MEASURE ENERGY CONSUMPTION

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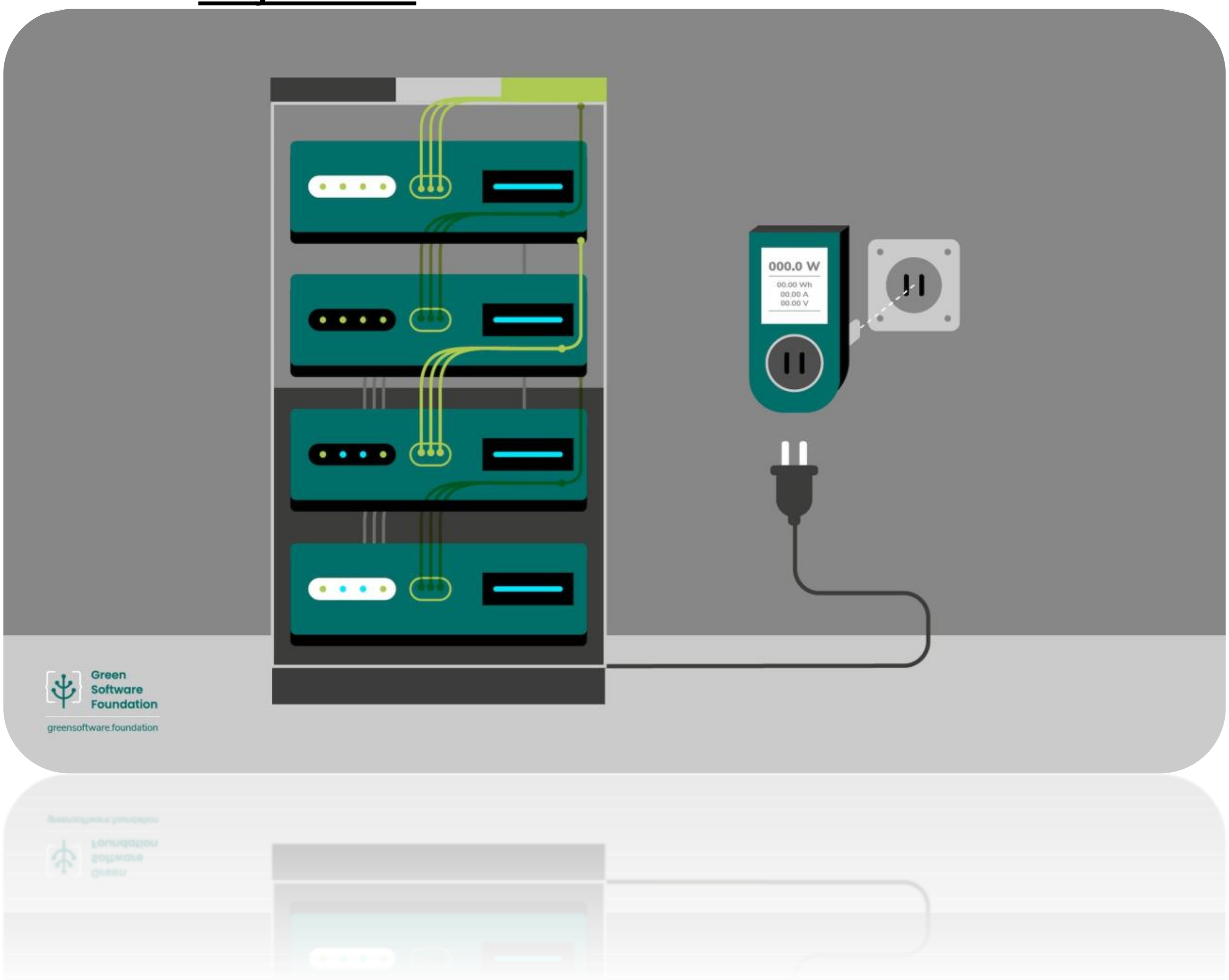
Phase 4 submission document

Project Title: MEASURE ENERGY CONSUMPTION



MEASURE ENERGY CONSUMPTION

INTRODUCTION:

- Over the years, the task to reduce energy consumed by a system has been mainly assigned to computer hardware developers. This is mainly because it is believed that the hardware is the principal component that consumes more electrical energy. However, the software also plays a vital role in power usage. Hardware works hand in hand with software programs. Gradually over recent years software engineers have been putting more effort in developing green software. As evidence has been presented over the years, it has become clear that computers and other IT infrastructure consume significant amounts of electricity, placing a heavy burden on our electric grids and contributing to greenhouse gas emissions. For this reason, the field of green software engineering has emerged.

- Green software engineering is concerned more about climate science, software architecture and practices, electronic devices power consumption, hardware, and data center design. The main question for green software engineers is about the greenness of software and hardware under development. Green software encompass three main phases of the software life cycle: (1) software usage, (2) software design, and (3) software implementation. The main goal is to reduce the amount of energy utilized in each of the phases and have minimal negative impact on the environment.

