MEASURE ENERGY CONSUMPTION

NAME:**S.SUGANTHAN-82262104305**

EMAIL:**ssuganthan370@gmail.com**

Phase 5- submission document

Project Title: MEASURE ENERGY CONSUMPTION

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INTRODUCTION:

Measuring energy consumption is a critical aspect of understanding, managing, and optimizing our use of energy resources. In a world where energy efficiency and sustainability are of increasing importance, accurate and comprehensive energy consumption measurements play a pivotal role in various sectors, including residential, commercial, industrial, and environmental.

Energy consumption refers to the amount of energy used by a particular system, device, building, or even an entire nation over a specified period. It encompasses various forms of energy, such as electricity, gas, fossil fuels, and renewable sources like solar and wind power. Measuring energy consumption provides valuable insights into the patterns and trends of energy usage, allowing us to make informed decisions and take actions to reduce waste, lower costs, and decrease our environmental footprint.

Energy measurement and monitoring involve the use of specialized tools and technology, such as smart meters, sensors, data analytics, and software platforms, to gather, process, and analyze energy consumption data. These

measurements are crucial for a range of purposes, including:

1. **Cost Management:** Businesses and homeowners use energy consumption data to control energy costs, identify inefficiencies, and make informed decisions about energy usage, such as optimizing lighting, heating, and cooling systems.

2. **Environmental Impact:** Reducing energy consumption is a key component of mitigating climate change and minimizing the environmental impact of energy production. Accurate measurements help in assessing the carbon footprint and developing strategies for sustainability.

3. **Regulatory Compliance:** Many governments and regulatory bodies require organizations to report their energy consumption to ensure compliance with energy efficiency and emissions reduction standards.

4. **Energy Efficiency:** Measuring energy consumption is crucial for identifying areas where energy efficiency improvements can be made, leading to reduced waste and improved overall efficiency.

5. **Resource Planning**: Utilities and energy providers use consumption data to plan and manage energy production, distribution, and infrastructure upgrades more effectively.

6. **Renewable Energy Integration**: Measuring consumption helps balance energy supply and demand when incorporating renewable energy sources into the grid, as these sources can be intermittent.

7. **Performance Benchmarking**: Comparing energy consumption data with industry benchmarks and best practices can help organizations gauge their performance and set improvement targets.

The methods for measuring energy consumption can vary depending on the scale and complexity of the system being assessed. From simple utility bills in households to sophisticated energy management systems in industrial facilities, the overarching goal remains the same: to gain insights, drive efficiency, and contribute to a more sustainable and economically viable energy future.

As we face the challenges of energy security and climate change, understanding how to accurately measure and manage energy consumption is a critical step in the pursuit of a more sustainable and efficient global energy landscape.

Tools used for the process:

Measuring energy consumption requires a variety of tools and equipment, depending on the scale and purpose of the measurement. Here are some common tools and technologies used to measure energy consumption:

1. **Electricity Meters:**

- Standard electricity meters are installed by utility companies to measure electricity consumption in homes and businesses. They typically provide readings in kilowatt-hours (kWh).

2. **Smart Meters:**

- Smart meters are advanced electricity meters that can provide real-time data on energy consumption. They may also offer two-way communication between the meter and the utility company, allowing for more detailed monitoring and control.

3. **Gas Meters:**

- Gas meters are used to measure the consumption of natural gas or propane in residential and commercial settings.

4. **Water Meters:**

- In some cases, water consumption may be an indirect indicator of energy usage, especially in heating and cooling systems.

5. **Energy Management Systems (EMS):**

- Energy management systems are software solutions that can collect and analyze data from various energy meters and sensors to provide insights into energy consumption patterns. These systems are commonly used in commercial and industrial settings.

6. **Data Loggers:**

- Data loggers are devices that record and store data from various sensors and meters. They are often used for collecting data over time for analysis.

7. **Current and Voltage Sensors:**

- These sensors are used to measure the electrical current and voltage in a circuit. By combining these measurements, you can calculate real-time power consumption.

8. **Temperature Sensors:**

- Temperature sensors are often used in energy consumption analysis, especially in HVAC (heating, ventilation, and air conditioning) systems, where temperature variations can significantly impact energy use.

9. **Lighting Control Systems:**

- Lighting control systems can be used to monitor and control lighting energy consumption in buildings. They may include occupancy sensors, dimmers, and timers.

10. **Submeters:**

- Submeters are installed at the circuit or device level to measure energy consumption in specific areas or equipment within a building. This can provide more granular data for analysis.

11. **Energy Auditing Tools:**

- Energy auditors use specialized tools like thermal imaging cameras, blower door tests, and infrared thermometers to identify areas of energy waste and inefficiency in buildings.

12. **Renewable Energy Monitoring Systems:**

- For those with renewable energy systems, monitoring tools can track the production and consumption of energy from sources like solar panels and wind turbines.

13. **Remote Monitoring Systems:**

- These systems allow users to remotely monitor and control energy consumption in buildings and industrial facilities.

14. **Energy Monitoring Software:**

- Software solutions, such as energy management software or Building Energy Management Systems (BEMS), can provide a user-friendly interface for analyzing and visualizing energy consumption data.

15. **Home Energy Monitors:**

- These devices are designed for residential use and provide homeowners with real-time information on their electricity consumption, helping them make informed decisions about energy use.

16. **Environmental Sensors:**

- Environmental sensors, such as air quality monitors, can help assess the impact of energy consumption on indoor air quality and overall environmental conditions.

When selecting tools for measuring energy consumption, consider your specific needs, the type of energy sources you are monitoring, the level of detail required, and your budget. Additionally, ensure that the tools you choose are accurate, calibrated, and compliant with relevant standards and regulations.

Design thinking is a problem-solving approach that focuses on understanding and addressing the needs of users or stakeholders. When applying design thinking to measure energy consumption, you can create a document to guide the process. This document should emphasize a user-centric perspective and encourage creativity and innovation. Below is a suggested structure for such a document:

Design Thinking Document: Measuring Energy Consumption

Project Overview

- **Project Name**: [Provide a concise name for the project]

- **Project Team**: [List the names and roles of team members]

- **Date**: [Date of document creation]

Problem Statement

- Define the energy consumption measurement challenge or opportunity. Consider who the primary users and stakeholders are, their pain points, and the objectives of the measurement.

Empathize (Understanding)

- Describe the research and data collection phase.

- **User Interviews**: Summarize insights gained from interviews with users and stakeholders.

- **Observations**: Highlight key observations and behaviors related to energy consumption.

- **User Personas**: Create personas to represent the diverse user groups and their needs.

- **Define**: Formulate the problem statement more clearly based on empathy findings.

Ideate (Ideation)

- Outline the brainstorming and idea generation phase.

- **Brainstorming Sessions**: Describe sessions held to generate innovative ideas for measuring energy consumption.

- **Idea Generation Tools**: Mention the tools or techniques used, such as mind mapping or brainstorming exercises.

- **Ideation Workshops**: Document workshops involving cross-functional teams to encourage diverse perspectives.

- **Prototyping**: Discuss early concept prototypes or mock-ups for measurement solutions.

Prototype (Prototyping)

- Detail the development of prototypes for potential solutions.

- **Prototyping Tools**: Specify the software or hardware used for creating prototypes.

- **Usability Testing**: Document user testing sessions to gather feedback on prototypes.

- **Iterations**: Mention how prototypes evolved based on user feedback.

Test (Testing)

- Explain the testing phase for the proposed solutions.

- **Testing Methods**: Describe the methods employed to evaluate the effectiveness of measurement solutions.

- **Feedback Analysis**: Summarize feedback and insights gathered from testing.

- **Iterate**: Document any changes or refinements made to the measurement solutions based on testing outcomes.

Implement (Implementation)

- Discuss the steps involved in implementing the chosen solution.

- **Rollout Plan**: Provide a plan for the deployment of the energy consumption measurement solution.

- **Training and Adoption**: Outline training programs and strategies to ensure user adoption.

- **Data Collection**: Explain how the solution will collect and process energy consumption data.

Measure (Evaluation)

- Discuss ongoing evaluation and monitoring of the solution's performance.

- **KPIs and Metrics**: Identify key performance indicators and metrics for measuring the effectiveness of energy consumption measurement.

- **Feedback Loop**: Describe the process for continuous feedback and improvement.

Conclusion

- Summarize the journey and the outcomes of applying design thinking to measure energy consumption.

- **Achievements**: Highlight the accomplishments and impact of the project.

- **Next Steps**: Identify any further actions or areas of improvement.

Appendices

- Include any supplementary materials, such as user personas, prototypes, or test results.

This document serves as a guideline for implementing design thinking principles in the context of measuring energy consumption. It encourages a user-centered approach, creativity, and iteration throughout the design process, ultimately leading to more effective and user-friendly solutions for measuring and managing energy consumption.

