

```
In [1]: import pandas as pd
import matplotlib.pyplot as plt
import os

BASE_dir = os.getcwd()
DATA_PATH = os.path.abspath(BASE_dir + '..\data\smart_home_energy.csv')
FIG_PATH = os.path.abspath(BASE_dir + '../reports/Milestone1/figures')

df_initial = pd.read_csv(DATA_PATH)
df_initial
```

Out [1]:

	home_id	timestamp	device_id	device_type	room	status	power_watt	user_present	activity	indoor_temp	outdoor_temp
0	1	2022-01-01 00:00:00	air_conditioner1	air_conditioner	bedroom	off	0.000000	1	sleeping	11.4	11.9
1	1	2022-01-01 00:00:00	light1	light	living_room	on	105.880000	1	sleeping	11.4	11.9
2	1	2022-01-01 00:00:00	tv1	tv	living_room	off	0.000000	1	sleeping	11.4	11.9
3	1	2022-01-01 00:00:00	fridge1	fridge	kitchen	on	223.460000	1	sleeping	11.4	11.9
4	1	2022-01-01 00:00:00	washer1	washer	laundry_room	off	0.000000	1	sleeping	11.4	11.9
...	...	...	...	...	...	...	...	...	...	...	...
1751995	10	2022-12-31 23:45:00	air_conditioner10	air_conditioner	bedroom	off	0.000000	1	sleeping	10.8	11.1
1751996	10	2022-12-31 23:45:00	light10	light	living_room	off	0.000000	1	sleeping	10.8	11.1
1751997	10	2022-12-31 23:45:00	tv10	tv	living_room	off	0.000000	1	sleeping	10.8	11.1
1751998	10	2022-12-31 23:45:00	fridge10	fridge	kitchen	on	261.350000	1	sleeping	10.8	11.1
1751999	10	2022-12-31 23:45:00	washer10	washer	laundry_room	on	1884.819597	1	sleeping	10.8	11.1

1752000 rows × 16 columns

In [2]: `print(df_initial.columns)`

```
Index(['home_id', 'timestamp', 'device_id', 'device_type', 'room', 'status',
       'power_watt', 'user_present', 'activity', 'indoor_temp', 'outdoor_temp',
       'humidity', 'light_level', 'day_of_week', 'hour_of_day', 'price_kWh'],
      dtype='object')
```

## Checking the data types for all columns

In [3]: `df_initial.info()`

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1752000 entries, 0 to 1751999
Data columns (total 16 columns):
 #   Column        Dtype  
 --- 
 0   home_id       int64  
 1   timestamp     object  
 2   device_id     object  
 3   device_type   object  
 4   room          object  
 5   status         object  
 6   power_watt    float64 
 7   user_present  int64  
 8   activity       object  
 9   indoor_temp   float64 
 10  outdoor_temp  float64 
 11  humidity      float64 
 12  light_level   float64 
 13  day_of_week   int64  
 14  hour_of_day   int64  
 15  price_kWh    int64  
dtypes: float64(5), int64(5), object(6)
memory usage: 213.9+ MB
```

## Converting the timestamp column to appropriate type for further analysis

```
In [4]: df_initial['timestamp'] = pd.to_datetime(df_initial['timestamp'])
df_initial.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1752000 entries, 0 to 1751999
Data columns (total 16 columns):
 #   Column        Dtype  
--- 
 0   home_id       int64  
 1   timestamp     datetime64[ns]
 2   device_id     object  
 3   device_type   object  
 4   room          object  
 5   status         object  
 6   power_watt    float64 
 7   user_present  int64  
 8   activity       object  
 9   indoor_temp   float64 
10  outdoor_temp  float64 
11  humidity       float64 
12  light_level   float64 
13  day_of_week   int64  
14  hour_of_day   int64  
15  price_kWh    int64  
dtypes: datetime64[ns](1), float64(5), int64(5), object(5)
memory usage: 213.9+ MB
```

## Checking for null values column-wise

```
In [5]: for attr in df_initial.columns:
    print(df_initial[attr].isnull().value_counts())
    print()
```

```
home_id
False    1752000
Name: count, dtype: int64

timestamp
False    1752000
Name: count, dtype: int64

device_id
False    1752000
Name: count, dtype: int64

device_type
False    1752000
Name: count, dtype: int64

room
False    1752000
Name: count, dtype: int64

status
False    1752000
Name: count, dtype: int64

power_watt
False    1752000
Name: count, dtype: int64

user_present
False    1752000
Name: count, dtype: int64

activity
False    1752000
Name: count, dtype: int64

indoor_temp
False    1752000
Name: count, dtype: int64

outdoor_temp
False    1752000
Name: count, dtype: int64

humidity
False    1752000
Name: count, dtype: int64

light_level
False    1752000
Name: count, dtype: int64

day_of_week
False    1752000
Name: count, dtype: int64

hour_of_day
False    1752000
Name: count, dtype: int64

price_kWh
False    1752000
Name: count, dtype: int64
```

No null values found

Since all columns have valid repeated data, checking for duplicates isn't necessary

## Type of appliances considered in dataset

```
In [6]: df_initial['device_type'].value_counts()
```

```
Out [6]: device_type
air_conditioner    350400
light             350400
tv                350400
fridge            350400
washer            350400
Name: count, dtype: int64
```

## Finding the difference in intervals between timestamps

```
In [7]: df_unique_ts = df_initial.drop_duplicates(subset='timestamp')['timestamp']
df_unique_ts.diff().value_counts().head()
```

```
Out [7]: timestamp
0 days 00:15:00    35039
Name: count, dtype: int64
```

## Since there is 15 min difference between each timestamp, checking for any missing interval

```
In [8]: full_range = pd.date_range(start=df_unique_ts.min(), end=df_unique_ts.max(), freq='15min')
missing = full_range.difference(df_unique_ts)
print(f'missing timestamps: {missing}')
```