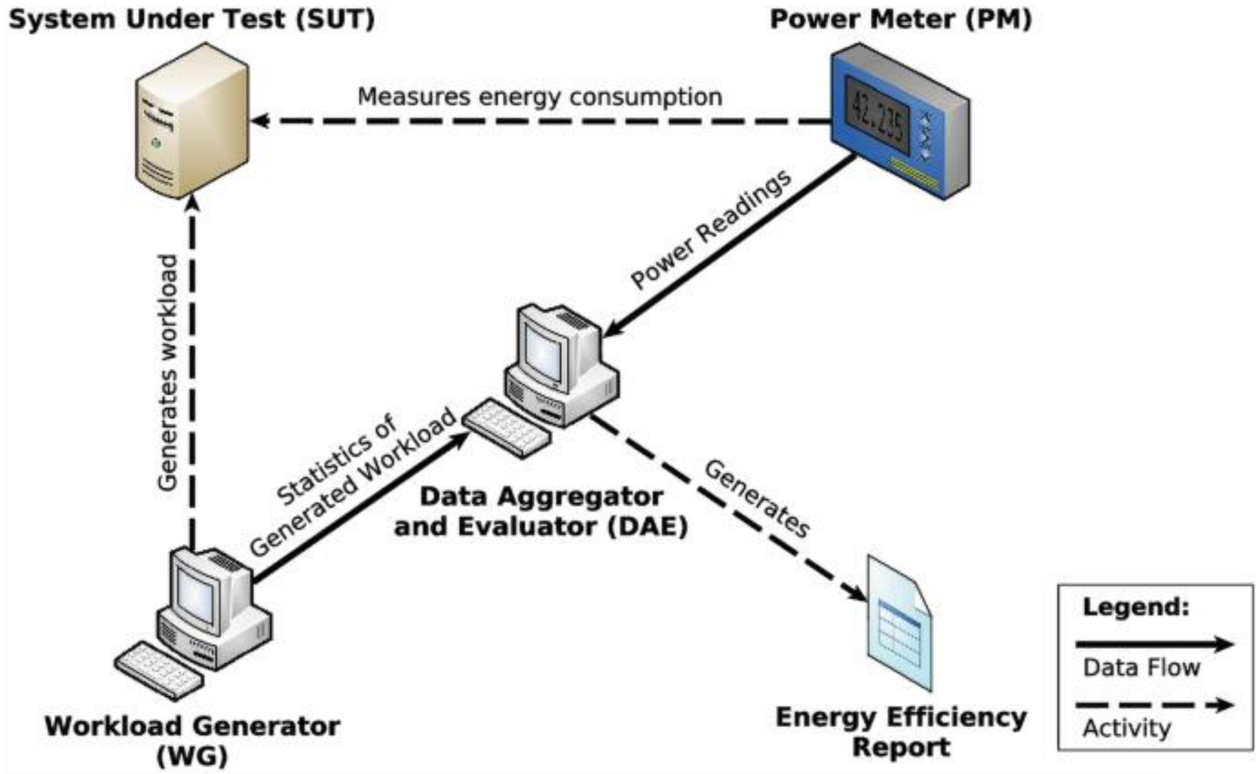

System Under Test (SUT)
Power Meter (PM)
Measures energy consumption
Power Readings
Generates workload
Statistics of Generated Workload
Data Aggregator and Evaluator (DAE)
Generates
Workload Generator (WG)
Energy Efficiency Report
Legend:
Data Flow
Activity

Table 1. Description of features available in data set.

Number	Feature	Description
1	Code	A unique identifier code for clients, which has no any legal or practical use. It has been created by this data release authors for data set structuring purposes.
2	Area	U: Urban area of the municipality. R: Rural area of the municipality.
3	Date	It corresponds to date when measure was registered. In format yyyy-dd-mm
4	Municipality	It can be one of the following municipalities: Barbacoas, Cumbitara, El Rosario, Leiva, Magui, Policarpa, Roberto Payan.
5	Use	Type of client. It can be: Residential, Residential Sub, Industrial, Official, Commercial, Special.
6	Stratum	It represents the social strata, they range from 0 to 3, with 0 being the lowest. It corresponds to: 0=Low-low, 1=Low, 2=Medium-Low, 3=Medium
7	Consumption	Power consumption in kWh. It is the predictor variable.

Table 2. Example of instances available in the data set.

Code	Area	Date	Municipality	Use	Stratum	Consumption
8UBARE0	U	31-01-2016	BARBACOAS	Special	0	75.608
C0UCUMR3	U	28-02-2011	CUMBITARA	Residential	3	75.672
C0RPOLR1	R	30-11-2014	POLICARPA	Residential	1	77.516
8UBARE0	U	29-02-2016	BARBACOAS	Special	0	77.936
C0UCUMR3	U	31-08-2011	CUMBITARA	Residential	3	78.370
C0RCUMR1	R	31-12-2010	CUMBITARA	Residential	1	78.674
C2UCUMR1	U	31-01-2013	CUMBITARA	Residential	1	79.379
C1RCUME0	R	31-08-2012	CUMBITARA	Special	0	79.570
C0RCUMR1	R	28-02-2013	CUMBITARA	Residential	1	79.835
C2RCUMO0	R	31-12-2010	CUMBITARA	Official	0	83.622
C0UCUMR3	U	31-01-2015	CUMBITARA	Residential	3	84.220
C1UPOLR1	U	31-10-2015	POLICARPA	Residential	1	84.303
C1RPOLO0	R	30-04-2016	POLICARPA	Official	0	84.708
C0UCUMC0	U	31-12-2012	CUMBITARA	Commercial	0	85.445

