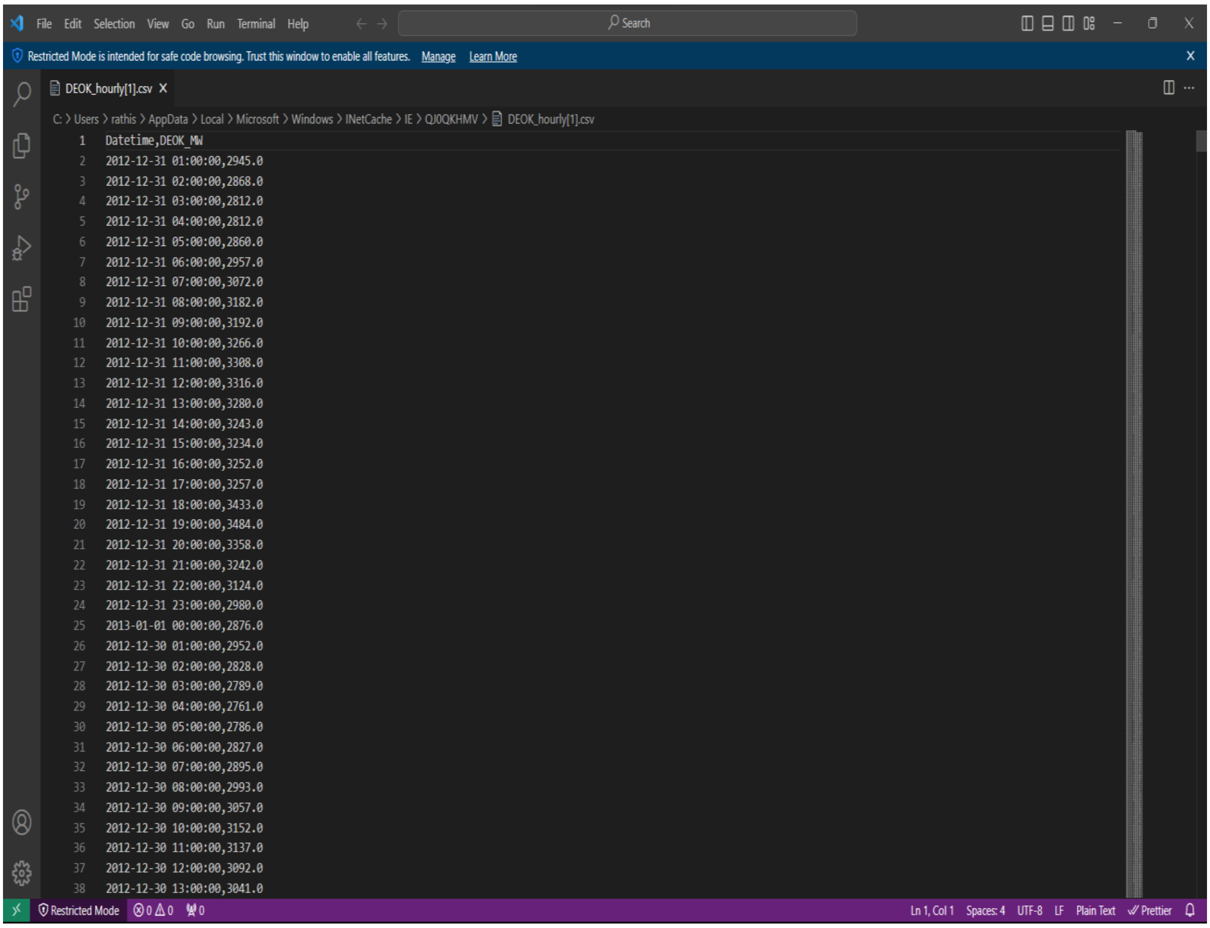
This is a very extensive dataset on Energy by Our World in Data This dataset is a collection of key metrics maintained by Our World in Data. It is updated regularly and includes data on energy consumption (primary energy, per capita, and growth rates), energy mix, electricity mix and other relevant metrics.