```
missing timestamps: DatetimeIndex([], dtype='datetime64[ns]', freq='15min')
```

no missing timestamp

## Computing Energy in kWh from power logs for each interval

```
In [9]: df_initial['energy_kwh'] = (df_initial['power_watt'] * 0.25) / 1000 # since power is energy consumed in unit
df_initial['energy_kwh']
```

```
Out [9]: 0      0.000000
1      0.026470
2      0.000000
3      0.055865
4      0.000000
...
1751995  0.000000
1751996  0.000000
1751997  0.000000
1751998  0.065338
1751999  0.471205
Name: energy_kwh, Length: 1752000, dtype: float64
```

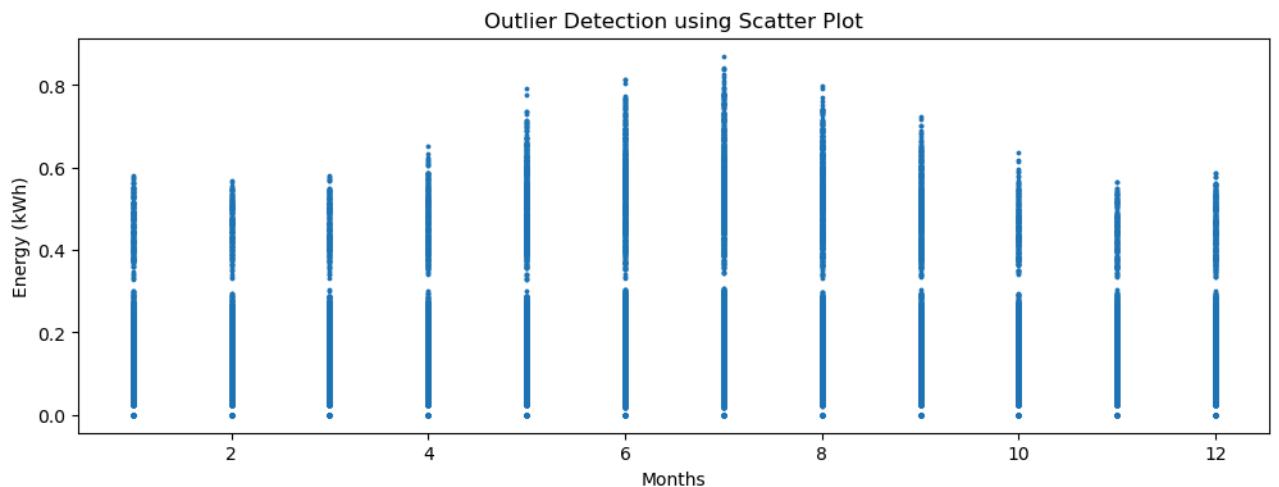
## Checking for any invalid values of energy consumption (negative)

```
In [10]: (df_initial['energy_kwh'] < 0).value_counts() # as no device can consume negative energy
```

```
Out [10]: energy_kwh
False    1752000
Name: count, dtype: int64
```

## Outlier Detection using scatter plot in month-wise distribution

```
In [11]: plt.figure(figsize=(12,4))
plt.scatter(df_initial['timestamp'].dt.month, df_initial['energy_kwh'], s = 3)
plt.title("Outlier Detection using Scatter Plot")
plt.xlabel('Months')
plt.ylabel('Energy (kWh)')
plt.savefig(FIG_PATH+'\Energy_Month_Wise.png')
plt.show()
```



**no outlier observed**

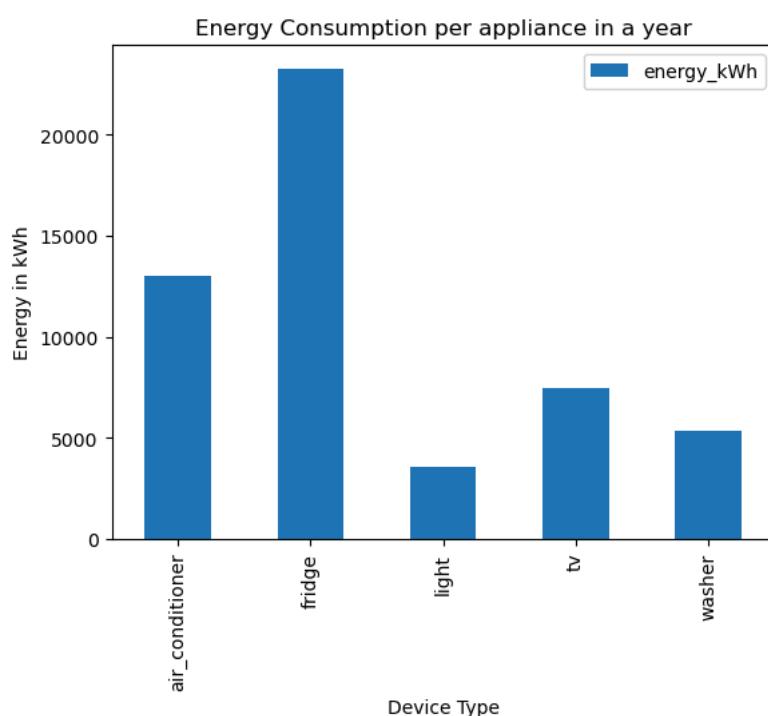
### distribution plots wrt different features

```
In [12]: df_subset1 = df_initial.pivot_table(index='device_type', values='energy_kWh', aggfunc='sum')
df_subset1.round(2)
```

```
Out [12]: energy_kWh
```

device_type	energy_kWh
air_conditioner	13001.83
fridge	23248.45
light	3539.48
tv	7448.75
washer	5315.65

