Project: *Measure Energy Consumption*

Introduction:

- **Certainly, using time series analysis and machine learning models to predict future energy consumption patterns is a promising approach.**
- **Here's how you can explore these techniques for energy consumption prediction.**

Objective

- **Explore innovative techniques such as time series analysis and machine learning models to predict future energy consumption patterns**

- In PHASE 1 we discussed about the problem definition and their application used in artificial intelligence.

Phase 2:

- Consider Certainly, using time series analysis and machine learning models to predict future energy consumption patterns is a promising approach.
- Here's how you can explore these techniques for energy consumption prediction..Here is the following contents.
- Here are some key components and methods commonly used in such solutions:

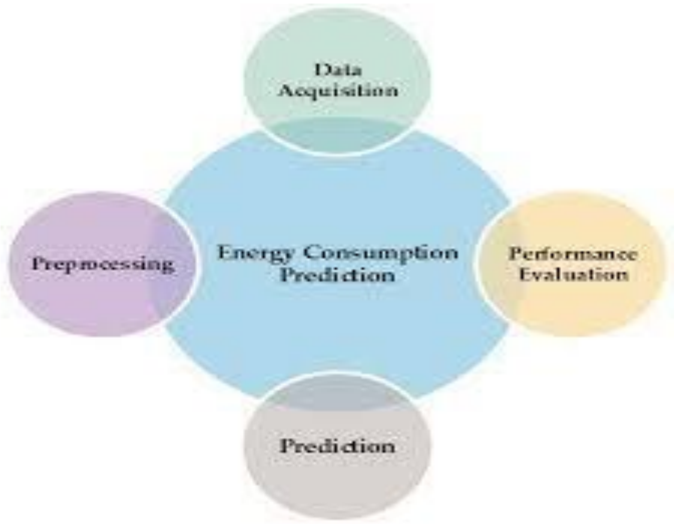
1.Data Collection:

- Gather historical energy consumption data.
- This data should include information about the time and date of measurements, energy usage, and potentially other relevant factors like temperature, holidays, or special events.
- Dataset link is below here:
  https://www.kaggle.com/datasets/robikscube/hourly-energy-consumption

QuestionPro
DATA COLLECTION
Statistical Methods
Surveys
Polls
Interview
Delphi Technique
Focus Groups
Primary Data Collection Methods
Secondary Data Collection Methods
Financial Reports
Sales Reports
Government Reports
Mission
Vision Statement
Internet

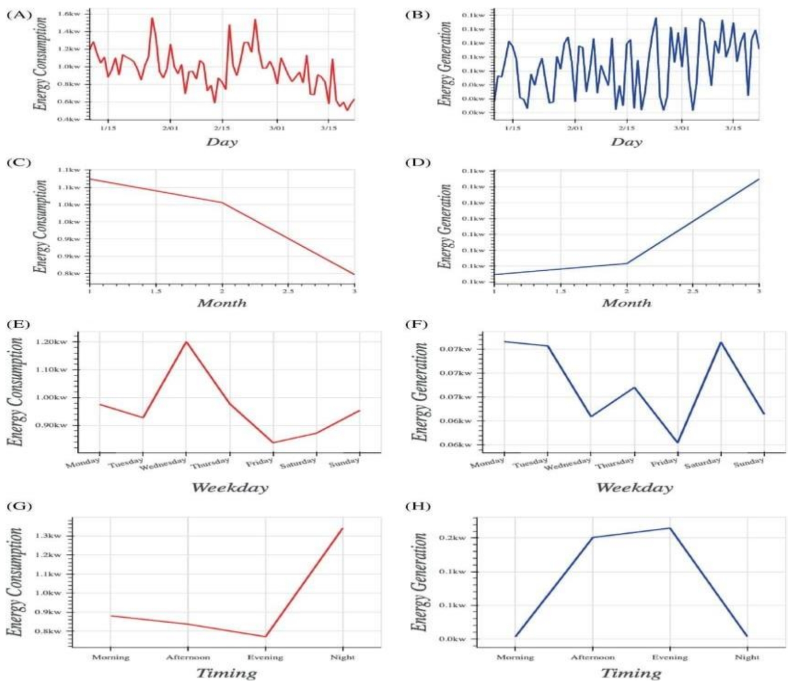
2. Data Preprocessing:

- **Data preprocessing is an important step before applying machine learning methods for energy or load prediction.**
- **It improves accuracy and reliability.**
- **There are four types of data processing**
  1. **Data cleaning**
  2. **Data integration**
  3. **Data transformation**
  4. **Data reduction**



3.Exploratory Data Analysis (EDA):

- **Perform EDA to gain insights into the data.**
- **Learn everything you need to know about exploratory data analysis, a method used to analyze and summarize data sets.**
- **Exploratory data analysis (EDA) is used by data scientists to analyze and investigate data sets and summarize their main characteristics, often employing data visualization methods.**
- **Visualize trends, seasonality, and correlations between energy consumption and other variables.**

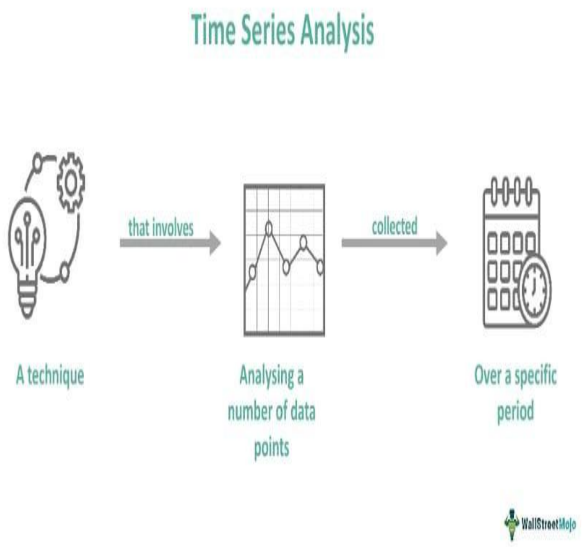


4.Time Series Analysis:

It comprises of ordered sequence of data at equally spaced interval.

- **In particular, a time series allows one to see what factors influence certain variables from period to period.**

1. **Decomposition:**
   Decompose the time series data into its trend, seasonal, and residual components to understand underlying patterns.
2. **Smoothing:**
   Apply smoothing techniques like moving averages or exponential smoothing to reduce noise in the data.



5.Feature Engineering:

Create additional features that could impact energy consumption, such as holidays, weather data, day of the week, and time of day.

- **This includes the use of electricity, gas, diesel, oil, and biomass. The concept of energy consumption is directly related to energy efficiency since higher consumption results in lower energy efficiency.**
- **TEE includes three core components**

1.Resting metabolic rate, or resting energy expenditure (REE)

2.The thermic effect of food (TEF)

3. Diet-induced thermogenesis DIT)

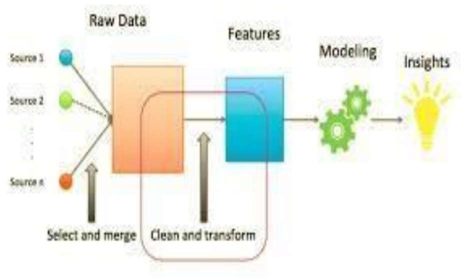


Figure 1-2. The place of feature engineering in the machine learning workflow.

6.Machine Learning Models:

A) Regression Models:

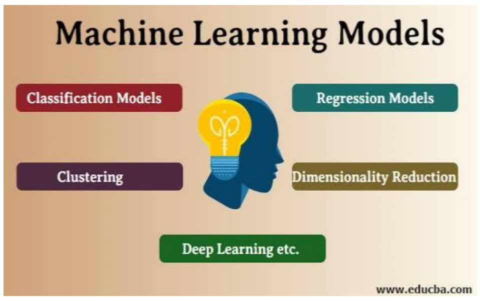
- **Utilize linear regression, decision trees, or random forests to build models that predict energy consumption based on relevant features.**

B) Time Series Forecasting:

- **Implement specialized time series forecasting models like ARIMA, Prophet, or LSTM (Long Short-Term Memory) neural networks.**

C)Ensemble Methods:

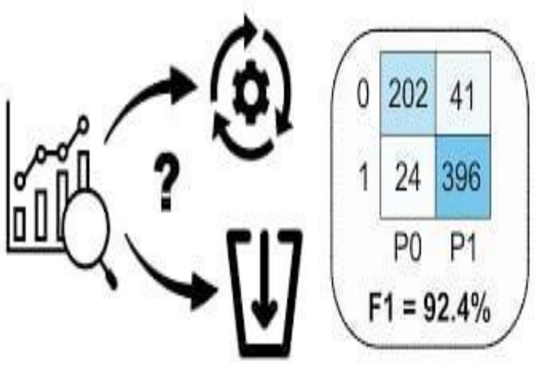
- **Combine multiple models to improve prediction accuracy.**



7.Model Evaluation:

- **Energy consumption modeling seeks to determine energy requirements as a function of input parameters.**
- **Models may be used for determining the requirements of energy supply and the consumer consumption variations while an upgrade or addition of technology exist.**
- **Use appropriate metrics such as**

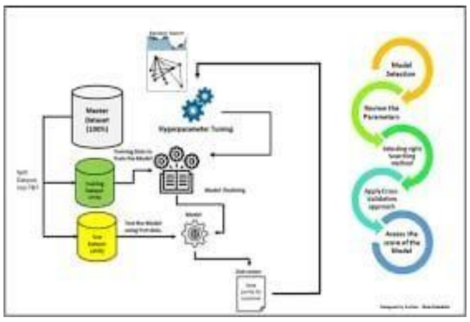
I. **Mean Absolute Error (MAE)**
II. **Mean Squared Error (MSE)**
III. **Root Mean Squared Error (RMSE)**



8.Hyperparameter Tuning:

Optimize model hyperparameters to enhance predictive accuracy.

Hyperparameter tuning allows data scientists to tweak model performance for optimal results.

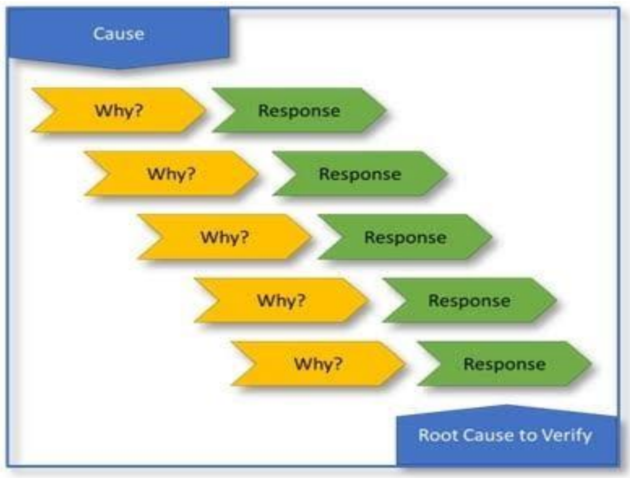


9.Cross-Validation:

Employ cross-validation techniques to assess the model’s generalization performance.

Cross-validation is a statistical method used to estimate the performance (or accuracy) of machine learning models.

It is used to protect against overfitting in a predictive model, particularly in a case where the amount of data may be limited.



10.Monitoring and Updating:

- **Continuously monitor the model's performance and update it as needed with new data.**

11.Deployment:

- **Once you have a reliable model, deploy it in a real-world environment to make real-time predictions.**

12.Interpretability:

- **Understand the factors driving energy consumption by examining feature importance and model explanations.**

13.Integration:

- Integrate the energy consumption prediction model into your energy management system to optimize resource allocation and reduce costs.

Source code:

Int[1]:

```
Import numpy as np
Import pandas as pd
Import matplotlib.pyplot as plt
Import matplotlib.dates as mdates
%matplotlib inline
Import seaborn as sns
Import warnings
Warnings.filterwarnings("ignore")
From pandas.plotting import lag_plot
From pylab import rcParams
From statsmodels.tsa.seasonal import
seasonal_decompose
From pandas import DataFrame
From pandas import concat
```

Int[2]:

```
Df=pd.read_csv("../input/hourly-energy-consumptio
n/AEP_hourly.csv",index_col='Datetime',parse_date
s=True) Df.head()
```

Out[2]:

	AEP_MW
Datetime	
2004-12-31 01:00:00	13478.0
2004-12-31 02:00:00	12865.0
2004-12-31 03:00:00	12577.0
2004-12-31 04:00:00	12517.0
2004-12-31 05:00:00	12670.0

Int[3]:

```
 df.sort_values(by='Datetime', inplace=True)
print(df)
```

Int[4]:

```
df.shape
```

Out[4]:

```
(121273, 1)
```

Int[5]:

```
df.info()
```

Out[5]:

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 121273 entries, 2004-10-01 01:00:00 to 2018-08-03 00:00:00
Data columns (total 1 columns):
 # Column Non-Null Count Dtype
--- ------ -------------- -----
 0 AEP_MW 121273 non-null float64
dtypes: float64(1)
memory usage: 1.9 MB
```

Int[6]:

```
df.describe()
```

Out[6]:

	AEP_MW
count	121273.000000
mean	15499.513717

std	2591.399065
min	9581.000000
25%	13630.000000
50%	15310.000000
75%	17200.000000
100%	25695.000000

Int[7]:

```
df.index = pd.to_datetime(df.index)
```

Int[8]:

```
# Extract all Data Like Year MOnth Day Time etc

df["Month"] = df.index.month df["Year"] =

df.index.year df["Date"] = df.index.date

df["Hour"] = df.index.hour df["Week"] =

df.index.week df["Day"] = df.index.day_name()

df.head()
```

Out[8]:

	AEP_MW	Month	Year	Date	Hour	Week	Day
Datetime							
2004-10-01 01:00:00	12379.0	10	2004	2004-10-01 1	1	4	Friday
2004-10-01 02:00:00	11935.0	10	2004	2004-10-01 1	2	4	Friday
2004-10-01 03:00:00	11692.0	10	2004	2004-10-01 1	3	4	Friday

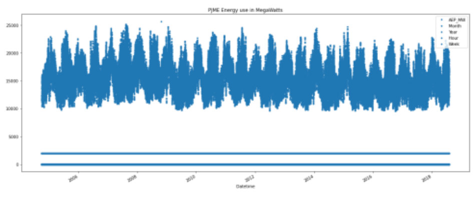
2004-10-01 04:00:00	11597.0	10	2004	2004-10-01 1	4	4	Friday
2004-10-01 05:00:00	05:00:00	10	2004	2004-10-01 1	5	4	Friday

Int[9]:

```
df.plot(title="PJME Energy use in MegaWatts",
        figsize=(20, 8), style=".",
        color=sns.color_palette()[0])

plt.show()
```

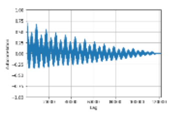
Out[9]:



Int[10]:

```
from pandas.plotting import autocorrelation_plot
autocorrelation_plot(df['AEP_MW']) plt.show()
```

Out[10]:



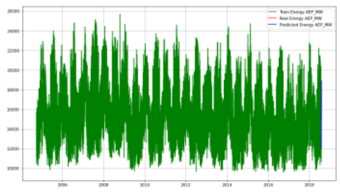
Int[11]:

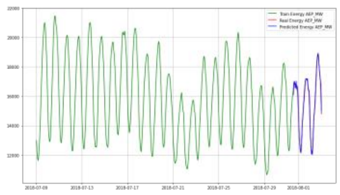
```
#Train Arima Model train_arima =
train_data['AEP_MW'] test_arima =
test_data['AEP_MW']

history = [x for x in train_arima]
y = test_arima # make first
prediction predictions = list()
model = sm.tsa.arima.ARIMA(history,
order=(5,1,0)) model_fit = model.fit()
yhat = model_fit.forecast()[0]
predictions.append(yhat)
history.append(y[0]) # rolling
forecasts for i in range(1, len(y)):
    # predict
    model = sm.tsa.arima.ARIMA(history,
order=(5,1,0))
    model_fit = model.fit() yhat =
    model_fit.forecast()[0] # invert
    transformed prediction
    predictions.append(yhat)
    # observation obs =
    y[i]
    history.append(obs
    )

plt.figure(figsize=(14,8))
plt.plot(df.index, df['AEP_MW'], color='green',
label = 'Train Energy AEP_MW')
plt.plot(test_data.index, y, color = 'red', label = 'Real
Energy AEP_MW')
plt.plot(test_data.index, predictions, color = 'blue',
label = 'Predicted Energy AEP_MW')
plt.legend()
plt.grid(True)
plt.show()
plt.figure(figsize=(14,8))
plt.plot(df.index[-600:], df['AEP_MW'].tail(600),
color='green', label = 'Train Energy AEP_MW')
plt.plot(test_data.index, y, color = 'red', label = 'Real
Energy AEP_MW')
plt.plot(test_data.index, predictions, color = 'blue',
label = 'Predicted Energy AEP_MW')
plt.legend()
plt.grid(True)
plt.show()


print('MSE: '+str(mean_squared_error(y,
predictions)))
print('MAE: '+str(mean_absolute_error(y,
predictions)))
print('RMSE: '+str(sqrt(mean_squared_error(y,
predictions)))) Out[11]:
```





Conclusion:

- **Remember that the accuracy of your predictions will depend on the quality and quantity of data, as well as the choice of the most appropriate modelling techniques.**
- **Regularly updating the model with new data is crucial to ensure it remains accurate as consumption patterns evolve.**

TEAM MEMBERS	E-MAIL ID
DEEPAK.S	deepaksubramani144@gmail.com
LOGESH.U	logeshulaganathan98@gmail.com
JAIGHER DANIEL.F	jaigherd@gmail.com
JEROME.X	Jeromejamals6@gmail.com