DESIGN INTO INNOVATION

Designing innovation to measure energy consumption involves creating new and more efficient methods, devices, or systems for monitoring and managing energy usage. Here's a step-by-step guide to help you design innovative solutions for measuring energy consumption:

1. Identify the Problem:

Start by identifying the specific energy consumption challenges or opportunities in your target area. Is it for a home, office, industrial facility, or a specific device? Understanding the problem is the first step in designing a solution.

2. Research and Benchmark:

Study existing energy measurement technologies, standards, and best practices in the field. This will help you identify gaps and areas for improvement.

3. Set Objectives:

Define clear objectives for your innovation. Consider what you want to achieve, such as accurate real-time measurement, ease of use, scalability, or cost-effectiveness.

4. User-Centered Design:

Keep the end-users in mind during the design process. The innovation should be intuitive, user-friendly, and cater to the needs and preferences of the users.

5. Technology Selection:

Choose the appropriate technologies to measure energy consumption. This might include sensors, IoT devices, smart meters, data analytics, or a combination of these. Consider the type of energy you're measuring (electricity, gas, water, etc.) and the level of granularity required.

6. Data Collection and Analysis:

Develop a system to collect and analyze energy consumption data. Utilize data analytics, machine learning, or artificial intelligence to gain insights into consumption patterns and identify potential areas for optimization.

7. Real-Time Monitoring:

If applicable, design your innovation to provide real-time energy consumption data. This enables users to make immediate adjustments to reduce energy waste.

8. Energy Efficiency Recommendations:

Implement features that provide users with actionable recommendations to reduce energy consumption. This could include suggestions for optimizing equipment, improving insulation, or adjusting usage patterns.

9. Scalability:

Ensure that your innovation can scale to accommodate different environments, from individual homes to large industrial facilities.

10. Cost-Effectiveness:

Strive to make your innovation cost-effective, considering both the initial investment and long-term operational costs.

11. Data Security and Privacy:

Address data security and privacy concerns, especially if your innovation involves collecting sensitive information about energy usage. Ensure compliance with relevant regulations.

12. Sustainability:

Design your innovation with sustainability in mind. Use eco-friendly materials, consider the energy impact of the devices themselves, and aim to reduce the overall environmental footprint.

13. Prototyping and Testing:

Develop prototypes of your innovation and conduct thorough testing. Collect feedback from potential users and iterate on your design based on their input.

14. Partnerships and Integration:

Consider partnerships with utility companies, energy management firms, or other stakeholders in the energy industry to ensure compatibility and integration with existing infrastructure.

15. Education and User Engagement:

Create educational materials and engage with users to ensure they understand how to make the most of the energy consumption data your innovation provides.

16. Marketing and Adoption:

Develop a marketing strategy to promote your innovation and encourage its adoption.

17. Continuous Improvement:

Be prepared to update and improve your innovation as technology and user needs evolve.

18. Compliance and Standards:

Ensure that your innovation complies with relevant industry standards and regulations.

By following these steps and maintaining a focus on user needs and sustainability, you can design an innovative solution for measuring and managing energy consumption effectively.

Importing Libraries

In [1]:

```
#!pip install pmdarima
```

In [2]:

```
import pandas as pd
import numpy as np

from pandas import datetime
from matplotlib import pyplot as plt
import os


from statsmodels.tsa.arima_model
import ARIMAfrom matplotlib import
pyplot
from pandas.tools.plotting import autocorrelation_plot
```

```
#from pyramid.arima import auto_arima
#from pmdarima.arima import
auto_arimaimport pyflux as pf

from sklearn.cluster import KMeans
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import
MinMaxScaler

from statsmodels.graphics.tsaplots import
plot_acf, plot_pacfimport statsmodels.api as sm
from statsmodels.tsa.statespace.sarimax import

SARIMAXimport math


from sklearn.preprocessing import
MinMaxScalerfrom sklearn.metrics
import mean_squared_error

from keras.models import Sequential
from keras.layers  import  Dense
from keras.layers import LSTM
```

Energy Data

We are predicting for energy demand in the future- therefore we are taking only energy sum i.e.total energy use per day for a given household.

In [3]:

```
# Combining all blocks
for num in range(0,112):
    df = pd.read_csv("../input/daily_dataset/daily_dataset/block_"+str(num)+"
.csv")
    df = df[['day','LCLid','energy_sum']]
    df.reset_index()
    df.to_csv("hc_"+str(num)+".csv")


fout= open("energy.csv","a")
# first file:
for line in
    open("hc_0.csv"):
    fout.write(line)
# now the rest:
for num in range(0,112):
    f = open("hc_"+str(num)+".csv")
    f.readline() # skip the header for
    line in f:
        fout.write(l
    ine)f.close()
fout.close()
```

Energy at Day Level

In [4]:

```
energy = pd.read_csv('energy.csv')
len(energy)
```

Out[4]:

3536007

House Count

In the dataset we see that the number of households for which energy data was collected acrossdifferent days are different. This is probably due to the gradually increasing adoption of smart meters in London. This could lead to false interpretation that the energy for a particular day might be high when it could be that the data was only collected for more number of houses. Wewill look at the house count for each day.

In [5]:

linkcode

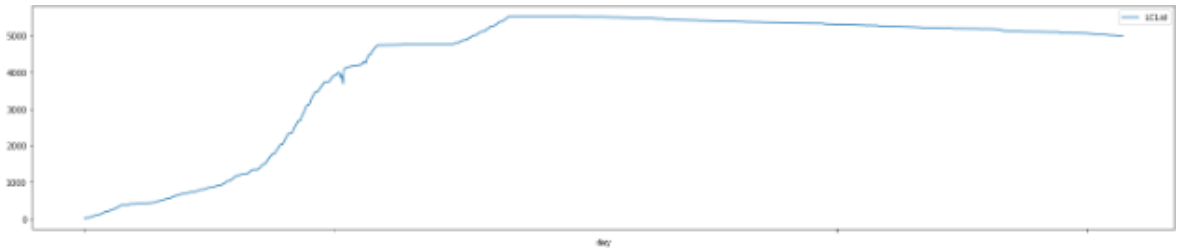
```
housecount =
energy.groupby('day')[['LCLid']].nunique()
housecount.head(4)
```

	LCLid
day	
2011-11-23	13
2011-11-24	25
2011-11-25	32
2011-11-26	41

```
housecount.plot(figsize=(25,5))
```

Out[6]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1d0e44d6d8>
```



Normalization across households

The data collection across households are inconsistent- therefore we will be using *energy per household* as the target to predict rather than energy alone. This is an optional step as we can also predict for energy sum as whole for each household. However there are quite a lot of unique households for which we have to repeat the exercise and our ultimate

goal is to predict overall consumption forecast and not at household level.

This also means that since household level is removed, we are not looking into the ACORN details which is available at household level

```
In [7]:
 energy = energy.groupby('day')[['energy_sum']].sum()
 energy = energy.merge(housecount, on = ['day']) energy
 = energy.reset_index()
```

```
In [8]:
 energy.count()


Out[8]:
day          829
energy_sum   829
LCLid        829

dtype:
int64In
[9]:
 energy.day = pd.to_datetime(energy.day,format='%Y-%m-%d').dt.date
In [10]:
 energy['avg_energy']  =  energy['energy_sum']/energy['LCLid']
 print("Starting Point of Data at Day Level",min(energy.day))
 print("Ending Point of Data at Day Level",max(energy.day))
Starting Point of Data at Day Level
2011-11-23Ending Point of Data at
Day Level 2014-02-28 In [11]:
 energy.describe()
```

	energy_sum	LCLid	avg_energy
count	829.000000	829.000000	829.000000
mean	43535.325676	4234.539204	10.491862
std	20550.594031	1789.994799	1.902513
min	90.385000	13.000000	0.211766
25%	34665.436003	4084.000000	8.676955
50%	46641.160997	5138.000000	10.516983
75%	59755.616996	5369.000000	12.000690
max	84156.135002	5541.000000	15.964434

Weather Information

Daily level weather information is taken using darksky api in the dataset

```
weather = pd.read_csv('../input/weather_daily_darksky.csv')weather.head(4)
```

	temperatureMax	temperatureMaxTime	windBearing	icon	dewPoint	temperatureMinTime	cloudCover	windSpeed
0	11.96	2011-11-11 23:00:00	123	fog	9.40	2011-11-11 07:00:00	0.79	3.88
1	8.59	2011-12-11 14:00:00	198	partly-cloudy-day	4.49	2011-12-11 01:00:00	0.56	3.94
2	10.33	2011-12-27 02:00:00	225	partly-cloudy-day	5.47	2011-12-27 23:00:00	0.85	3.54
3	8.07	2011-12-02 23:00:00	232	wind	3.69	2011-12-02 07:00:00	0.32	3.00