```
In [13]: df_subset1.plot(kind='bar')
plt.title('Energy Consumption per appliance in a year')
plt.xlabel('Device Type')
plt.ylabel('Energy in kWh')
plt.savefig(FIG_PATH+'\Energy_Apppliance_Wise.png')
plt.show()
```



Here it is clearly seen the order of energy consumption in appliance: **fridge > air\_conditioner > tv > washer > light**

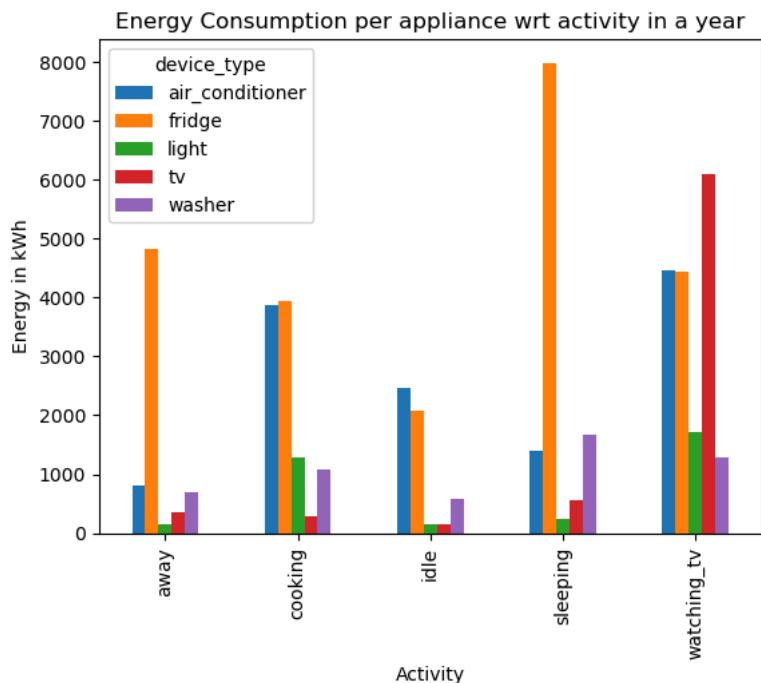
```
In [14]: df_subset2 = df_initial.pivot_table(index='activity', columns='device_type', values='energy_kWh', aggfunc='sum')
df_subset2.round(2)
```

Out [14]:

device_type	air_conditioner	fridge	light	tv	washer
activity					
away	803.07	4821.68	153.43	350.79	700.70
cooking	3871.85	3937.49	1276.43	296.00	1084.80
idle	2470.21	2071.30	152.74	150.47	572.87
sleeping	1400.06	7989.06	231.36	559.09	1661.87
watching_tv	4456.64	4428.91	1725.52	6092.40	1295.40

In [15]:

```
df_subset2.plot(kind='bar')
plt.title('Energy Consumption per appliance wrt activity in a year')
plt.xlabel('Activity')
plt.ylabel('Energy in kWh')
plt.savefig(FIG_PATH+'\Energy_Per_Device_Activity_Wise.png')
plt.show()
```



from above plot we can infer which device is majorly used for a certain activity like an association rule

In [16]:

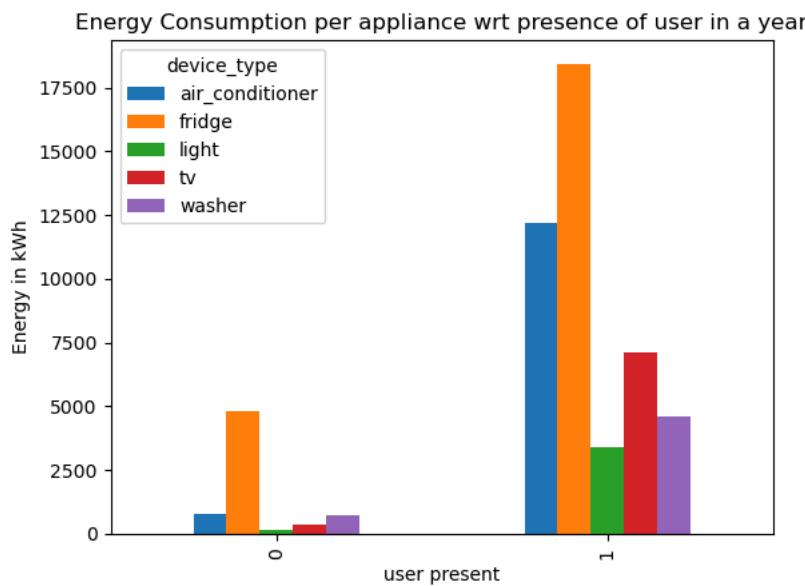
```
df_subset3 = df_initial.pivot_table(index='user_present', columns='device_type', values='energy_kWh', aggfunc=
df_subset3.round(2)
```

Out [16]:

device_type	air_conditioner	fridge	light	tv	washer
user_present					
0	803.07	4821.68	153.43	350.79	700.70
1	12198.76	18426.76	3386.05	7097.96	4614.94

In [17]:

```
df_subset3.plot(kind='bar')
plt.title('Energy Consumption per appliance wrt presence of user in a year')
plt.xlabel('user present')
plt.ylabel('Energy in kWh')
plt.savefig(FIG_PATH+'\Energy_Per_Device_User_Presence_Wise.png')
plt.show()
```



the above plot shows that fridge is always in use irrespective of user presence

```
In [18]: df_subset4 = df_initial.pivot_table(index='status', columns='device_type', values='energy_kwh', aggfunc='sum')
df_subset4.round(2)
```

```
Out [18]: device_type  air_conditioner      fridge      light       tv    washer
           status
           off      0.00        NaN      0.00      0.00      0.00
           on   13001.83    23248.45  3539.48  7448.75  5315.65
```

there is no device here that consumes energy when off