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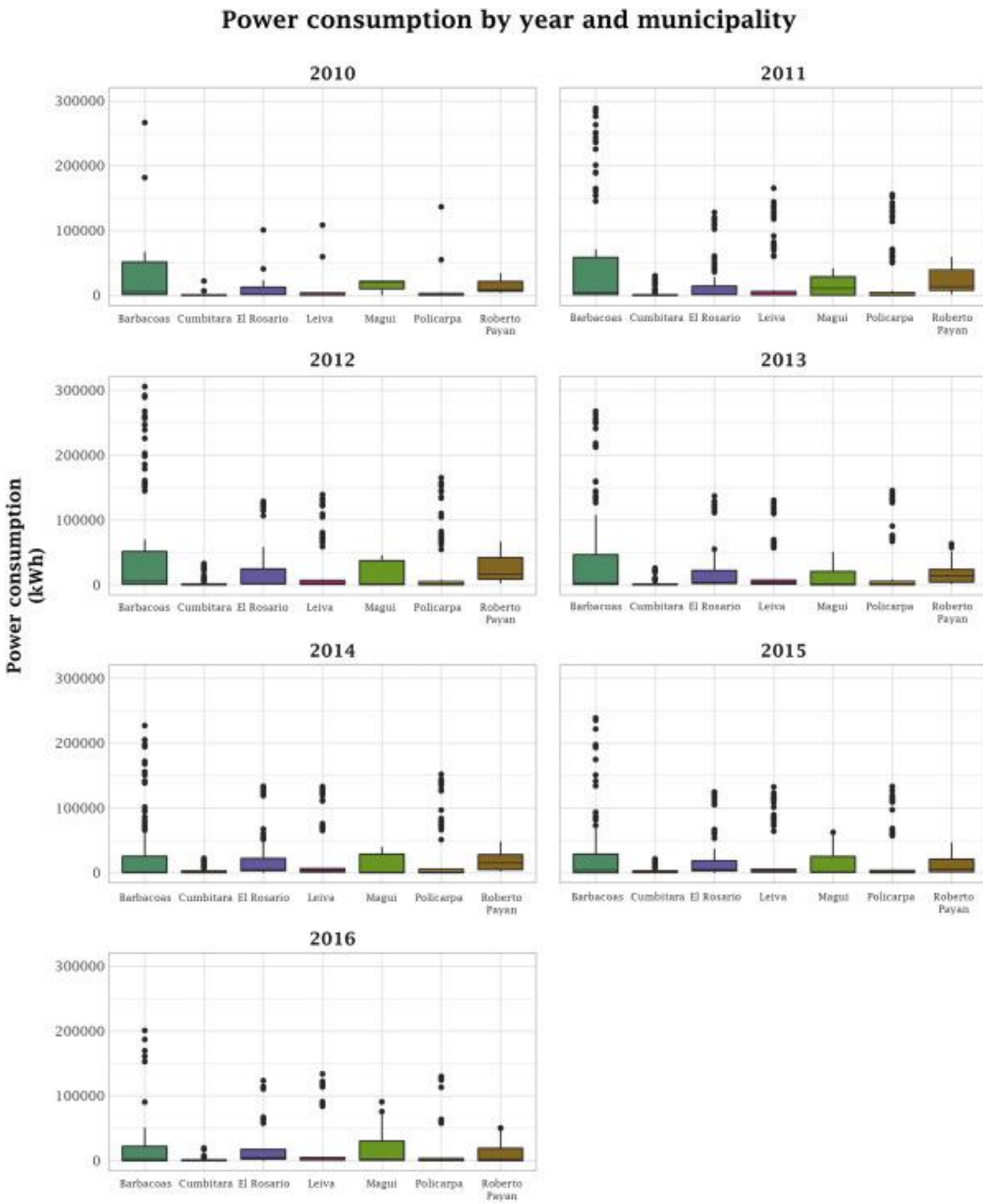
C0UCUMC0	U	31-12-2012	CUMBITARA	Commercial	0	85.445

Table 3. Location, entire population and selected instances for each municipality.

Municipality	Latitude	Longitude	Population	Instances	Total in data set
Barbacoas	1.67262 (1° 40′ 21″ N)	−78.1393 (78° 8′ 21″ W)	30.256	782	17.66%
Cumbitara	1.7644 (1° 45′ 52″ N)	−78.1817 (78° 10′ 54″ W)	13.831	833	18.82%
El Rosario	1.69632 (1° 41′ 47″ N)	−78.2443 (78° 14′ 39″ W)	17.286	625	14.12%
Leiva	1.74192 (1° 44′ 31″ N)	−77.3352 (77° 20′ 7″ W)	11.204	659	14.89%
Magui	1.933 (1° 55′ 59″ N)	−77.3 (77° 18′ 0″ W)	11.825	345	7.79%
Policarpa	1.6548 (1° 39′ 17″ N)	−77.5842 (77° 35′ 3″ W)	6.142	866	19.56%
Roberto Payan	1.6279 (1° 37′ 40″ N)	−77.4589 (77° 27′ 32″ W)	9.798	317	7.16%


Power consumption by year and municipality
2010
2011
2012
2013
2014
2015
2016
Power consumption (kWh)
300000
200000
100000
0
Barbacoas
Cumbitara
El Rosario
Leiva
Magui
Policarpa
Roberto Payan

Daily Energy Data Preparation

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 ARIMA
from matplotlib import pyplot
from pandas.tools.plotting import autocorrelation_plot

#from pyramid.arima import auto_arima
#from pmdarima.arima import auto_arima
import 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_pacf
import statsmodels.api as sm
from statsmodels.tsa.statespace.sarimax import SARIMAX

import math

from sklearn.preprocessing import MinMaxScaler
from 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(line)
    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 across different 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. We will look at the house count for each day.