```
weather.describe()
```

	temperatureMax	windBearing	dewPoint	cloudCover	windSpeed	pressure	apparentTemperatureHigh
count	882.000000	882.000000	882.000000	881.000000	882.000000	882.000000	882.000000
mean	13.660113	195.702948	6.530034	0.477605	3.581803	1014.127540	12.723866
std	6.182744	89.340783	4.830875	0.193514	1.694007	11.073038	7.279168
min	-0.060000	0.000000	-7.840000	0.000000	0.200000	979.250000	-6.460000
25%	9.502500	120.500000	3.180000	0.350000	2.370000	1007.435000	7.032500
50%	12.625000	219.000000	6.380000	0.470000	3.440000	1014.615000	12.470000
75%	17.920000	255.000000	10.057500	0.600000	4.577500	1021.755000	17.910000
max	32.400000	359.000000	17.770000	1.000000	9.960000	1040.920000	32.420000

```
weather['day']=   pd.to_datetime(weather['time']) # day is given as timestamp
weather['day']=   pd.to_datetime(weather['day'],format='%Y%m%d').dt.date
# selecting numeric variables
weather = weather[['temperatureMax', 'windBearing', 'dewPoint', 'cloudCover', 'windSpeed',
        'pressure', 'apparentTemperatureHigh', 'visibility', 'humidity','apparentTemperatureLow',
```

```
            'apparentTemperatureMin', 'moonPhase','day']]weather =
weather.dropna()
```

Relationship of weather conditions with electricity consumption

```
weather_energy = energy.merge(weather,on='day')weather_energy.head(2)
```

	day	energy_sum	LCLid	avg_energy	temperatureMax	windBearing	dewPoint	cloudCover	windSpeed	pressure	appare
0	2011-11-23	90.385	13	6.952692	10.36	229	6.29	0.36	2.04	1027.12	10.36
1	2011-11-24	213.412	25	8.536480	12.93	204	8.56	0.41	4.04	1027.22	12.93

1. Temperature

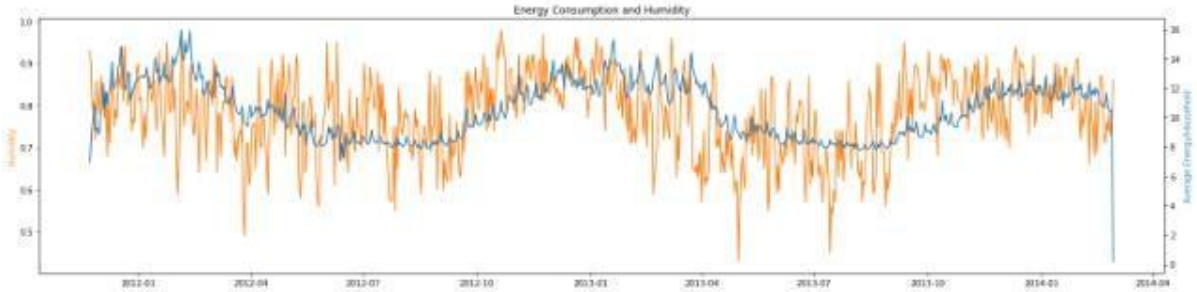
We can see that energy and temperature have an inverse relationship-we can see the peaks in one appearing with troughs in the other. This confirms the business intuition that during low temperature, it is likely that the energy consumption through heaters etc. increases.

```
fig, ax1 = plt.subplots(figsize = (20,5))

ax1.plot(weather_energy.day, weather_energy.temperatureMax, color = 'tab:orange')
ax1.plot(weather_energy.day, weather_energy.temperatureMin, color = 'tab:pink')
ax1.set_ylabel('Temperature')

ax1.legend()

ax2 = ax1.twinx() ax2.plot(weather_energy.day,weather_energy.avg_energy,color = 'tab:blue')
ax2.set_ylabel('Average Energy/Household',color = 'tab:blue') ax2.legend(bbox_to_anchor=(0.0,
1.02, 1.0, 0.102))

plt.title('Energy Consumption and Temperature')
fig.tight_layout()
```

2. Humidity

Humidity and the average consumption of energy seems to have the same trend.

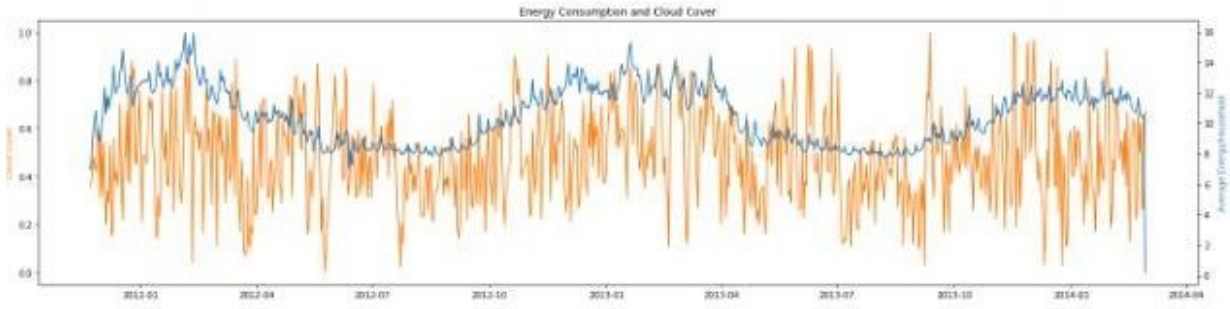
```
fig, ax1 = plt.subplots(figsize = (20,5))

ax1.plot(weather_energy.day, weather_energy.humidity, color = 'tab:orange')
ax1.set_ylabel('Humidity',color = 'tab:orange')

ax2 = ax1.twinx() ax2.plot(weather_energy.day,weather_energy.avg_energy,color = 'tab:blue')
ax2.set_ylabel('Average Energy/Household',color = 'tab:blue') plt.title('Energy Consumption and
Humidity')

fig.tight_layout()
plt.show()
```



3. Cloud Cover

The cloud cover value seems to be following the same pattern as the energy consumption.

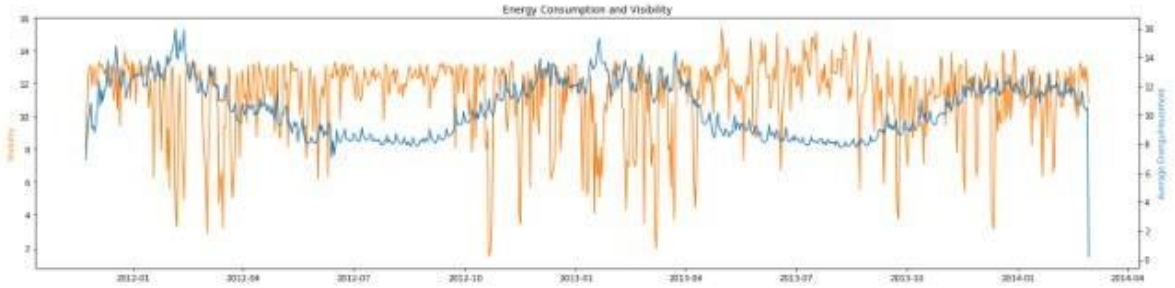
```
fig, ax1 = plt.subplots(figsize = (20,5))

ax1.plot(weather_energy.day, weather_energy.cloudCover, color = 'tab:orange')ax1.set_ylabel('Cloud
Cover',color = 'tab:orange')

ax2 = ax1.twinx() ax2.plot(weather_energy.day,weather_energy.avg_energy,color = 'tab:blue')
ax2.set_ylabel('Average Energy/Household',color = 'tab:blue') plt.title('Energy Consumption and Cloud
Cover')

fig.tight_layout()
```



4. Visibility

The visibility factor does not seem to affect energy consumption at all- since visibility is most likely an outdoors factor, it is unlikely that it's increase or decrease affects energy consumption within a household.

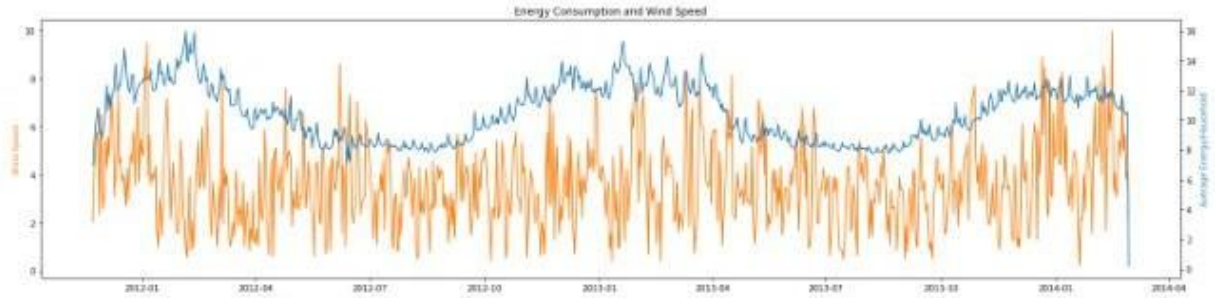
```
fig, ax1 = plt.subplots(figsize = (20,5))