```
In [19]: df_subset5 = df_initial.pivot_table(index='hour_of_day', columns='device_type', values='energy_kwh', aggfunc='sum')
df_subset5.round(2)
```

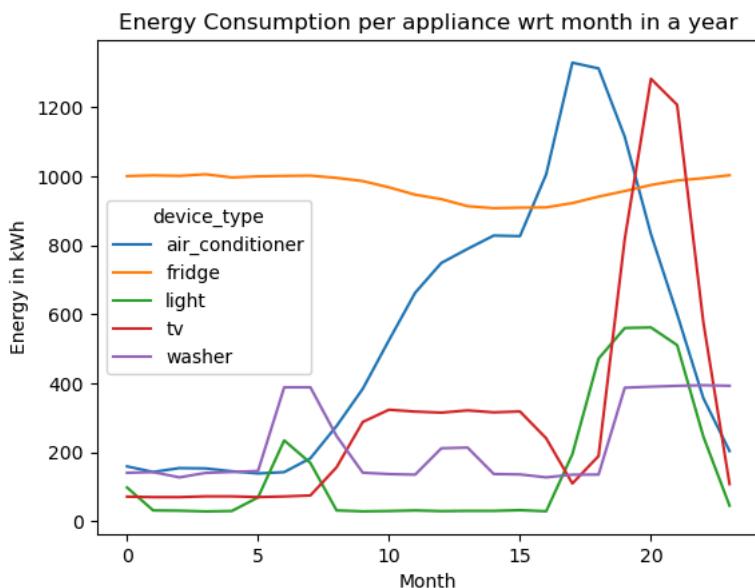
```
Out [19]: device_type  air_conditioner      fridge      light       tv    washer
           hour_of_day
           0      158.53    1000.05   97.34    70.82   139.99
           1      142.36    1002.17   30.89   69.48   141.92
           2      153.64    1000.74   30.10   69.47   126.74
           3      152.70    1005.37   28.04   71.74   139.75
           4      144.41    996.14    29.27   71.70   142.34
           5      138.14    999.31    68.53   69.61   145.22
           6      141.96    1000.57   233.94   71.42   387.80
           7      182.06    1001.42   168.40   74.26   387.77
           8      275.64    994.88    30.90   156.07   246.50
           9      383.66    985.69    28.23   287.43   140.34
           10     524.43    967.43    29.19   322.85   136.31
           11     662.08    946.19    30.85   317.42   134.69
           12     748.38    933.28    28.89   314.42   211.03
           13     789.10    912.90    29.57   320.85   213.12
           14     827.75    906.99    29.59   315.22   136.45
           15     826.02    908.66    31.62   317.78   135.28
           16     1005.22   909.43    28.46   240.00   126.80
           17     1328.95   921.83    193.86   108.98   134.52
           18     1312.26   940.58    471.00   188.58   134.84
           19     1113.84   956.73    559.65   818.14   386.61
           20     831.58    974.24    561.28   1282.21  389.58
           21     599.84    987.28    510.09   1206.63  392.10
           22     356.28    994.07    245.03   576.26   393.78
           23     203.01    1002.50   44.75   107.41   392.17
```

```
In [20]: df_subset5.plot(kind='line')
plt.title('Energy Consumption per appliance wrt month in a year')
plt.xlabel('Month')
```

```

plt.ylabel('Energy in kWh')
plt.savefig(FIG_PATH+'\Energy_Per_Device_Month_Wise.png')
plt.show()

```



the above plot shows the use/consumption of which device spikes up or drops down during a certain month of year

```
In [21]: df_subset5 = df_initial.pivot_table(index='room', columns='device_type', values='energy_kWh', aggfunc='sum')
df_subset5.round(2)
```

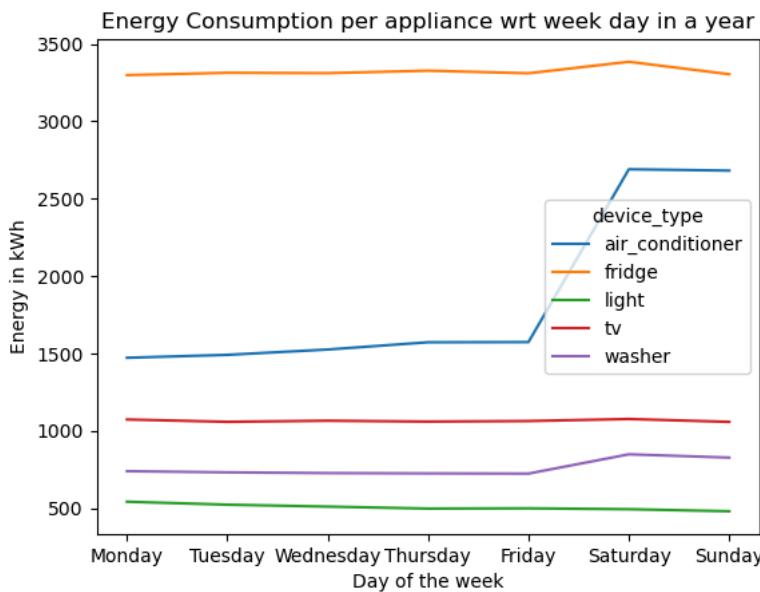
	device_type	air_conditioner	fridge	light	tv	washer
room						
bedroom	13001.83	NaN	NaN	NaN	NaN	
kitchen	NaN	23248.45	NaN	NaN	NaN	
laundry_room	NaN	NaN	NaN	NaN	5315.65	
living_room	NaN	NaN	3539.48	7448.75	NaN	

from the above table it can be inferred that air\_conditioner is installed in bedrooms only, fridge in kitchen, washer in laundry room while both light and tv are in living room