In [5]:

linkcode

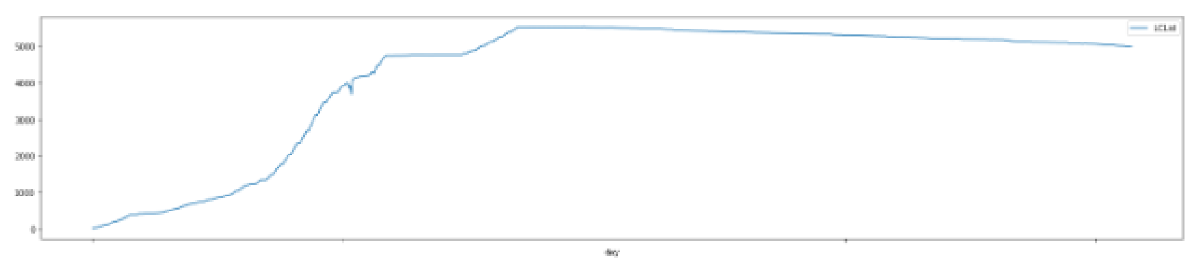
```
housecount = energy.groupby('day')[['LCLid']].nunique()
housecount.head(4)
```

	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: int64
```

In [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 2011-11-23
Ending 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', 'wi
ndSpeed',
       'pressure', 'apparentTemperatureHigh', 'visibility', 'humidity',
       'apparentTemperatureLow', 'apparentTemperatureMax', 'uvIndex',
       'temperatureLow', 'temperatureMin', 'temperatureHigh',
```

```
        '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

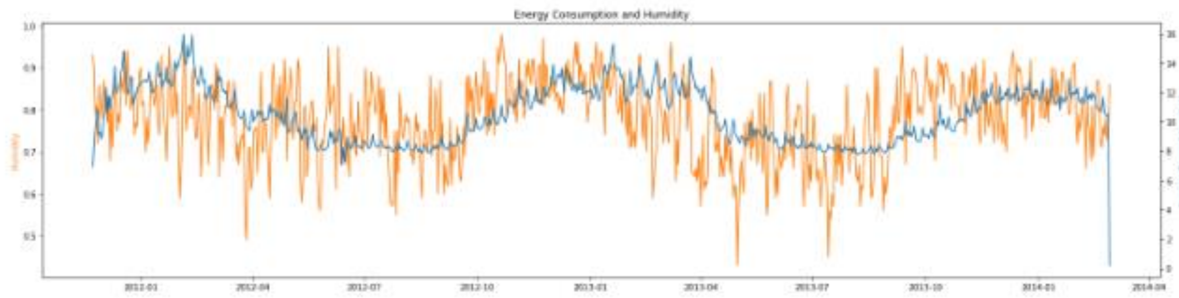
We can see that energy and temperature have an inverse relationship-we can see the peaks in one appearing with troughs in the other. This confirms the business intuition that during low temperature, it is likely that the energy consumption through heaters etc. increases.

```
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()
plt.show()
```

2. Humidity

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

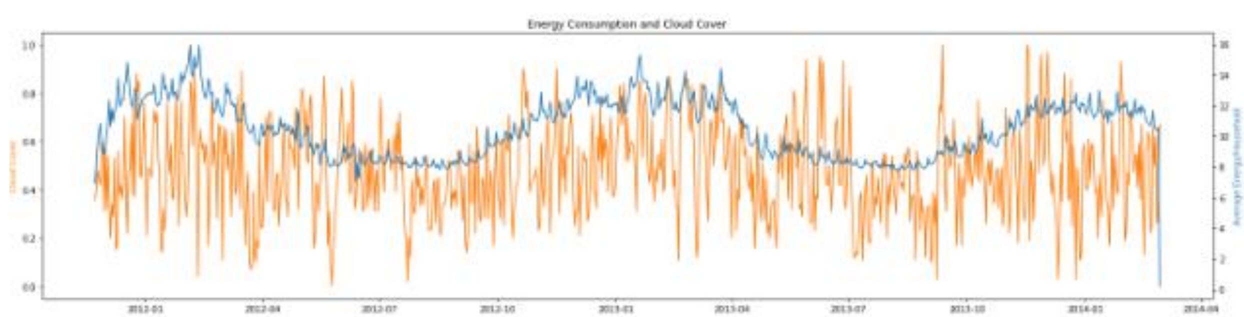
```
fig, ax1 = plt.subplots(figsize = (20,5))
ax1.plot(weather_energy.day, weather_energy.humidity, color = 'tab:orange')
ax1.set_ylabel('Humidity',color = 'tab:orange')
ax2 = ax1.twinx()
ax2.plot(weather_energy.day,weather_energy.avg_energy,color = 'tab:blue')
ax2.set_ylabel('Average Energy/Household',color = '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()
plt.show()
```



4. Visibility

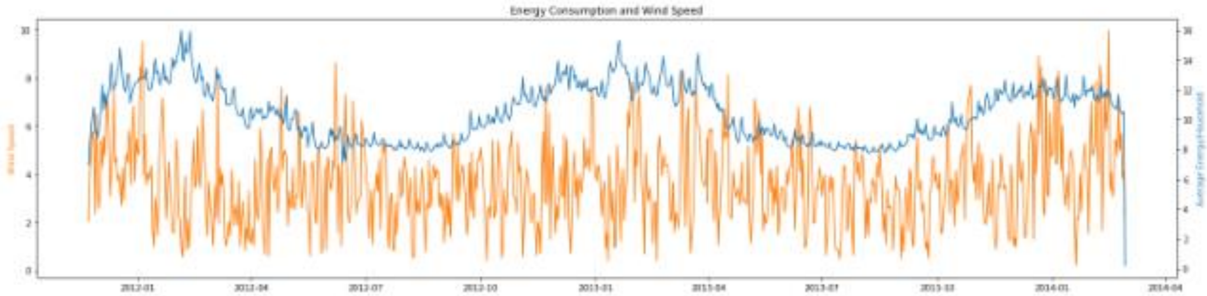
The visibility factor does not seem to affect energy consumption at all- since visibility is most likely an outdoors factor, it is unlikely that it's increase or decrease affects energy consumption within a household.