ax1.plot(weather_energy.day, weather_energy.visibility, color = 'tab:orange')
ax1.set_ylabel('Visibility',color = 'tab:orange')

ax2 = ax1.twinx() ax2.plot(weather_energy.day,weather_energy.avg_energy,color = 'tab:blue')
ax2.set_ylabel('Average Energy/Household',color = 'tab:blue') plt.title('Energy Consumption and
Visibility')

fig.tight_layout()
```



5. Wind Speed

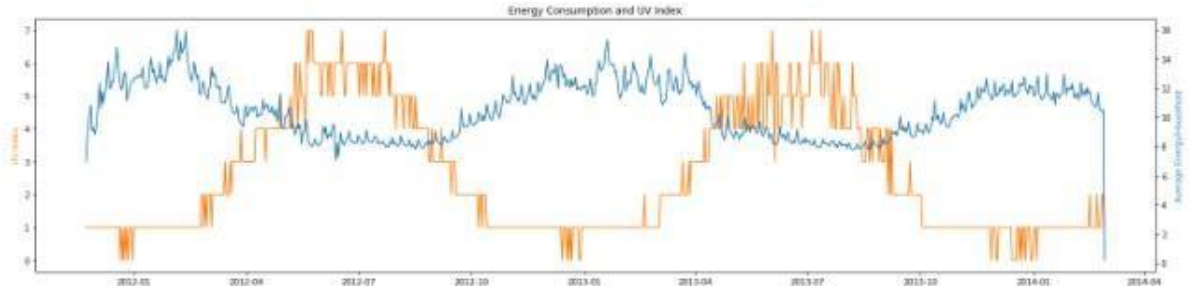
Like visibility, wind speed seems to be an outdoors factor which does not affect in the energyconsumption as such.

```
fig, ax1 = plt.subplots(figsize = (20,5))
ax1.plot(weather_energy.day, weather_energy.windSpeed, color =
'tab:orange')ax1.set_ylabel('Wind Speed',color = 'tab:orange')
ax2 = ax1.twinx()
ax2.plot(weather_energy.day,weather_energy.avg_energy,color
= 'tab:blue')ax2.set_ylabel('Average Energy/Household',color
= 'tab:blue') plt.title('Energy Consumption and Wind Speed')
fig.tight_layou
t()plt.show()
```



6. UV Index

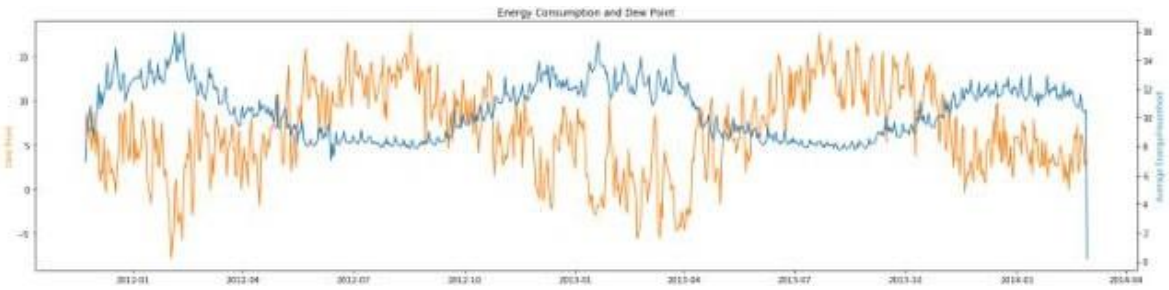
The UV index has an inverse relationship with energy consumption- why?



7. dewPoint

Dew Point- is a function of humidity and temperature therefore it displays similar relation to energyconsumption.

```
fig, ax1 = plt.subplots(figsize = (20,5))

ax1.plot(weather_energy.day, weather_energy.dewPoint, color = 'tab:orange')ax1.set_ylabel('Dew Point',color =
'tab:orange')

ax2 = ax1.twinx() ax2.plot(weather_energy.day,weather_energy.avg_energy,color = 'tab:blue')
ax2.set_ylabel('Average Energy/Household',color = 'tab:blue') plt.title('Energy Consumption and Dew
Point')

fig.tight_layout()
```



Correlation between Weather Variables and Energy Consumption

- Energy has high positive correlation with humidity and high negative correlation withtemperature.
- Dew Point, UV Index display multicollinearity with Temperature, hence discarded
- Cloud Cover and Visibility display multicollinearity with Humidity, hence discarded
- Pressure and Moon Phase have minimal correlation with Energy, hence discarded
- Wind Speed has low correlation with energy but does not show multicollinearity

```
cor_matrix = weather_energy[['avg_energy','temperatureMax','dewPoint', 'cloudCover', 'windSpeed','pressure', 'visibility', 'humidity','uvIndex', 'moonPhase']].corr()

cor_matrix
```

	avg_energy	temperatureMax	dewPoint	cloudCover	windSpeed	pressure	visibility	humidity	uvindex
avg_energy	1.000000	-0.846965	-0.755901	0.241779	0.149624	-0.028851	-0.246404	0.361237	-0.733
temperatureMax	-0.846965	1.000000	0.865038	-0.333409	-0.153602	0.118933	0.259108	-0.404899	0.6964
dewPoint	-0.755901	0.865038	1.000000	-0.025207	-0.092212	-0.028121	0.042633	0.055514	0.4866
cloudCover	0.241779	-0.333409	-0.025207	1.000000	0.170235	-0.101079	-0.330177	0.480056	-0.248
windSpeed	0.149624	-0.153602	-0.092212	0.170235	1.000000	-0.344354	0.281088	-0.042391	-0.152
pressure	-0.028851	0.118933	-0.028121	-0.101079	-0.344354	1.000000	-0.012508	-0.250941	0.1007
visibility	-0.246404	0.259108	0.042633	-0.330177	0.281088	-0.012508	1.000000	-0.578130	0.2404
humidity	0.361237	-0.404899	0.055514	0.480056	-0.042391	-0.250941	-0.578130	1.000000	-0.533
uvindex	-0.733171	0.696497	0.486692	-0.248695	-0.152634	0.100774	0.240485	-0.533919	1.0000
moonPhase	-0.031716	0.003636	-0.008239	-0.062126	-0.023273	0.038462	0.062813	-0.013997	0.0128

Creating Weather Clusters

The weather information has a lot of variables- which might not all be useful. We will attempt to create weather clusters to see if we can define a weather of the day based on the granular weatherdata like temperature, precipitation etc.

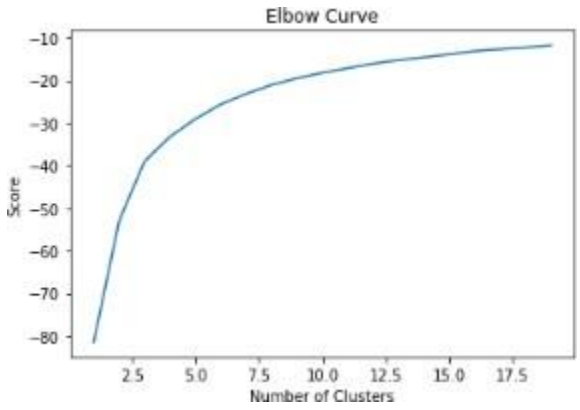
#scaling

```
scaler = MinMaxScaler()
weather_scaled =
scaler.fit_transform(weather_energy[['temperatureMax','humidity','w
indSpeed']])
```

In [25]:
linkcode

 # optimum K

```
Nc = range(1, 20)
kmeans = [KMeans(n_clusters=i) for i in
Nc]kmeans

score = [kmeans[i].fit(weather_scaled).score(weather_scaled) for i in
range(len(kmeans))]
score
plt.plot(Nc,score)
plt.xlabel('Number of
Clusters')plt.ylabel('Score')
plt.title('Elbow Curve')
plt.show()
```