```
In [22]: df_subset6 = df_initial.pivot_table(index='day_of_week', columns='device_type', values='energy_kWh', aggfunc='sum',
weekdays={
    0: 'Monday',
    1: 'Tuesday',
    2: 'Wednesday',
    3: 'Thursday',
    4: 'Friday',
    5: 'Saturday',
    6: 'Sunday'
})
df_subset6.index = df_subset6.index.map(weekdays)
df_subset6.round(2)
```

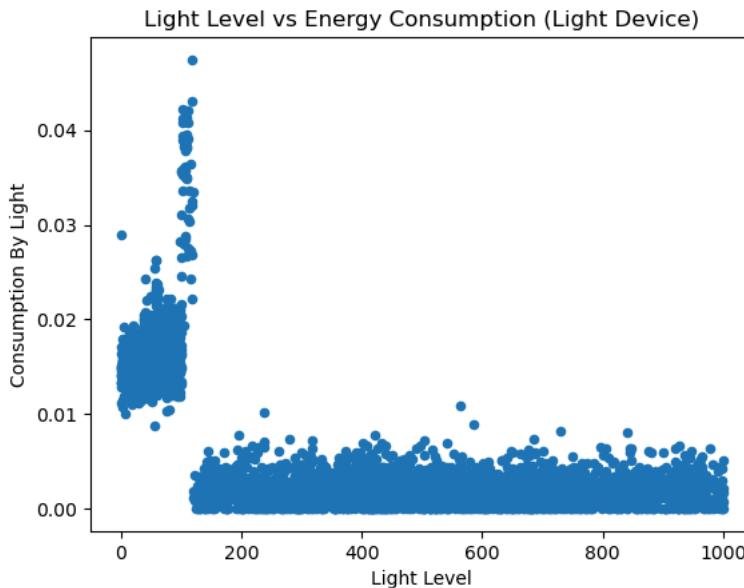
	device_type	air_conditioner	fridge	light	tv	washer
day_of_week						
Monday	1471.41	3298.33	541.05	1072.53	738.38	
Tuesday	1490.25	3313.36	521.87	1057.42	730.77	
Wednesday	1524.76	3311.07	509.49	1064.57	726.06	
Thursday	1571.67	3326.80	496.72	1058.90	724.06	
Friday	1572.81	3310.20	498.31	1062.52	722.74	
Saturday	2689.86	3384.52	492.65	1075.67	847.47	
Sunday	2681.08	3304.16	479.40	1057.14	826.18	

```
In [23]: df_subset6.plot(kind='line')
plt.title('Energy Consumption per appliance wrt week day in a year')
plt.xlabel('Day of the week')
plt.ylabel('Energy in kWh')
plt.savefig(FIG_PATH+'\Energy_Per_Device_WeekDay_Wise.png')
plt.show()
```



this plot shows the spike in the use of air conditioner and slight spike in use of washer near the weekends, others are used steadily throughout the week

```
In [24]: df_subset7 = df_initial[df_initial['device_type'] == 'light']
df_subset7 = df_subset7.pivot_table(index='light_level', values='energy_kwh', aggfunc='mean')
df_subset7=df_subset7.reset_index()
df_subset7.plot(kind='scatter', x='light_level', y='energy_kwh')
plt.title('Light Level vs Energy Consumption (Light Device)')
plt.xlabel('Light Level')
plt.ylabel('Consumption By Light')
plt.savefig(FIG_PATH+'\Light_level_light_consumption.png')
plt.show()
```



from above plot it can be concluded that when light level is low naturally the consumption of electricity by light device is high.

## observing relation between values of 'price\_kWh' and other features

```
In [25]: df_initial['price_kWh'].describe()
```

```
Out [25]: count    1.752000e+00
mean     2.250000e+03
std      5.590172e+02
min     1.500000e+03
25%    1.500000e+03
50%    2.500000e+03
75%    2.500000e+03
max     3.000000e+03
Name: price_kWh, dtype: float64
```

```
In [26]: for attr in df_initial.columns:
    if attr != 'energy_kWh' and (df_initial[attr].dtype != object):
        print(df_initial[[attr, 'energy_kWh']].corr())
        print()
```

```

          home_id  energy_kWh
home_id      -0.046145      1.000000
timestamp    1.000000     0.008793
energy_kWh    0.008793     1.000000

          power_watt  energy_kWh
power_watt      1.0          1.0
energy_kWh      1.0          1.0

          user_present  energy_kWh
user_present    1.000000     0.108452
energy_kWh      0.108452     1.000000

          indoor_temp  energy_kWh
indoor_temp    1.000000     0.136976
energy_kWh      0.136976     1.000000

          outdoor_temp  energy_kWh
outdoor_temp   1.000000     0.136327
energy_kWh      0.136327     1.000000

          humidity  energy_kWh
humidity      1.000000     -0.044761
energy_kWh    -0.044761     1.000000

          light_level  energy_kWh
light_level    1.000000     0.019396
energy_kWh      0.019396     1.000000

          day_of_week  energy_kWh
day_of_week    1.000000     0.031299
energy_kWh      0.031299     1.000000

          hour_of_day  energy_kWh
hour_of_day   1.000000     0.145333
energy_kWh      0.145333     1.000000