Dataset link: (https://www.kaggle.com/pralabhpoudel/world-energy-consumption)

The reason that I chose this dataset to carryout the project is :

- It has categorical data columns which would be useful in data visualization .

- It has numerical data columns which would be useful for simple statistical applications.
- It's a very interesting dataset where we can apply several analytical questions and get valuable insights



1.Importing Libraries:

- import pandas as pd
- import numpy as np
- from sklearn.preprocessing import StandardScaler
- from sklearn.cluster import KMeans, AffinityPropagation
- import matplotlib.pyplot as plt
- import seaborn as sns
- %matplotlib inline

- import warnings
- warnings.filterwarnings("ignore")
- import plotly as py
- import plotly.graph_objs as go
- import os
- py.offline.init_notebook_mode(connected = True)
- *#print(os.listdir("../input"))*
- import datetime as dt
- import missingno as msno
- plt.rcParams['figure.dpi'] = 140

2.Importing the Dataframe:

- country
- year
- carbonintensityelec
- coal_production
- electricity_generation
- biofuel_electricity
- coal_electricity
- fossil_electricity
- gas_electricity
- hydro_electricity
- nuclear_electricity
- oil_electricity
- renewables_electricity
- solar_electricity
- wind_electricity
- energypergdp
- energypercapita
- fossilshareelec

- gasshareelec
- gas_production
- lowcarbonshare_elec
- oil_production
- population
- gdp *

```
#import DataFrame
DF = pd.read_csv('/kaggle/input/world-energy-consumption/World Energy Consumption.csv')
#Filter on needed columns
DF=DF[['country','year','coal_production','electricity_generation','biofuel_electricity','coal_electricity','fossil_electricity','gas_electricity','hydro_electricity','nuclear_electricity','oil_electricity','renewables_electricity','oil_production','population','gdp','solar_electricity','wind_electricity','energy_per_gdp','energy_per_capita','fossil_share_elec','gas_share_elec','gas_production','low_carbon_share_elec']]
#Filter on year >=1985
DF=DF[DF['year']>=1990]
#Filter on countries
Countries=['Egypt','Saudi Arabia','United Kingdom','France','Germany','United States','Japan','India']
#filter columns
DF=DF.loc[DF['country'].isin(Countries)]
```

3.Cleaning the data:

```
#looks like we have a lot of empty Values
nulls=DF.isna().sum()
nulls
```

OUTPUT:

```
country                    0
year                       0
coal_production           96
electricity_generation     0
biofuel_electricity       80
coal_electricity          10
fossil_electricity        10
gas_electricity           10
hydro_electricity          0
nuclear_electricity        0
oil_electricity           10
renewables_electricity     0
oil_production            96
population                 6
gdp                       30
solar_electricity          0
wind_electricity           0
energy_per_gdp            30
energy_per_capita          6
fossil_share_elec         10
gas_share_elec            10
gas_production            66
low_carbon_share_elec      0
```

```
#For Items like GDP  it doesnt make sense to replace the null values with a 0 ,so let's try FWD fill and then backwards fill
#looks like we have a lot of empty Values
nulls=DF.isna().sum()
for i in nulls.index:
    if nulls[i]>0:
        DF[i].ffill(inplace=True)
        DF[i].bfill(inplace=True)
DF.isna().sum()
```

OUTPUT:

country	0
year	0
coal_production	0
electricity_generation	0
biofuel_electricity	0
coal_electricity	0
fossil_electricity	0
gas_electricity	0
hydro_electricity	0
nuclear_electricity	0
oil_electricity	0
renewables_electricit	0
oil_production	0
population	0
gdp	0
solar_electricity	0
wind_electricity	0
energy_per_gdp	0
energy_per_capita	0
fossil_share_elec	0
gas_share_elec	0
gas_production	0
low_carbon_share_elec	0

CONCLUSION:

Energy consumption and storage is often focused on electric power. However, electric power often is a secondary energy source, which I s transformed into useful energy during different production process es and steps. The approach of a multienergy storage system for dair y production may increase the flexibility potential of the production process, which is indicated by the amount of energy that is transform ed into storable end or useful energy forms.