```
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()
plt.show()
```

5. Wind Speed

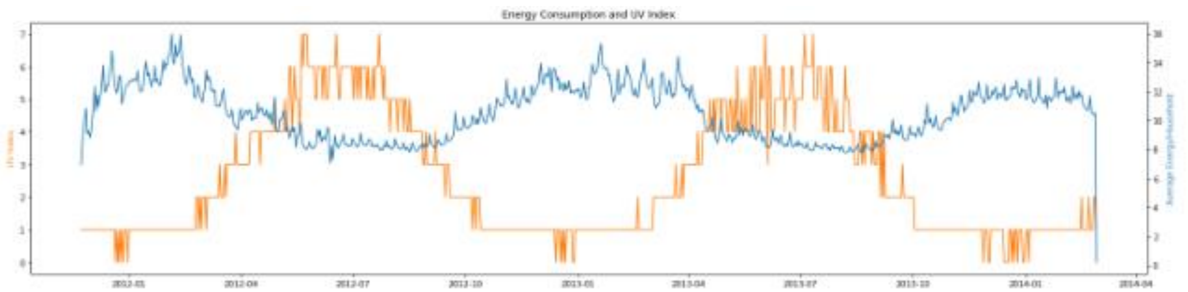
Like visibility, wind speed seems to be an outdoors factor which does not affect in the energy consumption as such.

```
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_layout()
plt.show()
```



6. UV Index

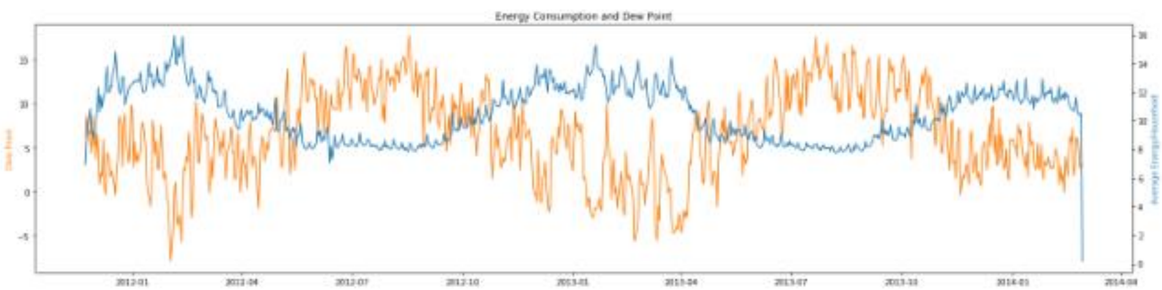
The UV index has an inverse relationship with energy consumption- why?



7. dewPoint

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

```
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()
plt.show()
```



Correlation between Weather Variables and Energy Consumption

- Energy has high positive correlation with humidity and high negative correlation with temperature.
- 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	uvInde
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

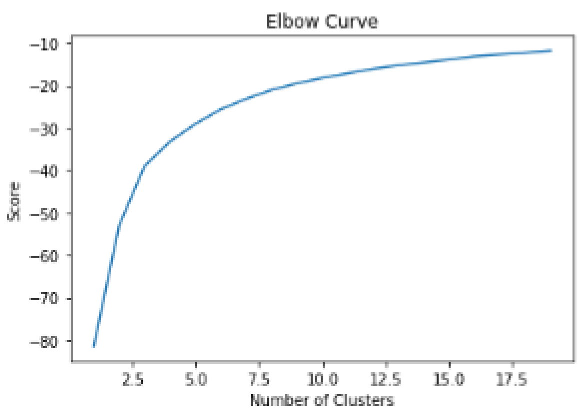
The weather information has a lot of variables- which might not all be useful. We will attempt to create weather clusters to see if we can define a weather of the day based on the granular weather data like temperature, precipitation etc.

```
#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(kmea
ns))]
score
plt.plot(Nc,score)
plt.xlabel('Number of Clusters')
plt.ylabel('Score')
plt.title('Elbow Curve')
plt.show()
```



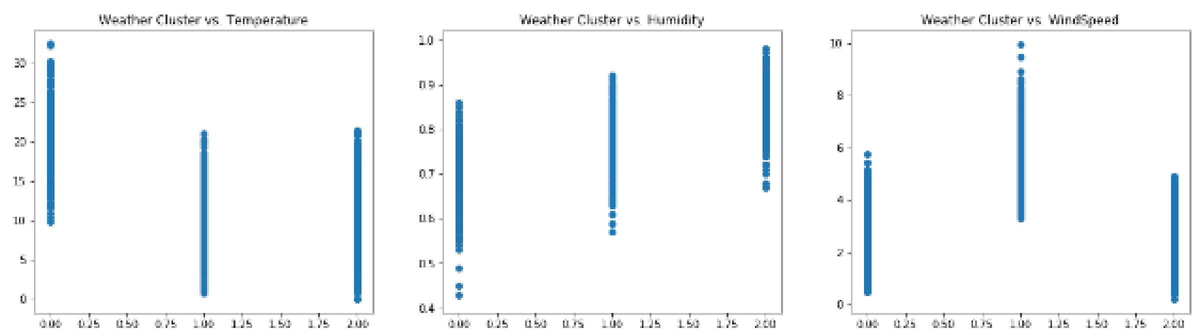

```
kmeans = KMeans(n_clusters=3, max_iter=600, algorithm = 'auto')
kmeans.fit(weather_scaled)
weather_energy['weather_cluster'] = kmeans.labels_
```

In [27]:
linkcode

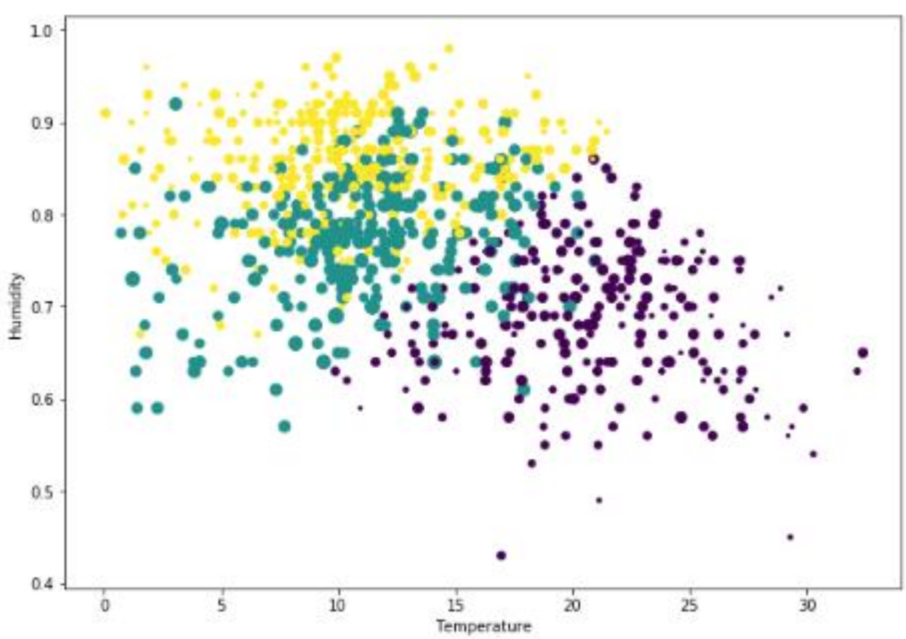
```
# Cluster Relationships with weather variables
plt.figure(figsize=(20,5))
plt.subplot(1, 3, 1)
plt.scatter(weather_energy.weather_cluster,weather_energy.temperatureMax)
plt.title('Weather Cluster vs. Temperature')
plt.subplot(1, 3, 2)
plt.scatter(weather_energy.weather_cluster,weather_energy.humidity)
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')
plt.show()
```



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 holid
ays',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

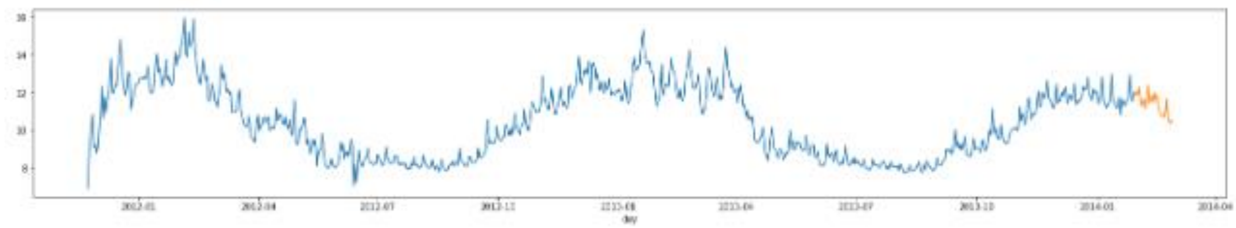
In [32]:

```
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))
```

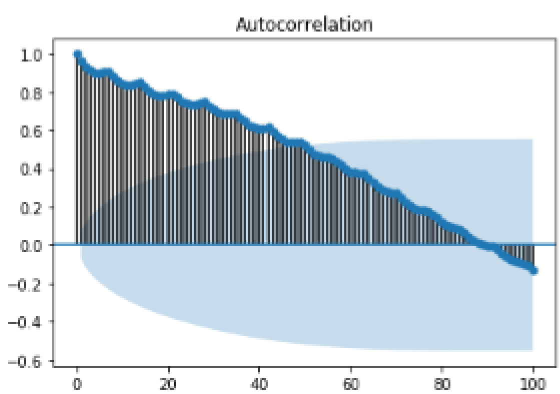


```
test.head(1)
```

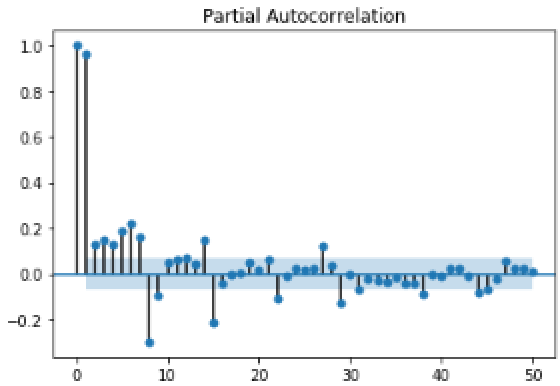
	avg_energy	weather_cluster	holiday_ind
day			
2014-01-30	11.886982	2	0

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 Observat
ions Used'])
```

Out[37]:
```
Test Statistic                  -1.872794
p-value                          0.344966
#Lags Used                      21.000000
Number of Observations Used    776.000000
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 Observat
ions Used'])
```

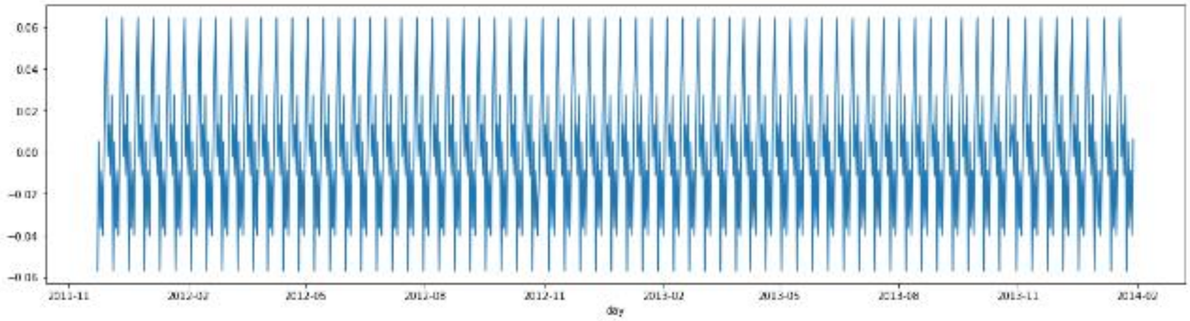
Out[39]:
```
Test Statistic                -6.715004e+00
p-value                        3.600554e-09
#Lags Used                     2.000000e+01
Number of Observations Used    7.760000e+02
dtype: float64
```

Seasonal Decomposition

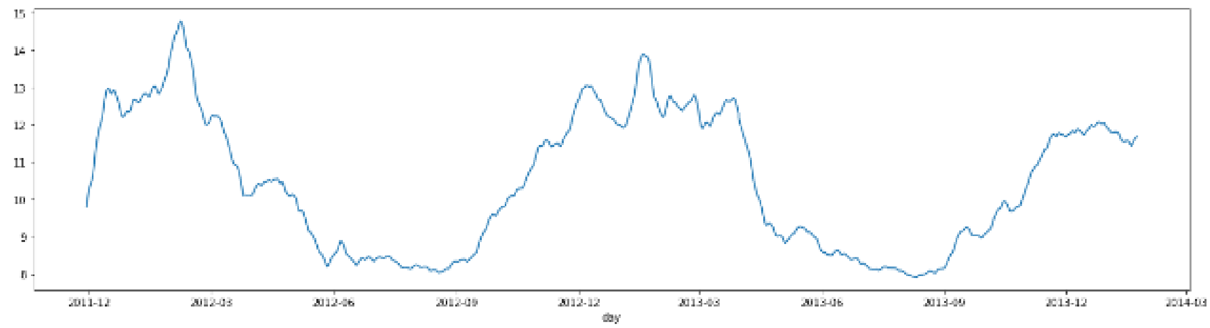
The seasonal component is quite low while the trend is quite strong with obvious dips in electricity consumption during summers i.e. April to September. This may be attributed to longer days during summer.

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')
model_fit = mod.fit()
model_fit.summary()
```

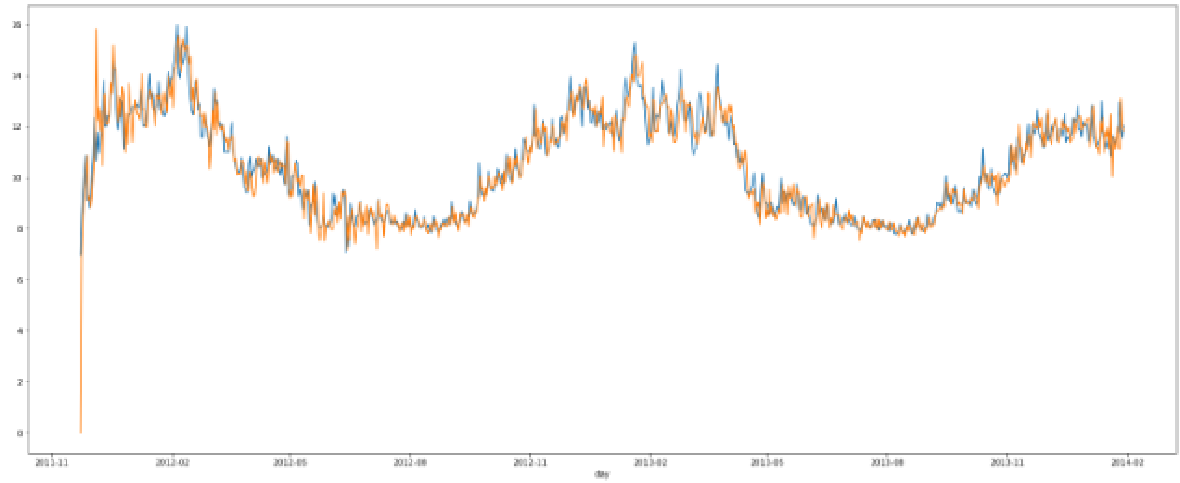
Statespace Model Results

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

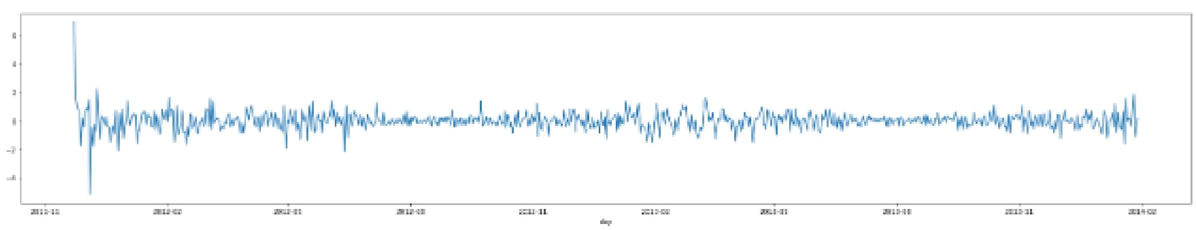
```
test['residual'] = abs(test['avg_energy']-test['predicted'])
MAE = test['residual'].sum()/len(test)
MAPE = (abs(test['residual'])/test['avg_energy']).sum()*100/len(test)
print("MAE:", MAE)
print("MAPE:", MAPE)
```