          price_kWh  energy_kWh
price_kWh     1.000000     0.130418
energy_kWh      0.130418     1.000000

```

In [27]:

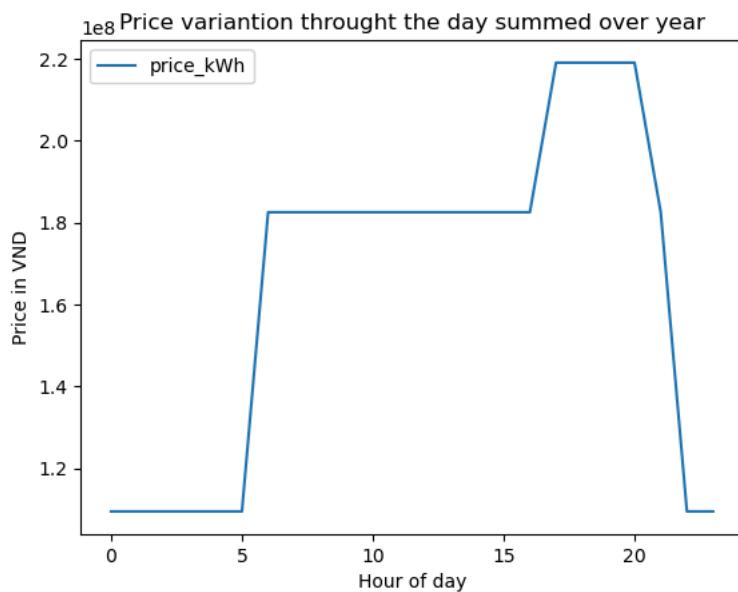
```
df_subset8 = df_initial.pivot_table(index='hour_of_day', values='price_kWh', aggfunc='sum')
df_subset8.round(2)
```

Out [27]:

	price_kWh
hour_of_day	
0	109500000
1	109500000
2	109500000
3	109500000
4	109500000
5	109500000
6	182500000
7	182500000
8	182500000
9	182500000
10	182500000
11	182500000
12	182500000
13	182500000
14	182500000
15	182500000
16	182500000
17	219000000
18	219000000
19	219000000
20	219000000
21	182500000
22	109500000
23	109500000

In [28]:

```
df_subset8.plot(kind='line')
plt.title('Price variation through the day summed over year')
plt.xlabel('Hour of day')
plt.ylabel('Price in VND')
plt.savefig(FIG_PATH+'\VND_price_Distribution.png')
plt.show()
```



```
In [29]: df_subset9 = df_initial.pivot_table(index='home_id', values='price_kWh', aggfunc='sum')
df_subset9
```

```
Out [29]:      price_kWh
home_id
1    394200000
2    394200000
3    394200000
4    394200000
5    394200000
6    394200000
7    394200000
8    394200000
9    394200000
10   394200000
```

While the 'price\_kWh' shows appropriate distribution and correlation with other features, the original dataset follows VND currency so these values might make sense by that country standards but seems incomprehensible for Indian (INR) standards.

**Hence, dropping 'price\_kWh'**

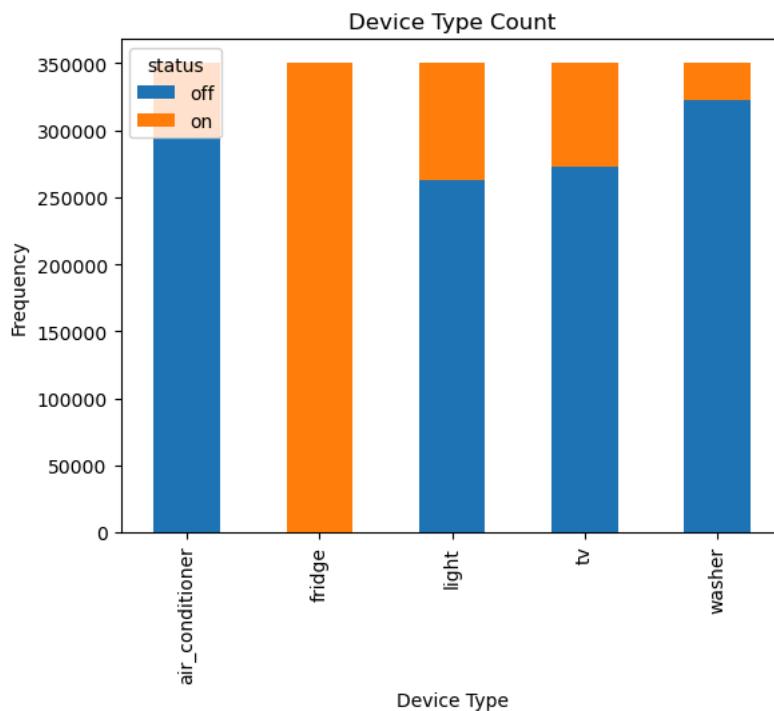
```
In [30]: df_initial.drop('price_kWh', axis=1, inplace=True)
```

## Checking imbalance in record entries

since the timestamp-appliance follow a panel-logging system, there will be balanced entries for the columns: timestamp, home\_id, device\_id, device\_type, room, day\_of\_week and hour\_of\_day

### appliance-wise status imbalance

```
In [31]: pd.crosstab(df_initial['device_type'], df_initial['status']).plot(kind='bar', stacked=True)
plt.title('Device Type Count')
plt.xlabel('Device Type')
plt.ylabel('Frequency')
plt.savefig(FIG_PATH+'\Device_Type_Record_Value_Count.png')
plt.show()
```

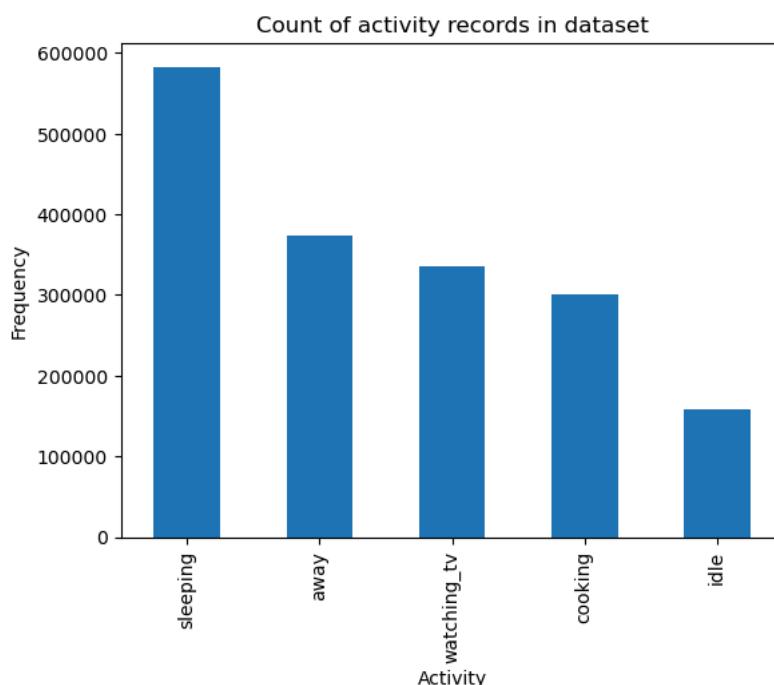


here it is observed that fridge is never off and so always consumes energy