```
kmeans = KMeans(n_clusters=3, max_iter=600,
algorithm = 'auto')kmeans.fit(weather_scaled)
weather_energy['weather_cluster'] = kmeans.labels_
```

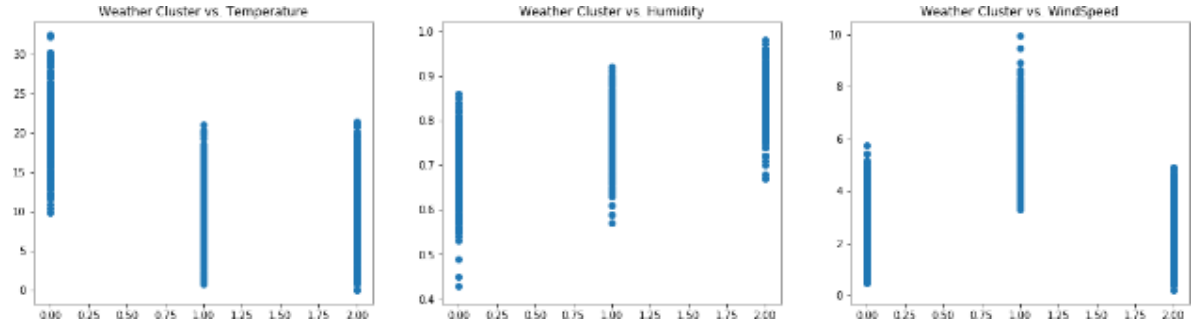
In [27]:
linkcode

 # Cluster Relationships with weather variables

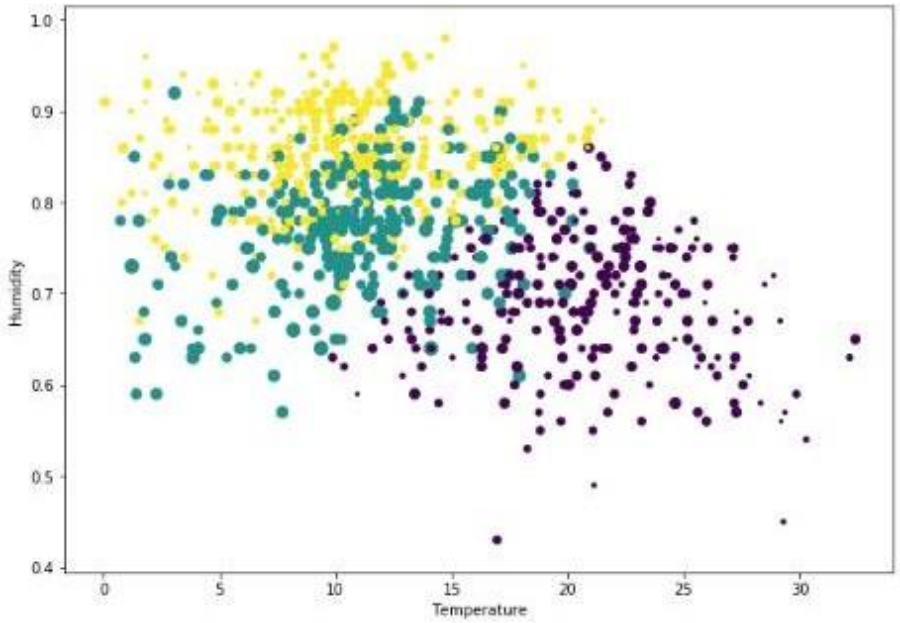
```
plt.figure(figsize=(20,5))
plt.subplot(1, 3, 1)
plt.scatter(weather_energy.weather_cluster,weather_energy.temperatu
```

```
reMax)plt.title('Weather Cluster vs. Temperature')
plt.subplot(1, 3, 2)
plt.scatter(weather_energy.weather_cluster,weather_energy.humidity)
plt.title('Weather Cluster vs. Humidity')
plt.subplot(1, 3, 3)
```

```
plt.scatter(weather_energy.weather_cluster,weather_energy.windSpeed)
plt.title('Weather Cluster vs. WindSpeed')

plt.show()
# put this in a loop
```




```
fig, ax1 = plt.subplots(figsize = (10,7))
ax1.scatter(weather_energy.temperatureMax,
                    weather_energy.humidity,
                    s = weather_energy.windSpeed*10,
                    c = weather_energy.weather_cluster)
ax1.set_xlabel('Temperature') ax1.set_ylabel('Humidity')
```



UK Bank Holidays

In [29]:

linkcode

```
holiday = pd.read_csv('../input/uk_bank_holidays.csv')
holiday['Bank holidays'] = pd.to_datetime(holiday['Bank holidays'],format='%Y-%m-%d')
.dt.date
holiday.head(4)
```

	Bank holidays	Type
0	2012-12-26	Boxing Day
1	2012-12-25	Christmas Day
2	2012-08-27	Summer bank holiday
3	2012-05-06	Queen?s Diamond Jubilee (extra bank holiday)

Creating a holiday indicator on weather data

```
weather_energy = weather_energy.merge(holiday, left_on =
'day',right_on = 'Bank holidays',how = 'left')
weather_energy['holiday_ind'] = np.where(weather_energy['Bank
holidays'].isna(),0,1)
```

ARIMAX

In [31]:

```
weather_energy['Year'] =
pd.DatetimeIndex(weather_energy['day']).year
weather_energy['Month'] =
pd.DatetimeIndex(weather_energy['day']).month
weather_energy.set_index(['day'],inplace=True)
```

Subset for required columns and 70-30 train-test split

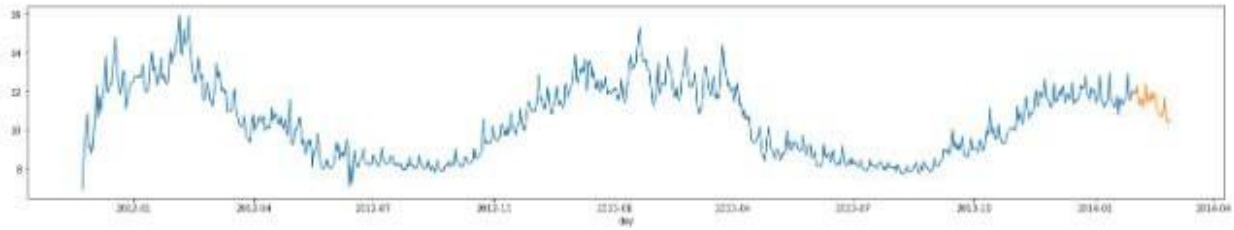
In [32]:

```
model_data = weather_energy[['avg_energy','weather_cluster','holiday_ind']]
# train = model_data.iloc[0:round(len(model_data)*0.90)]#
test = model_data.iloc[len(train)-1:]

train = model_data.iloc[0:(len(model_data)-30)]
test = model_data.iloc[len(train):(len(model_data)-1)]
```

In [33]:

linkcode

```
train['avg_energy'].plot(figsize=(25,4))
test['avg_energy'].plot(figsize=(25,4))
```

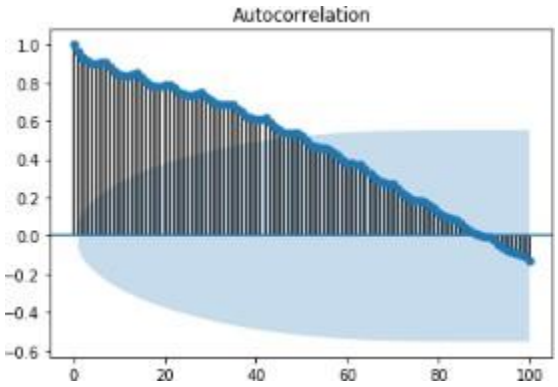


```
test.head(1)
```

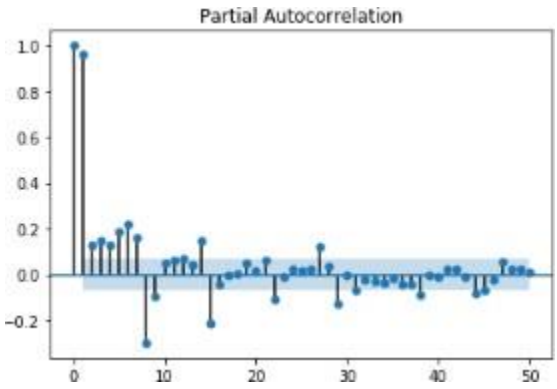
	avg_energy	weather_cluster	holiday_ind
day			
2014-01-30	11.886982	2	0

ACF PACF

```
plot_acf(train.avg_energy,lags=100)plt.show()
```




```
plot_pacf(train.avg_energy,lags=50)plt.show()
```



Dickey Fuller's Test

p is greater than 0.05 therefore the data is not stationary. After differencing, p < 0.05.

In [37]:

```
t = sm.tsa.adfuller(train.avg_energy, autolag='AIC')
pd.Series(t[0:4], index=['Test Statistic','p-value','#Lags
Used','Number of Observations Used'])
```

```
Out[37]:
Test Statistic             -1.872794
p-value                     0.344966
#Lags Used                 21.000000
Number of           Used  776.000000
Observations
dtype: float64
```

In [38]:

```
# function for differencing

def difference(dataset,
    interval):diff = list()
    for i in range(interval, len(dataset)):
        value = dataset.iloc[i] - dataset.iloc[i -
        interval]diff.append(value)
    return diff
```

In [39]:

```
t  = sm.tsa.adfuller(difference(train.avg_energy,1), autolag='AIC')
pd.Series(t[0:4], index=['Test Statistic','p-value','#Lags
Used','Number of Observations Used'])
```

```
Out[39]:
Test Statistic                  -6.715004e+00
p-value                         3.600554e-09
#Lags Used                      2.000000e+01
Number of Observations Used 7.760000e+02 dtype:
float64
```

Seasonal Decomposition

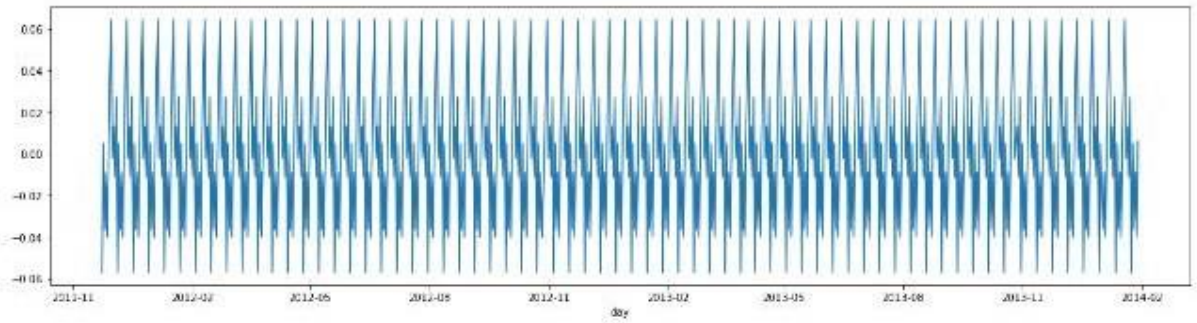
The seasonal component is quite low while the trend is quite strong with obvious dips in electricityconsumption during summers i.e. April to September. This may be attributed to longer days duringsummer.

In [40]:

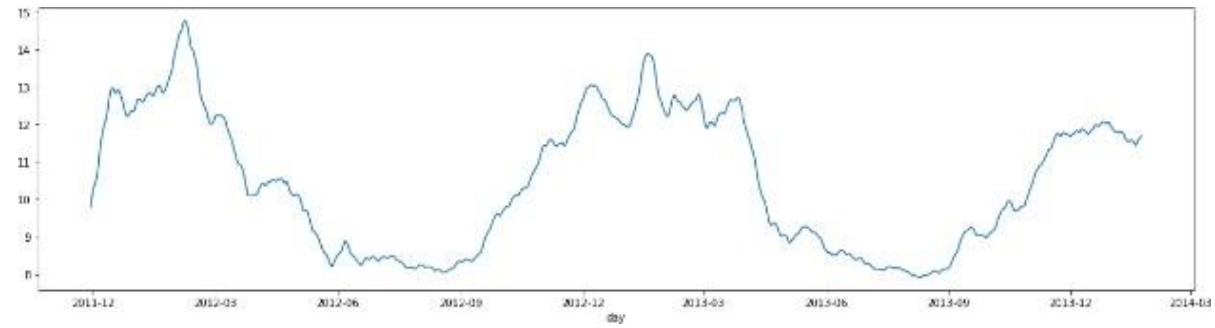
```
s = sm.tsa.seasonal_decompose(train.avg_energy,freq=12)
```

In [41]:
linkcode

```
s.seasonal.plot(figsize=(20,5))
```



```
s.trend.plot(figsize=(20,5))
```



```
s.resid.plot(figsize=(20,5))
```

```
endog = train['avg_energy']

exog = sm.add_constant(train[['weather_cluster','holiday_ind']])


mod = sm.tsa.statespace.SARIMAX(endog=endog, exog=exog, order=(7,1,1),seasonal_order=(1,1, 0,
12),trend='c')
```

Statespace Model Results

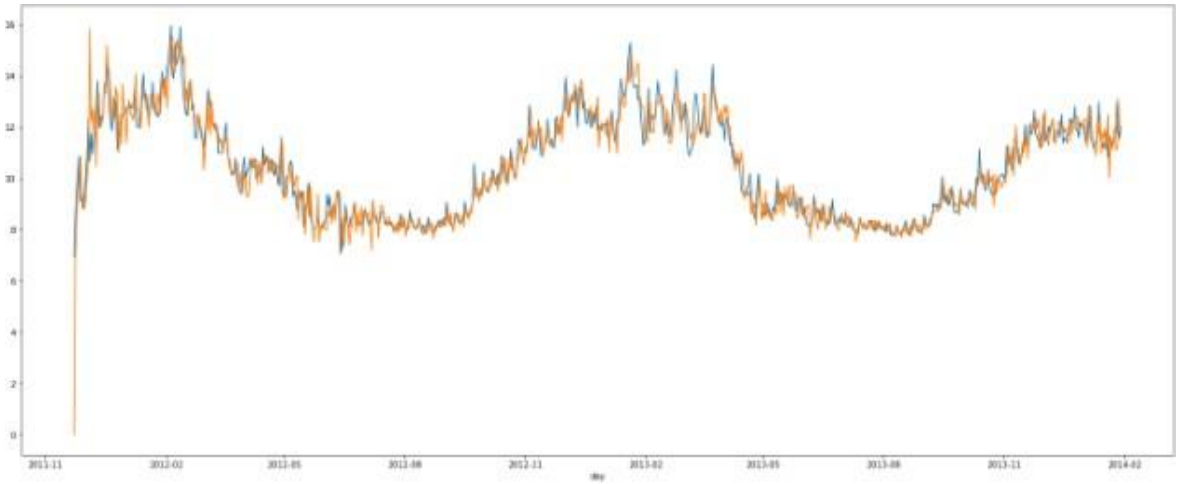
Dep. Variable:	avg_energy	No. Observations:	798
Model:	SARIMAX(7, 1, 1)x(1, 1, 0, 12)	Log Likelihood	-649.420
Date:	Tue, 11 Dec 2018	AIC	1326.841
Time:	10:40:33	BIC	1392.160
Sample:	0	HQIC	1351.956
	- 798		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	-0.0064	0.017	-0.379	0.705	-0.039	0.027
const	-3.162e-08	2.89e-10	-109.267	0.000	-3.22e-08	-3.1e-08
weather_cluster	0.0031	0.023	0.134	0.893	-0.042	0.048
holiday_ind	-0.0344	0.088	-0.392	0.695	-0.207	0.138
ar.L1	-0.0011	0.086	-0.013	0.990	-0.170	0.168
ar.L2	-0.1545	0.032	-4.841	0.000	-0.217	-0.092
ar.L3	-0.1434	0.038	-3.763	0.000	-0.218	-0.069
ar.L4	-0.1513	0.038	-3.987	0.000	-0.226	-0.077
ar.L5	-0.1632	0.040	-4.107	0.000	-0.241	-0.085
ar.L6	0.0087	0.036	0.239	0.811	-0.062	0.080
ar.L7	0.3526	0.029	12.333	0.000	0.297	0.409
ma.L1	-0.1860	0.091	-2.043	0.041	-0.365	-0.008
ar.S.L12	-0.4836	0.032	-14.939	0.000	-0.547	-0.420
sigma2	0.3041	0.013	24.110	0.000	0.279	0.329

Model Fit

In [45]:

```
linkcode
 train['avg_energy'].plot(figsize=(25,10))
 model_fit.fittedvalues.plot()
 plt.show()
```



Prediction

In [46]:
linkcode

```
predict = model_fit.predict(start = len(train),end = len(train)+len(test)-1,exog = s
m.add_constant(test[['weather_cluster','holiday_ind']]))
test['predicted'] = predict.values
test.tail(5)
```

	avg_energy	weather_cluster	holiday_ind	predicted
day				
2014-02-23	11.673756	1	0	11.554959
2014-02-24	10.586235	1	0	10.704375
2014-02-25	10.476498	1	0	11.441180
2014-02-26	10.375366	1	0	11.866796
2014-02-27	10.537250	1	0	11.480418

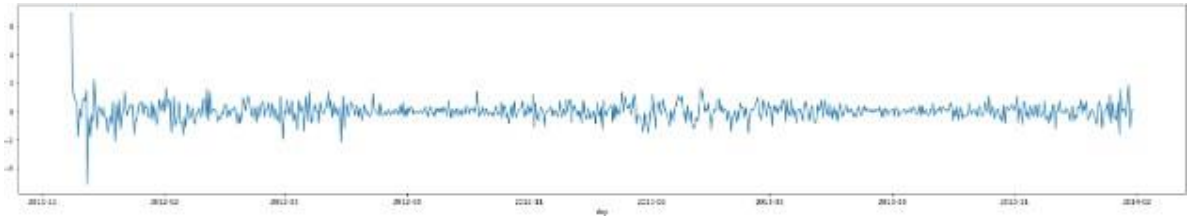
```
test['residual'] = abs(test['avg_energy']-
test['predicted'])MAE =
test['residual'].sum()/len(test)
MAPE =
(abs(test['residual'])/test['avg_energy']).sum()*100/len(test)
print("MAE:", MAE)
print("MAPE:", MAPE)
```

MAE: 0.5853190227226445
MAPE: 5.237822685938685

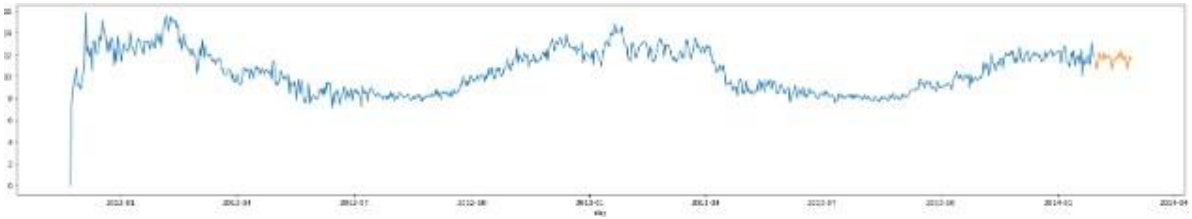
In [48]:
linkcode

```
test['avg_energy'].plot(figsize=(25,10),color =
'red')test['predicted'].plot()
plt.show()
```

```
model_fit.resid.plot(figsize= (30,5))
```



```
model_fit.fittedvalues.plot(figsize = (30,5))
test.predicted.plot()
```



```
test['predicted'].tail(5)
```

Out[51]:

```
day
2014-02-23 11.554959
2014-02-24 10.704375
2014-02-25 11.441180
2014-02-26 11.866796
2014-02-27 11.480418
```

Name: predicted, dtype: float64

LSTM

Using lags of upto 7 days we are going to convert this into a supervised problem. I have taken the function to create lags from this tutorial by Jason Brownlee. He has also applied the same to convertmultivariate data to a supervised dataframe which he has in turn applied LSTM on.

In [52]:

```
np.random.seed(11)
dataframe =
weather_energy.loc[:,'avg_energy']
dataset = dataframe.values
dataset = dataset.astype('float32')
```

In [53]:

```
# convert series to supervised learning
def series_to_supervised(data, n_in=1, n_out=1,
    dropnan=True):n_vars = 1
    df = pd.DataFrame(data)
    cols, names = list(),
    list()
    # input sequence (t-n, ... t-1)
    for i in range(n_in, 0,
        -1):
        cols.append(df.shift
        (i))
        names += [('var%d(t-%d)' % (j+1, i)) for j in range(n_vars)]
    # forecast sequence (t, t+1, ... t+n)
    for i in range(0,
        n_out):
        cols.append(df.shift(
        -i))if i == 0:
            names += [('var%d(t)' % (j+1)) for j in
        range(n_vars)]else:
            names += [('var%d(t+%d)' % (j+1, i)) for j in range(n_vars)]
    # put it all together
    agg = pd.concat(cols,
    axis=1)agg.columns =
    names
    # drop rows with NaN values
    if dropnan:
        agg.dropna(inplace=T
    rue)return agg
```

In [54]:

```
reframed =
series_to_supervised(dataset, 7,1)
reframed.head(3)
```

	var1(t-7)	var1(t-6)	var1(t-5)	var1(t-4)	var1(t-3)	var1(t-2)	var1(t-1)	var1(t)
7	6.952693	8.536480	9.499782	10.267707	10.850805	9.103382	9.274873	8.813513
8	8.536480	9.499782	10.267707	10.850805	9.103382	9.274873	8.813513	9.227707
9	9.499782	10.267707	10.850805	9.103382	9.274873	8.813513	9.227707	10.145910

```
reframed['weather_cluster'] =
weather_energy.weather_cluster.values[7:]
reframed['holiday_ind']=
weather_energy.holiday_ind.values[7:]
```

```
In [56]:
reframed = reframed.reindex(['weather_cluster', 'holiday_ind','var1(t-7)',
'var1(t-6
)', 'var1(t-5)', 'var1(t-4)', 'var1(t-3)','var1(t-2)', 'var1(t-1)',
'var1(t)'], axis
=1)
reframed = reframed.values
```

Normalization

```
In [57]:
scaler =
MinMaxScaler(feature_range=(0, 1))
reframed =
scaler.fit_transform(reframed)
```

```
In [58]:
# split into train and test sets
train = reframed[:(len(reframed)-30), :]
test = reframed[(len(reframed)-30):len(reframed), :]
```

```
In [59]:
train_X, train_y = train[:, :-1], train[:, -1]
test_X, test_y = test[:, :-1], test[:, -1]
```

```
In [60]:
# reshape input to be 3D [samples, timesteps, features]
train_X = train_X.reshape((train_X.shape[0], 1,
train_X.shape[1]))test_X =
test_X.reshape((test_X.shape[0], 1, test_X.shape[1]))
print(train_X.shape, train_y.shape, test_X.shape,
test_y.shape)
```

(791, 1, 9) (791,) (30, 1, 9) (30,)

Modelling

```
In [61]:
```
linkcode

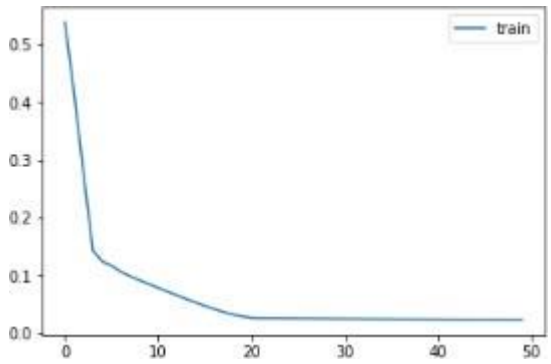
```
# design network
model = Sequential()
```

```
model.add(LSTM(50, input_shape=(train_X.shape[1],
train_X.shape[2])))model.add(Dense(1))
model.compile(loss='mae', optimizer='adam')
# fit network
history = model.fit(train_X, train_y, epochs=50, batch_size=72,
verbose=2, shuffle=False)
# plot history
pyplot.plot(history.history['loss'],
label='train')pyplot.legend()
pyplot.show()
```

```
Epoch 1/50
 - 1s - loss: 0.5382
```

```
Epoch 2/50
 - 0s - loss: 0.4130
Epoch 3/50
 - 0s - loss: 0.2755
Epoch 4/50
 - 0s - loss: 0.1430
Epoch 5/50
 - 0s - loss: 0.1240
Epoch 6/50
 - 0s - loss: 0.1169
Epoch 7/50
 - 0s - loss: 0.1062
Epoch 8/50
 - 0s - loss: 0.0987
Epoch 9/50
 - 0s - loss: 0.0916
Epoch 10/50
 - 0s - loss: 0.0852
Epoch 11/50
 - 0s - loss: 0.0784
Epoch 12/50
 - 0s - loss: 0.0720
Epoch 13/50
 - 0s - loss: 0.0656
Epoch 14/50
 - 0s - loss: 0.0593
Epoch 15/50
 - 0s - loss: 0.0532
Epoch 16/50
 - 0s - loss: 0.0473
Epoch 17/50
 - 0s - loss: 0.0417
Epoch 18/50
 - 0s - loss: 0.0367
Epoch 19/50
 - 0s - loss: 0.0325
Epoch 20/50
 - 0s - loss: 0.0290
Epoch 21/50
 - 0s - loss: 0.0266
Epoch 22/50
 - 0s - loss: 0.0259
Epoch 23/50
 - 0s - loss: 0.0259
Epoch 24/50
 - 0s - loss: 0.0258
Epoch 25/50
 - 0s - loss: 0.0257
Epoch 26/50
 - 0s - loss: 0.0255
Epoch 27/50
 - 0s - loss: 0.0254
```

```
Epoch 28/50
 - 0s - loss: 0.0253
Epoch 29/50
 - 0s - loss: 0.0251
Epoch 30/50
 - 0s - loss: 0.0250
Epoch 31/50
 - 0s - loss: 0.0249
Epoch 32/50
 - 0s - loss: 0.0248
Epoch 33/50
 - 0s - loss: 0.0247
Epoch 34/50
 - 0s - loss: 0.0245
Epoch 35/50
 - 0s - loss: 0.0245
Epoch 36/50
 - 0s - loss: 0.0244
Epoch 37/50
 - 0s - loss: 0.0243
Epoch 38/50
 - 0s - loss: 0.0242
Epoch 39/50
 - 0s - loss: 0.0241
Epoch 40/50
 - 0s - loss: 0.0239
Epoch 41/50
 - 0s - loss: 0.0240
Epoch 42/50
 - 0s - loss: 0.0238
Epoch 43/50
 - 0s - loss: 0.0238
Epoch 44/50
 - 0s - loss: 0.0237
Epoch 45/50
 - 0s - loss: 0.0236
Epoch 46/50
 - 0s - loss: 0.0236
Epoch 47/50
 - 0s - loss: 0.0235
Epoch 48/50
 - 0s - loss: 0.0234
Epoch 49/50
 - 0s - loss: 0.0233
Epoch 50/50
 - 0s - loss: 0.0233
```



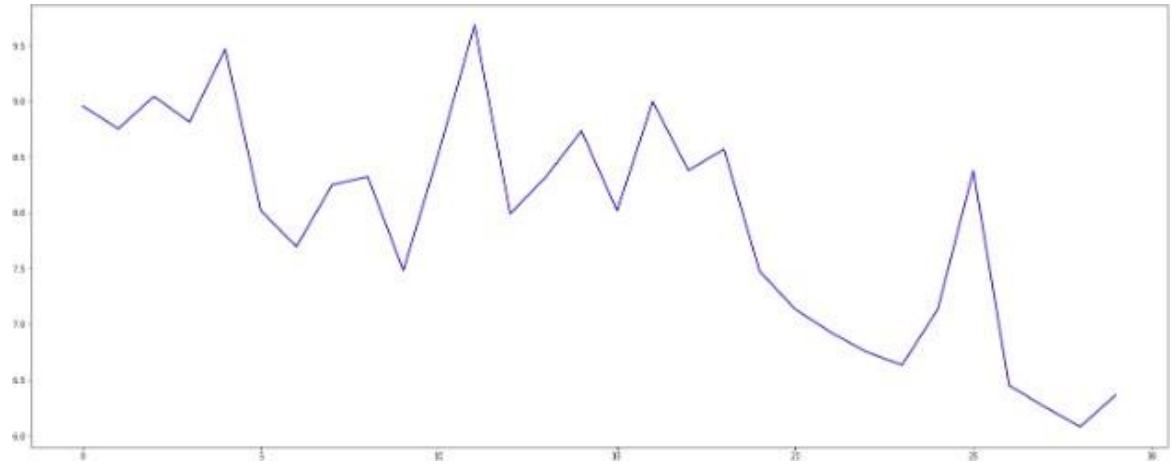
Prediction

```
In [62]:
 # make a prediction

 yhat = model.predict(test_X)

In [63]:
 test_X = test_X.reshape(test_X.shape[0], test_X.shape[2])

In [64]:
 # invert scaling for forecast

 inv_yhat = np.concatenate((yhat, test_X),
 axis=1)inv_yhat =
 scaler.inverse_transform(inv_yhat)

In [65]:
 # invert scaling for actual

 test_y = test_y.reshape((len(test_y), 1))
 inv_y = np.concatenate((test_y, test_X),
 axis=1)inv_y =
 scaler.inverse_transform(inv_y)
```

Performance

```
In [66]:
 act = [i[9] for i in inv_y] # last element is the predicted average energy

 pred = [i[9] for i in inv_yhat] # last element is the actual average energy


 # calculate RMSE

 import math
 rmse = math.sqrt(mean_squared_error(act,
 pred))print('Test RMSE: %.3f' % rmse)


In [67]:
linkcode
```

```
predicted_lstm =
pd.DataFrame({'predicted':pred,'avg_energy':act})
predicted_lstm['avg_energy'].plot(figsize=(25,10),color =
'red') predicted_lstm['predicted'].plot(color = 'blue')
plt.show()
```



ADVANTAGES:

Measuring energy consumption offers several advantages that can benefit individuals, businesses, and society as a whole. Some of the key advantages of measuring energy consumption include:

1. Energy Efficiency: Measurement provides insights into how energy is being used, making it easier to identify areas for improvement. This can lead to more efficient energy usage and cost savings.

2. Cost Reduction: By understanding where and how energy is consumed, individuals and organizations can take steps to reduce their energy bills, resulting in significant cost savings over time.

3. Environmental Impact: Reducing energy consumption can lower greenhouse gas emissions and decrease an individual or organization's carbon footprint, contributing to environmental sustainability.

4. Peak Load Management: Monitoring energy consumption helps utilities and grid operators manage peak loads more effectively, reducing the risk of power outages and the need for additional infrastructure.

5. Informed Decision-Making: Energy consumption data allows individuals and organizations to make informed decisions about energy-related investments, such as upgrading equipment, adopting renewable energy sources, or implementing energy-saving technologies.

6. Behavioral Changes: When individuals are aware of their energy usage and costs, they are more likely to adopt energy-saving behaviors, such as turning off lights and appliances when not in use.

7. Benchmarking: Measuring energy consumption allows for benchmarking against industry standards and peers, enabling organizations to assess their energy efficiency relative to others in their sector.

8. Verification and Accountability: Energy consumption data can be used to verify energy efficiency improvements and hold individuals and organizations accountable for their energy-saving initiatives.

9. Renewable Energy Integration: Measuring energy consumption helps optimize the integration of renewable energy sources, as it provides valuable information on when and how energy is used.

10. Predictive Maintenance: In industrial settings, monitoring energy consumption can help predict equipment failures and schedule maintenance to prevent costly downtime.

11. Resource Conservation: Reducing energy consumption is often linked to resource conservation, as less energy production and consumption can lead to reduced resource depletion and pollution.

12. Demand Response: Utilities and grid operators can use energy consumption data to implement demand response programs, encouraging consumers to reduce their energy usage during peak demand periods.

13. Incentive Programs: Some regions offer incentives, rebates, or tax credits for energy-efficient practices, and measuring energy consumption is often a prerequisite for participating in these programs.

14. Energy Audits: Accurate energy consumption data is essential for conducting energy audits, which can reveal opportunities for energy savings and sustainability improvements.

15. Enhanced Building Performance: Measuring energy consumption in buildings can lead to improved comfort, indoor air quality, and overall building performance.

16. Regulatory Compliance: Many industries and businesses are subject to energy efficiency regulations and reporting requirements, and measuring energy consumption is essential for complying with these regulations.

Overall, measuring energy consumption is a fundamental step in the journey toward energy efficiency, cost reduction, environmental sustainability, and better energy management. It enables individuals, businesses, and policymakers to make informed decisions and take actions that benefit both their bottom line and the planet.

DISADVANTAGES:

While measuring energy consumption offers numerous benefits, it's important to be aware of potential disadvantages and challenges associated with this practice. Some of the disadvantages of measuring energy consumption include:

1. Initial Investment: Installing energy measurement equipment or systems can require a significant upfront investment in hardware, software, sensors, and infrastructure, which may be a barrier for some individuals and organizations.

2. Implementation Complexity: Setting up accurate energy measurement systems can be technically complex, particularly for larger facilities or buildings. It may involve retrofitting or integrating existing infrastructure, which can be challenging and time-consuming.

3. Data Collection and Management: Gathering, storing, and managing energy consumption data can be resource-intensive. It requires ongoing monitoring, maintenance, and data processing, which may require dedicated personnel or software solutions.

4. Privacy Concerns: In some cases, measuring energy consumption can reveal sensitive information about occupants' habits and activities. This privacy concern can be a significant issue, especially in residential settings.

5. Data Accuracy: The accuracy of energy consumption measurements can be affected by factors such as sensor calibration, data transmission, and environmental conditions. Inaccurate data can lead to incorrect decisions and conclusions.

6. Maintenance and Calibration: Measurement equipment, such as sensors and meters, requires regular maintenance and calibration to ensure accurate readings. Neglecting this aspect can lead to data discrepancies.

CONCLUSION:

In conclusion, measuring energy consumption is a critical practice with a multitude of benefits for individuals, businesses, and society as a whole. It provides valuable insights into how energy is used, enabling informed decision-making, cost reduction, and environmental sustainability. Energy consumption measurement also fosters energy efficiency, enhances resource conservation, and supports the integration of renewable energy sources. Moreover, it plays a key role in demand response, regulatory compliance, and incentive programs, offering a pathway toward a more sustainable and efficient energy landscape.

However, it's important to acknowledge the potential disadvantages and challenges associated with energy consumption measurement, including the initial investment, data privacy concerns, accuracy issues, and the need for ongoing maintenance. These challenges should not deter us from the benefits of energy measurement but rather serve as reminders to plan and implement measurement systems thoughtfully, considering the unique needs and circumstances of each situation.

As technology and best practices continue to evolve, the advantages of measuring energy consumption become even more attainable. It is a practice that not only benefits the bottom line for businesses and individuals but also contributes to a more sustainable and resilient energy future, addressing the environmental and economic challenges of our time. To harness the full potential of energy consumption measurement, it's crucial to embrace innovation, data-driven insights, and collaborative efforts to shape a greener and more efficient world.