```
MAE: 0.5853190227226445
MAPE: 5.237822685938685
```

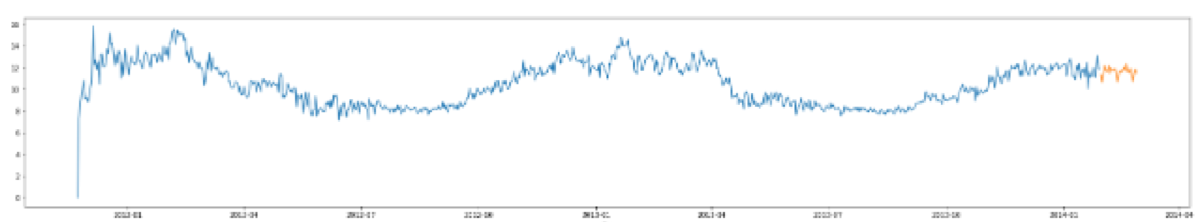
In [48]:
linkcode

```
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 convert multivariate 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=True)
    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,)
```

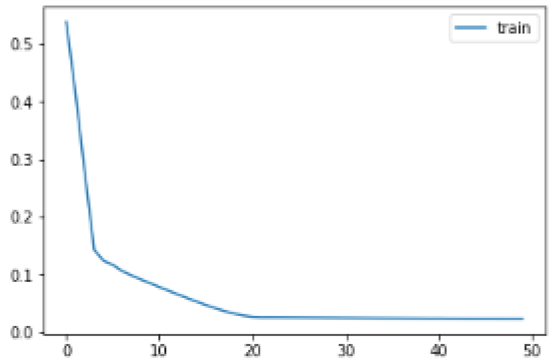
Modelling

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=F
alse)
# 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)
```

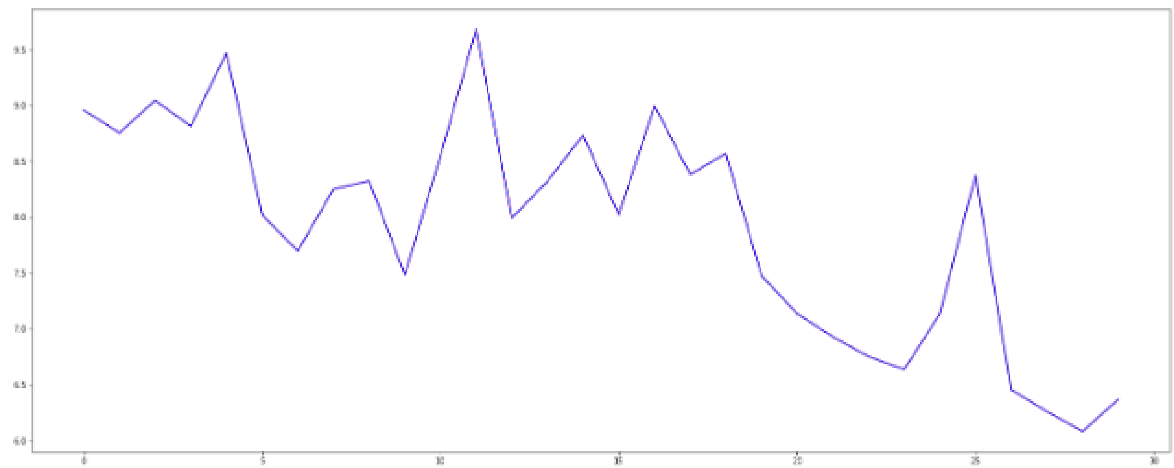
In [65]:
```
# invert scaling for actual
test_y = test_y.reshape((len(test_y), 1))
inv_y = np.concatenate((test_y, test_X), axis=1)
inv_y = scaler.inverse_transform(inv_y)
```

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()
```



Conclusion:

In conclusion, measuring energy consumption is a vital practice that empowers us to make informed decisions about energy usage, reduce costs, mitigate environmental impact, and contribute to a more sustainable future. Whether at the individual, industrial, or governmental level, understanding energy consumption is a critical step toward responsible and efficient energy management.