```
In [32]: activity_count = df_initial['activity'].value_counts()
activity_count
```

```
Out [32]: activity
sleeping      582955
away          373780
watching_tv   335850
cooking        300395
idle           159020
Name: count, dtype: int64
```

```
In [33]: activity_count.plot(kind='bar')
plt.title('Count of activity records in dataset')
plt.xlabel('Activity')
plt.ylabel('Frequency')
plt.savefig(FIG_PATH+'\Activity_Record_Value_Count.png')
plt.show()
```



From above, it can be concluded that sleeping is the most dominant activity in dataset

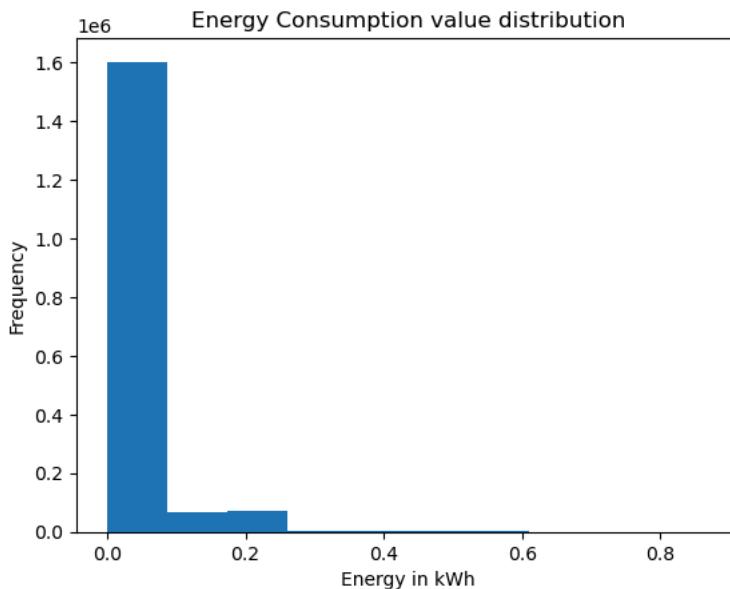
frequency order: sleeping > away > watching\_tv > cooking > idle

```
In [34]: df_initial['energy_kWh'].plot(kind='hist')
plt.title('Energy Consumption value distribution')
plt.xlabel('Energy in kWh')
```

```

plt.ylabel('Frequency')
plt.savefig(FIG_PATH+'\Energy_Consumption_Distribution_Initial.png')
plt.show()

```



Most 15-minute intervals show very low energy use, while only a few intervals spike because of heavy appliances like ACs, washers, and fridges.

This kind of skewed pattern is normal in smart-home data and will be taken care of during normalization in later stages.

```
In [35]: df_initial['energy_kWh'].describe().round(2)
```

```
Out [35]: count    1752000.00
mean      0.03
std       0.06
min      0.00
25%      0.00
50%      0.00
75%      0.05
max      0.87
Name: energy_kWh, dtype: float64
```

## Balanced Dataset For Plot

Since the dataset follows panel-logging system the count of timestamps, home\_id, device\_id, device\_type, hour\_of\_day, and day\_of\_week values are equal

The room values might be unequal for living room has 2 devices while the others have 1

for other categorical values (status, user\_present, and activity) sample creation:

Identifying the minimum value count for equal-sized samples

```
In [36]: df_initial['status'].value_counts()
```

```
Out [36]: status
off     1151365
on      600635
Name: count, dtype: int64
```

```
In [37]: df_initial['user_present'].value_counts()
```

```
Out [37]: user_present
1      1378220
0      373780
Name: count, dtype: int64
```

```
In [38]: df_initial['activity'].value_counts()
```

```
Out [38]: activity
sleeping      582955
away          373780
watching_tv   335850
cooking        300395
idle          159020
Name: count, dtype: int64
```

1,00,000 samples can be taken for each attribute value

```
In [39]: on_sample = df_initial[df_initial['status']=='on'].sample(100000)
off_sample = df_initial[df_initial['status']=='off'].sample(100000)

user_present_sample = df_initial[df_initial['user_present']==1].sample(100000)
user_absent_sample = df_initial[df_initial['user_present']==0].sample(100000)
```

```

sleeping_sample = df_initial[df_initial['activity']=='sleeping'].sample(100000)
away_sample = df_initial[df_initial['activity']=='away'].sample(100000)
watching_tv_sample = df_initial[df_initial['activity']=='watching_tv'].sample(100000)
cooking_sample = df_initial[df_initial['activity']=='cooking'].sample(100000)
idle_sample = df_initial[df_initial['activity']=='idle'].sample(100000)

```

obtain balanced dataset by concatenating the equal sized samples:

```

In [40]: df_status_balanced = pd.concat([on_sample, off_sample])
df_user_balanced = pd.concat([user_present_sample, user_absent_sample])
df_activity_balanced = pd.concat([
    sleeping_sample, away_sample, watching_tv_sample, cooking_sample, idle_sample
])

