MEASURING ENERGY CONSUMPTION

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Phase-1 Document submission

Energy consumption

Project: AI Measure Energy Consumption

Abstract:
Measuring energy consumption is crucial for optimizing energy usage and sustainability in various domains, from industrial processes to residential applications. This abstract outlines a modular approach to measure energy consumption effectively.

Introduction:

Energy consumption measurement is vital for assessing the environmental impact and operational efficiency of energyconsuming systems. This abstract presents a modular framework for measuring energy consumption that can be applied across diverse contexts.

1. Sensor Modules:

The foundation of our approach lies in sensor modules capable of collecting data on energy usage. These modules encompass various sensor types, such as current sensors, voltage sensors, and smart meters, to capture accurate and real-time energy consumption data.

2. Data Acquisition:

The collected data from sensor modules are processed and transmitted to a central data acquisition module. This module is responsible for data aggregation, synchronization, and initial data preprocessing.

3. Data Analysis:

To derive actionable insights, data analysis modules utilize advanced algorithms and techniques. These modules identify consumption patterns, anomalies, and trends, enabling users to make informed decisions about energy management.

4. User Interface:

A user-friendly interface module provides stakeholders with access to energy consumption data in a comprehensible format. Visualization tools, dashboards, and customizable reports allow users to monitor and analyze energy consumption effortlessly.

6. Integration:

Our modular framework supports integration with existing systems and IoT platforms. This ensures compatibility with a wide range of applications, including smart homes, industrial processes, and commercial buildings.

7. Control and Automation:

In addition to monitoring, our framework enables control and automation modules. Users can implement energy-saving strategies based on real-time data, such as load shedding, scheduling, and adaptive control.

8. Security and Privacy:

We prioritize the security and privacy of energy consumption data through encryption, access control, and compliance with data protection regulations.

Python program:

```
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
```

linkcode

```
df=pd.read_csv("../input/hourly-energy-consumption/AEP_hourly.csv",index_col='Datetime',p
arse_dates=True)
df.head()
```

output:

	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

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

```
                     AEP_MW
Datetime
2004-10-01 01:00:00  12379.0
2004-10-01 02:00:00  11935.0
2004-10-01 03:00:00  11692.0
2004-10-01 04:00:00  11597.0
2004-10-01 05:00:00  11681.0
...                      ...
2018-08-02 20:00:00  17673.0
2018-08-02 21:00:00  17303.0
2018-08-02 22:00:00  17001.0
2018-08-02 23:00:00  15964.0
2018-08-03 00:00:00  14809.0

[121273 rows x 1 columns]
In [4]:
```

```
df.shape
```

(121273, 1)

In [5]:

```
df.info()
```

<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
```

```
df.describe()
```

output:

	AEP_MW
count	121273.000000
mean	15499.513717
std	2591.399065
min	9581.000000
25%	13630.000000
50%	15310.000000
75%	17200.000000
max	25695.000000

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

In [8]:

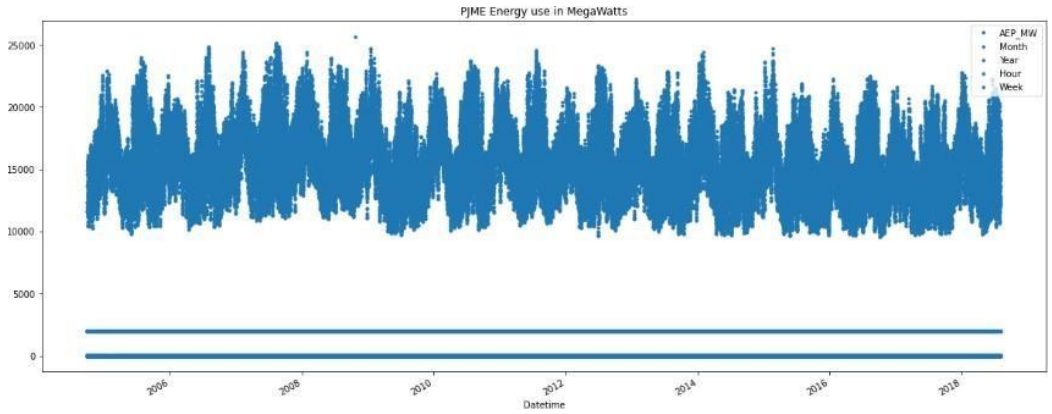
linkcode

```
# 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()
```

output:

	AEP_MW	Month	Year	Date	Hour	Week	Day
Datetime							
2004-10-01 01:00:00	12379.0	10	2004	2004-10-01	1	40	Friday
2004-10-01 02:00:00	11935.0	10	2004	2004-10-01	2	40	Friday
2004-10-01 03:00:00	11692.0	10	2004	2004-10-01	3	40	Friday
2004-10-01 04:00:00	11597.0	10	2004	2004-10-01	4	40	Friday
2004-10-01 05:00:00	11681.0	10	2004	2004-10-01	5	40	Friday

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

plt.show()
```




```
from sklearn.metrics import mean_squared_error, mean_absolute_error
from math import sqrt
from sklearn.preprocessing import MinMaxScaler

# Analysis imports
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
```

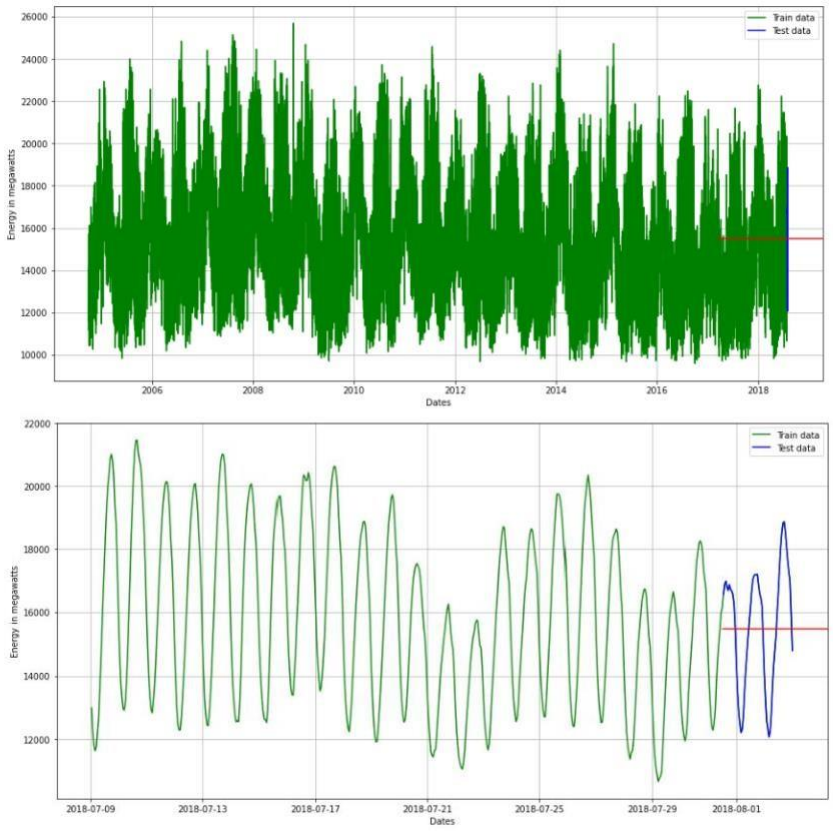
```
 # Modelling imports
 from statsmodels.tsa.ar_model import AR
 from  statsmodels.tsa.arima_model  import  ARMA
 from statsmodels.tsa.arima_model import ARIMA
 from keras.models import Sequential
 from keras.layers import Dense
 from keras.layers import LSTM, GRU, RNN
 from keras.layers import Dropout
In [13]:
linkcode
 values = DataFrame(df['AEP_MW'].values)
 dataframe = concat([values.shift(1),values.shift(5),values.shift(10),values.shift(30), values], axis
 =1)
 dataframe.columns = ['t', 't+1', 't+5', 't+10', 't+30']
 result = dataframe.corr()
 print(result)
```

output:

	t	t+1	t+5	t+10	t+30
t	1.000000	0.731161	0.345667	0.501972	0.976223
t+1	0.731161	1.000000	0.630009	0.847210	0.630007
t+5	0.345667	0.630009	1.000000	0.644479	0.317277
t+10	0.501972	0.847210	0.644479	1.000000	0.408315
t+30	0.976223	0.630007	0.317277	0.408315	1.000000

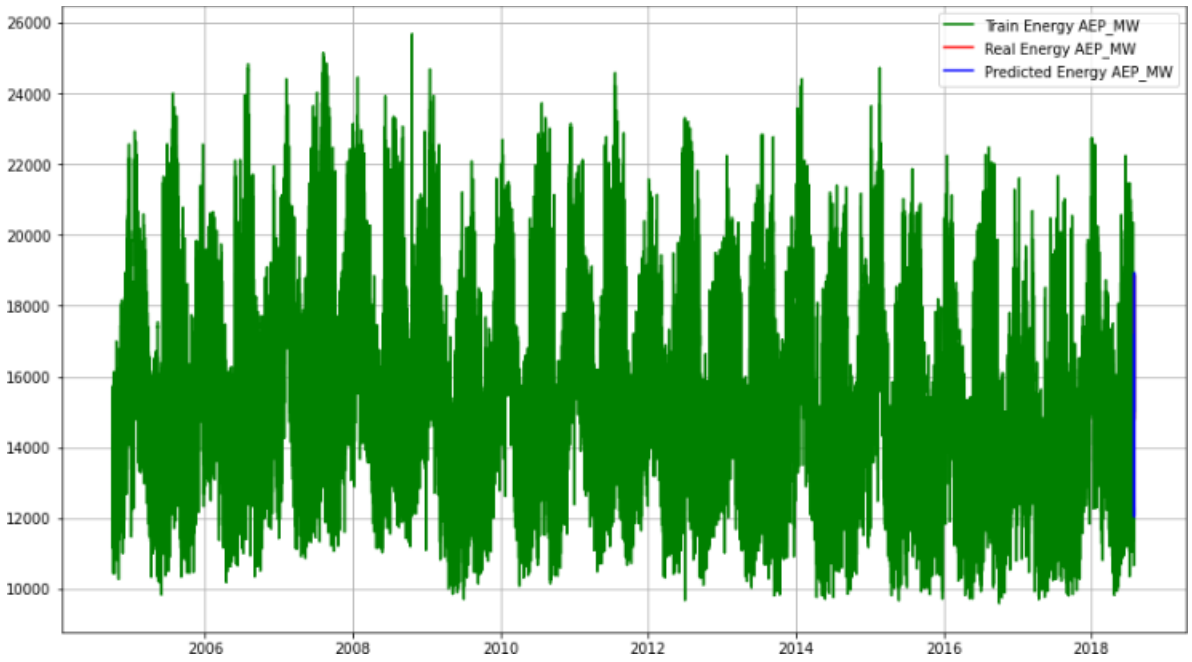
```
mean_value = df['AEP_MW'].mean() # calculation of mean price

plt.figure(figsize=(16,8))
plt.grid(True)
plt.xlabel('Dates')
plt.ylabel('Energy in megawatts')
plt.plot(df['AEP_MW'], 'green', label='Train data')
plt.plot(test_data['AEP_MW'], 'blue', label='Test data')
plt.axhline(y=mean_value, xmin=0.864, xmax=1, color='red')
plt.legend()

plt.figure(figsize=(16,8))
plt.grid(True)
plt.xlabel('Dates')
plt.ylabel('Energy in megawatts')
```

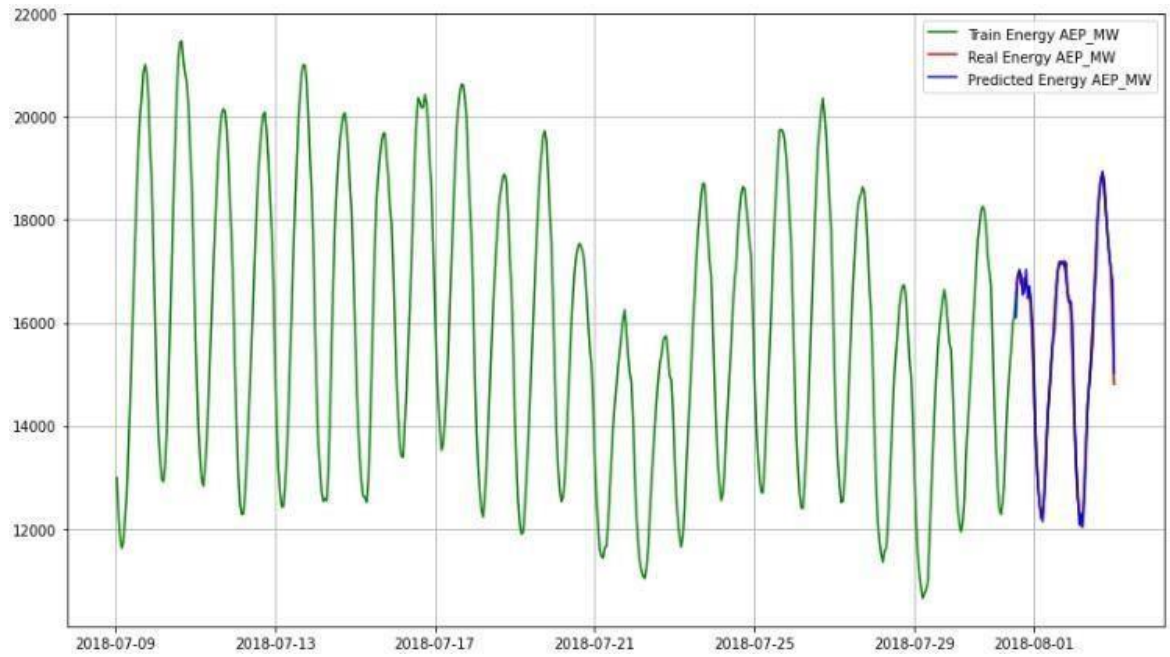
```
plt.plot(df['AEP_MW'].tail(600), 'green', label='Train data')
plt.plot(test_data['AEP_MW'], 'blue', label='Test data')
plt.axhline(y=mean_value, xmin=0.864, xmax=1, color='red')
plt.legend()

print('MSE: '+str(mean_squared_error(test_data['AEP_MW'], np.full(len(test_data), mean_valu
e))))
print('MAE: '+str(mean_absolute_error(test_data['AEP_MW'], np.full(len(test_data), mean_val
ue))))
print('RMSE: '+str(sqrt(mean_squared_error(test_data['AEP_MW'], np.full(len(test_data), mean
_value)))))
```




```
import statsmodels.api as sm

#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))))
```





MSE: 57710.45153428949

MAE: 177.320844006739

RMSE: 240.2299971574938

Scalability:

The modular design allows for easy scalability, accommodating both small-scale and large-scale energy monitoring applications.

Conclusion:

Measuring energy consumption using a modular approach enhances energy management, sustainability, and costefficiency. By leveraging sensor technology, data analysis, user-friendly interfaces, and integration capabilities, our framework empowers users to make informed decisions for a greener and more efficient future.

This abstract provides an overview of our modular framework for measuring energy consumption, offering a versatile and adaptable solution for various industries and applications.