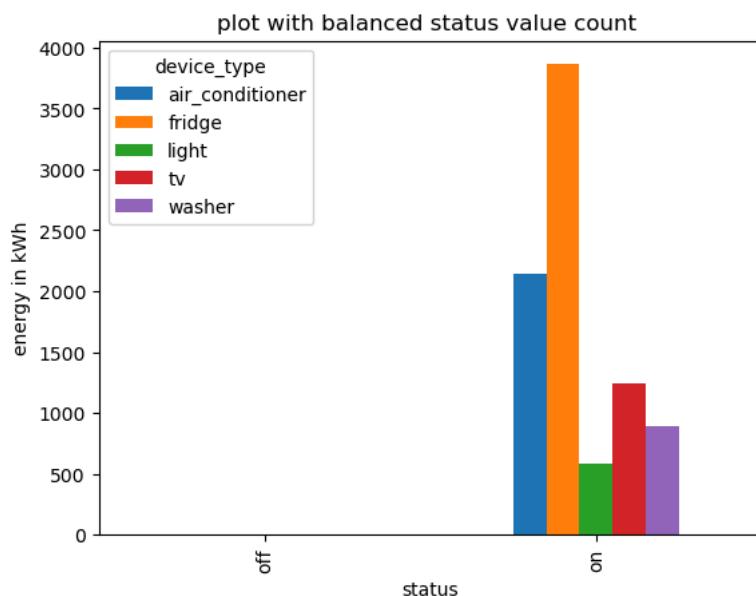
```

1. balanced status value count plot

```

In [41]: pivot_table1=df_status_balanced.pivot_table(index='status', columns='device_type', values='energy_kwh', aggfunc='sum')
pivot_table1.plot(kind='bar')
plt.title('plot with balanced status value count ')
plt.xlabel('status')
plt.ylabel('energy in kwh')
plt.savefig(FIG_PATH+'\Balanced_wrt_status.png')

```

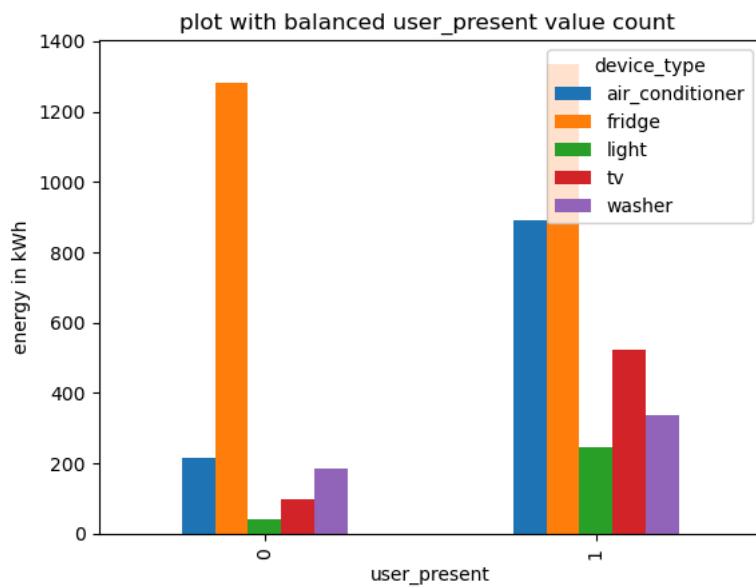


2. balanced user presence value count plot

```

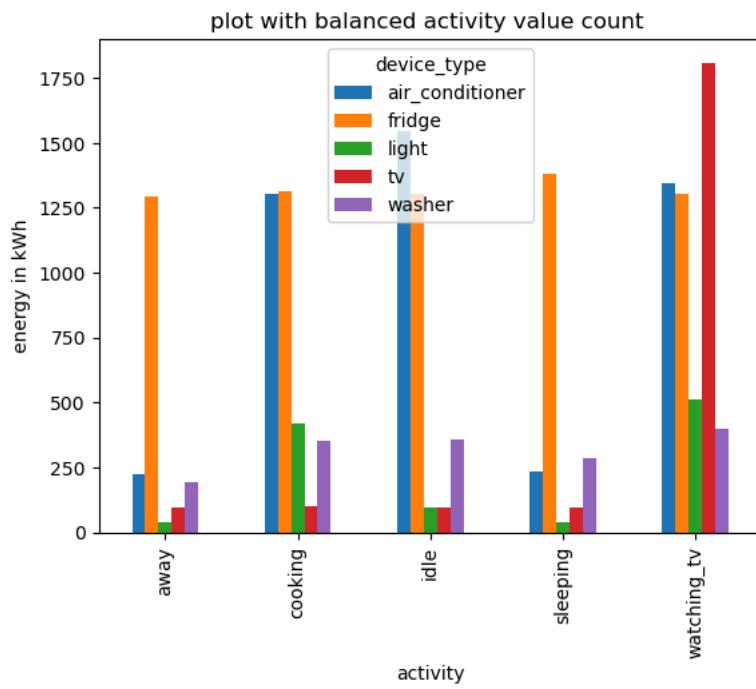
In [42]: pivot_table2=df_user_balanced.pivot_table(index='user_present', columns='device_type', values='energy_kwh', aggfunc='sum')
pivot_table2.plot(kind='bar')
plt.title('plot with balanced user_present value count ')
plt.xlabel('user_present')
plt.ylabel('energy in kwh')
plt.savefig(FIG_PATH+'\Balanced_wrt_user_presence.png')

```



3. balanced activity value count plot

```
In [43]: pivot_table3=df_activity_balanced.pivot_table(index='activity', columns='device_type', values='energy_kwh', aggfunc='mean')
pivot_table3.plot(kind='bar')
plt.title('plot with balanced activity value count ')
plt.xlabel('activity')
plt.ylabel('energy in kWh')
plt.savefig(FIG_PATH+'\Balanced_wrt_activity.png')
```



In [ ]: