ANALYSIS AND PREDICTIVE MODELLING OF ENERGY CONSUMPTION BY APPLIANCES IN SMALL HOMES

1. Introduction

1.1 Centre for Policy Research India states (Centre for Policy Research, 2017) that electricity consumption in Indian homes has increased 50 times between today and 1971. Residential electricity now outpaces growth in industrial, commercial and agriculture sectors. This striking statistic is on the increase, as India moves towards one of the largest urban transitions in history in the coming decades.

1.2 It is a fact that improving access to affordable modern energy is critical to improving living standards in the country. The electricity demand of a nation speaks of its social standard, pace of economic growth, geographical variations and demography of the population at large. Thus, as the country treks on a path to human resource development, the electrical demand in India will increase. Understanding and forecasting of electrical load characteristics have been complex due to its dependency on large number of factors which affects it i.e. weather condition, geographical diversity, sunrise/sunset times, seasonal diversity etc. The detailed study of the electricity consumption invokes a knowledge of its trend and seasonality which can be exploited to extrapolate the demand characteristics. (Kajal Gaur, 2016). This report attempts at analyzing the electrical requirements of an average house so as to provide a basis for analyzing the overall residential demand of electricity.

2. Problem Statement/ Motivation

2.1 The scale of increased residential demand, the uncertainty in the extent to which it could increase, and the urban and demographic transitions underway make future electricity needs immense. If unaddressed, this demand will put serious constraints on already stretched national resources, posing serious social, local environmental and climate change related burdens.

2.2 More importantly, demand-side interventions could substantially reduce the requirements of energy supply, bypass the structural inefficiencies and financial losses prevalent in electricity distribution, and shape path-dependent consumption trajectories.

2.3 It would be prudent to understand in detail the factors which affect consumption in average households. The analysis of consumption of electrical energy by appliances within small households in relation to temperature, humidity, wind speed and atmospheric pressure so as to determine their effect on demand within a small household may provide an insight into requirements of electric generation at the regional and national level. Moreover, the understanding of these factors will help accrue advantages not only at the generation side but also at the consumer side through cost savings.

3. **Objective**

3.1 To carry out an analysis of the factors affecting electrical consumption in a small household in order to:-

(a) Study energy consumption behavior of consumers in a small household.

(b) Analyze the appliance energy consumption relation with factors such as temperature, humidity, wind speed and atmospheric pressure as prevalent inside a house.

(c) Develop a supervised learning model using regression algorithms thus provide information to consumer about the energy consumption by appliances so as to assist in reduction of electrical consumption.

4. **Review of literature**

4.1 The subject has been studied intensively by several authors. Some of the references on the subject are as follows:-

(a) Data driven prediction models of energy use of appliances in a low-energy house, by Luis M.Candanedo, VéroniqueFeldheim and Dominique Deramaix. Energy and Buildings, Volume 140, 1 April 2017, Pages 81-97.

(b) Energy Consumption - Appliances - (UCI DATASET), by Rui Sarmento. Researchgate, Feb 2020. https://www.researchgate.net/publication/339528253_Energy_Consumption_-_Appliances_-_UCI_DATASET.

5. **Methodology**

5.1 **Dataset**.

5.1.1 **Description**.

(a) The dataset used for the research is taken from UCI machine learning database (UCI, n.d.). The dataset is extracted from a house located in Stambruges (Belgium) by installing smart meter and ZigBee smart meter sensors which is capable of detecting energy consumption, humidity and temperature of each room where the appliances are used, the house contains three rooms, two bathrooms, living area, dining room, office, garage, kitchen, laundry, ironing room and game room, each of this room is equipped with electrical appliances and sensors to detect the energy consumption, humidity and temperature at a given time.

(b) The data set is at 10 min for about 4.5 months. The dataset contains 19735 rows and 29 attributes, the humidity and temperature of each area along with the total energy consumption of the house. The dataset also includes data related to outdoor climatic condition such as humidity, temperature, wind speed etc.

5.2 **Source**. UCI Machine Learning repository, Appliances energy prediction Data Set, available at - https://archive.ics.uci.edu/ml/datasets/Appliances+energy+prediction# (UCI, n.d.)

5.3 **Relevance of the Data**. Although the data has been collected in Belgium, however, it is resembles climatic conditions existing in parts of North India and provides some insight into electric consumption in northern India.

5.4 **Structure**. The dataset has 29 attributes which as follows:-

5.4.1 The input variables are:

Serial Number	Data Variables	Description	Data type
1.	lights	Energy use by light fixtures in the house	Integer
2.	T1	Temperature in kitchen area	Integer
3.	RH_1	Humidity in kitchen area	Integer
4.	T2	Temperature in living room area	Integer
5.	RH_2	Humidity in living room area	Integer
6.	T3	Temperature in laundry room area	Integer
7.	RH_3	Humidity in laundry room area	Integer
8.	T4	Temperature in office room	Integer
9.	RH_4	Humidity in office room	Integer
10.	T5	Temperature in bathroom	Integer
11.	RH_5	Humidity in bathroom	Integer
12.	T6	Temperature outside the building	Integer
13.	RH_6	Humidity outside the building	Integer
14.	T7	Temperature in ironing room	Integer
15.	RH_7	Humidity in ironing room	Integer
16.	T8	Temperature in teenager room 2	Integer
17.	RH_8	Humidity in teenager room 2	Integer
18.	T9	Temperature in parents room	Integer
19.	RH_9	Humidity in parents room	Integer
20.	T_out	Temperature outside (from Chievres weather station)	Integer
21.	Press_mm_hg	Pressure (from Chievres weather station)	Integer
22.	RH_out	Humidity outside (from Chievres weather station)	Integer
23.	Windspeed	Wind speed (from Chievres weather station)	Integer
24.	Visibility	Visibility (from Chievres weather station)	Integer
25.	Tdewpoint	Tdewpoint (from Chievres weather station)	Integer
26.	rv1	Random variable 1	Integer
27.	rv2	Random variable 2	Integer
28.	Date	Date and time format	String

5.4.2 Output variable

Serial Number	Data Variable	Description	Data type
1.	Appliances	Energy used by appliances	Integer

5.4.3. Measurement Units. Energy consumed by the appliances and lights are both in Wh (watt-hour). The temperature columns are all in degree Celsius and humidity columns are in %. The pressure column is in mm Hg, the wind speed column is in meters per second, visibility is in kilometers, and Tdewpoint is in degree Celsius.

5.5 Exploratory Data Analysis

5.5.1 Exploratory data analysis includes loading the data and using different viewing methods to better understand the instances and features. It also involves checking for missing values, outliers, and anomalies.

5.5.2 Viewing the Dataset. The head (Fig1) and tail (Fig 2) of the dataset were viewed to check that the dataset has been loaded.

Fig1. Head of Data

```
In [182]: energy.head(10)
Out[182]:
```

date	app_energy	light_energy	kitchen_t	kitchen_h	liv_t	liv_h	laun_t	laun_h	off_t	off_hum	...	out_h	wind	visibility	dew_p
2016-01-11 17:00:00	60	30	19.890000	47.596667	19.20	44.790000	19.79	44.730000	19.000000	45.566667	...	92.000000	7.000000	63.000000	5.30
2016-01-11 17:10:00	60	30	19.890000	46.693333	19.20	44.722500	19.79	44.790000	19.000000	45.992500	...	92.000000	6.666667	59.166667	5.20
2016-01-11 17:20:00	50	30	19.890000	46.300000	19.20	44.626667	19.79	44.933333	18.926667	45.890000	...	92.000000	6.333333	55.333333	5.10
2016-01-11 17:30:00	50	40	19.890000	46.066667	19.20	44.590000	19.79	45.000000	18.890000	45.723333	...	92.000000	6.000000	51.500000	5.00
2016-01-11 17:40:00	60	40	19.890000	46.333333	19.20	44.530000	19.79	45.000000	18.890000	45.530000	...	92.000000	5.666667	47.666667	4.90
2016-01-11 17:50:00	50	40	19.890000	46.026667	19.20	44.500000	19.79	44.933333	18.890000	45.730000	...	92.000000	5.333333	43.833333	4.80
2016-01-11 18:00:00	60	50	19.890000	45.766667	19.20	44.500000	19.79	44.900000	18.890000	45.790000	...	92.000000	5.000000	40.000000	4.70
2016-01-11 18:10:00	60	50	19.856667	45.560000	19.20	44.500000	19.73	44.900000	18.890000	45.863333	...	91.833333	5.166667	40.000000	4.68
2016-01-11 18:20:00	60	40	19.790000	45.597500	19.20	44.433333	19.73	44.790000	18.890000	45.790000	...	91.666667	5.333333	40.000000	4.66

Fig 2. Tail of Data

```
In [183]: energy.tail(10)
Out[183]:
```

date	app_energy	light_energy	kitchen_t	kitchen_h	liv_t	liv_h	laun_t	laun_h	off_t	off_hum	...	out_h	wind	visibility	dev
2016-05-27 16:30:00	220	0	25.426667	46.060000	26.000000	41.700000	28.000000	40.760000	24.7	45.400000	...	55.000000	2.500000	22.500000	13.
2016-05-27 16:40:00	180	0	25.500000	46.530000	26.000000	41.725714	27.856667	40.500000	24.7	45.500000	...	55.000000	2.666667	22.333333	13.
2016-05-27 16:50:00	120	0	25.500000	47.456667	26.000000	42.320000	27.663333	40.693333	24.7	45.560000	...	55.000000	2.833333	22.166667	13.
2016-05-27 17:00:00	110	0	25.600000	47.193333	25.968571	42.528571	27.390000	41.030000	24.7	45.626667	...	55.000000	3.000000	22.000000	13.
2016-05-27 17:10:00	90	0	25.533333	46.860000	25.978000	42.534000	27.323333	41.090000	24.7	45.626667	...	55.333333	3.166667	22.833333	13.
2016-05-27 17:20:00	100	0	25.566667	46.560000	25.890000	42.025714	27.200000	41.163333	24.7	45.590000	...	55.666667	3.333333	23.666667	13.
2016-05-27 17:30:00	90	0	25.500000	46.500000	25.754000	42.080000	27.133333	41.223333	24.7	45.590000	...	56.000000	3.500000	24.500000	13.
2016-05-27 17:40:00	270	10	25.500000	46.596667	25.628571	42.768571	27.050000	41.690000	24.7	45.730000	...	56.333333	3.666667	25.333333	13.
2016-05-27 17:50:00	420	10	25.500000	46.990000	25.414000	43.036000	26.890000	41.290000	24.7	45.790000	...	56.666667	3.833333	26.166667	13.

5.5.3 Some of the aspects brought forth during the analysis are as follows;-

(a) Comparing the 'date' columns in the head and tail of the dataset provides information that data has been collected over approximately 4.5 months—from January 11, 2016 to May 27, 2016.

(b) Check for null / missing values. The dataset doesn't have any missing values.

(c) Descriptive Statistical Analysis of the dataset. The analysis is as follows:

(i) The 'Lights (light_energy)' column has large number of zero values as evident from the percentiles. Box plot (Fig 3) and bar plot (Fig 4) visualization also indicates large number of zero values.

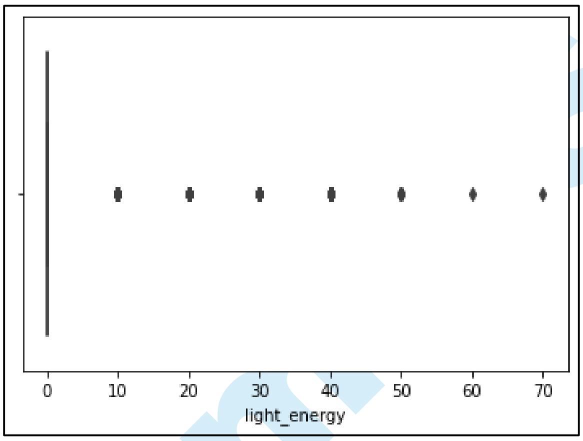


Fig 3. Box Plot of Lights

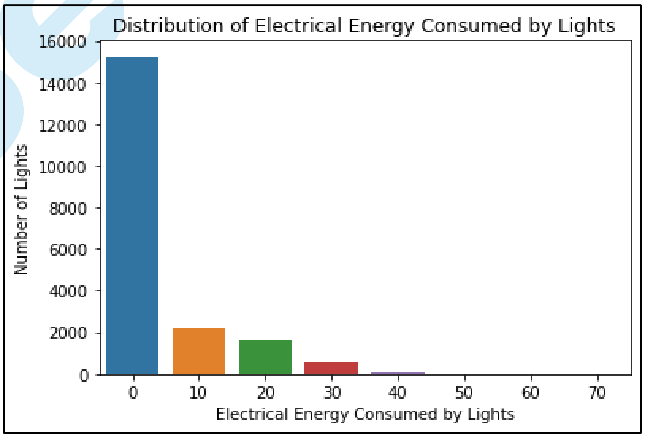


Fig 4. Electrical Energy Consumed by Lights

(ii) A count of the distinct values of the column "light_energy" (Fig 5) also indicates that there are 15252 instances which have a zero value. Maximum consumption is 70 Wh for a single instance. Major consumption is for 10, 20 and 30 Wh for a total of 4395 instances. Hence the consumption of electrical energy for the light column is not insignificant and cannot be neglected.

```
In [18]: #counting the distinct values of electrical consumption through use of electrical lights
         energy['light_energy'].value_counts()

Out[18]: 0     15252
         10     2212
         20     1624
         30      559
         40       77
         50        9
         60        1
         70        1
         Name: light_energy, dtype: int64
```

Fig 5. Count for the electrical energy consumed by lights

(ii) From the descriptive Statistics table (Table 1), it can be observed the 'Appliances Energy (app_energy)' column has maximum value of

1,080, but the mean is around 97. The range between maximum and minimum value is also very high. This implies that there are outliers.

	count	mean	std	min	25%	50%	75%	max
app_energy	19735.0	97.694958	102.524891	10.000000	50.000000	60.000000	100.000000	1080.000000
light_energy	19735.0	3.801875	7.935988	0.000000	0.000000	0.000000	0.000000	70.000000
kitchen_t	19735.0	21.686571	1.606066	16.790000	20.760000	21.600000	22.600000	26.260000
kitchen_h	19735.0	40.259739	3.979299	27.023333	37.333333	39.656667	43.066667	63.360000
liv_t	19735.0	20.341219	2.192974	16.100000	18.790000	20.000000	21.500000	29.856667
liv_h	19735.0	40.420420	4.069813	20.463333	37.900000	40.500000	43.260000	56.026667
laun_t	19735.0	22.267611	2.006111	17.200000	20.790000	22.100000	23.290000	29.236000
laun_h	19735.0	39.242500	3.254576	28.766667	36.900000	38.530000	41.760000	50.163333
off_t	19735.0	20.855335	2.042884	15.100000	19.530000	20.666667	22.100000	26.200000
off_hum	19735.0	39.026904	4.341321	27.660000	35.530000	38.400000	42.156667	51.090000
bath_t	19735.0	19.592106	1.844623	15.330000	18.277500	19.390000	20.619643	25.795000
bath_h	19735.0	50.949283	9.022034	29.815000	45.400000	49.090000	53.663333	96.321667
out_build_t	19735.0	7.910939	6.090347	-6.065000	3.626667	7.300000	11.256000	28.290000
out_build_h	19735.0	54.609083	31.149806	1.000000	30.025000	55.290000	83.226667	99.900000
iron_t	19735.0	20.267106	2.109993	15.390000	18.700000	20.033333	21.600000	26.000000
iron_h	19735.0	35.388200	5.114208	23.200000	31.500000	34.863333	39.000000	51.400000
teen_t	19735.0	22.029107	1.956162	16.306667	20.790000	22.100000	23.390000	27.230000
teen_h	19735.0	42.936165	5.224361	29.600000	39.066667	42.375000	46.536000	58.780000
par_t	19735.0	19.485828	2.014712	14.890000	18.000000	19.390000	20.600000	24.500000
par_h	19735.0	41.552401	4.151497	29.166667	38.500000	40.900000	44.338095	53.326667
out_t	19735.0	7.411665	5.317409	-5.000000	3.666667	6.916667	10.408333	26.100000
out_press	19735.0	755.522602	7.399441	729.300000	750.933333	756.100000	760.933333	772.300000
out_h	19735.0	79.750418	14.901088	24.000000	70.333333	83.666667	91.666667	100.000000
wind	19735.0	4.039752	2.451221	0.000000	2.000000	3.666667	5.500000	14.000000
visibility	19735.0	38.330834	11.794719	1.000000	29.000000	40.000000	40.000000	66.000000
dew_point	19735.0	3.760707	4.194648	-6.600000	0.900000	3.433333	6.566667	15.500000
rv1	19735.0	24.988033	14.496634	0.005322	12.497889	24.897653	37.583769	49.996530
rv2	19735.0	24.988033	14.496634	0.005322	12.497889	24.897653	37.583769	49.996530

Table 1. Descriptive Statistical Analysis of the dataset

5.5.4 <u>Date/time based analysis</u>.

(a) The plot of date Vs Wh (Fig 6 & 7) shows the trend in electrical consumption from 11 Jan to 27 May. Demand below 200 Wh is almost constant across the entire time period. Jan shows some outliers wherein demand has crossed 1000 Wh. End of Jan and beginning of May show some reduction in demand. Mean of the electrical demand appears to be about 400 Wh. However, it is to be noted that the data for the months of Jan and May is not complete.

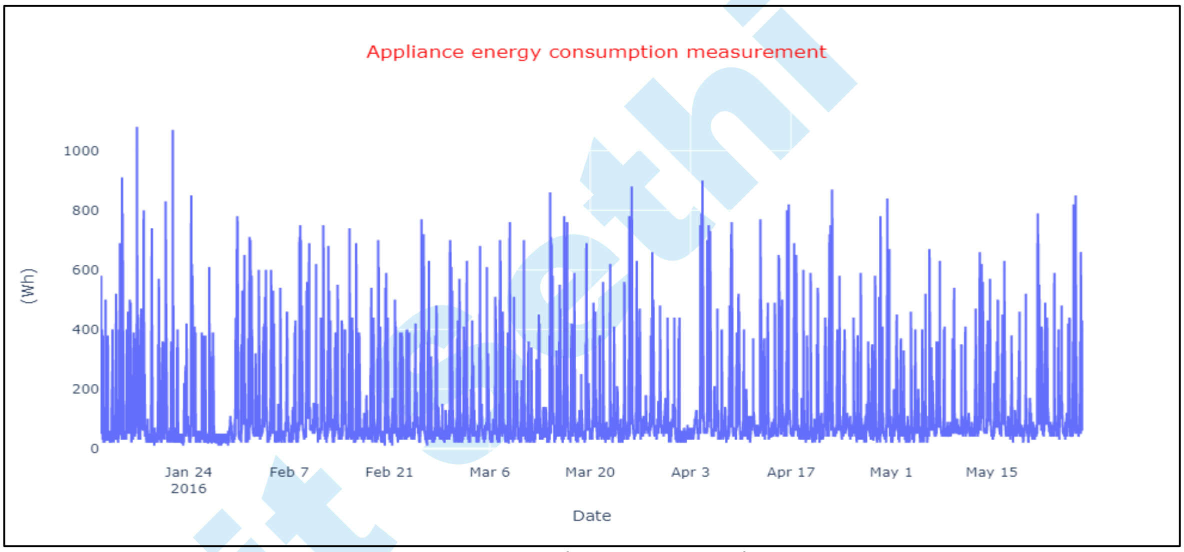


Fig 6. Line Plot : Date Vs Wh

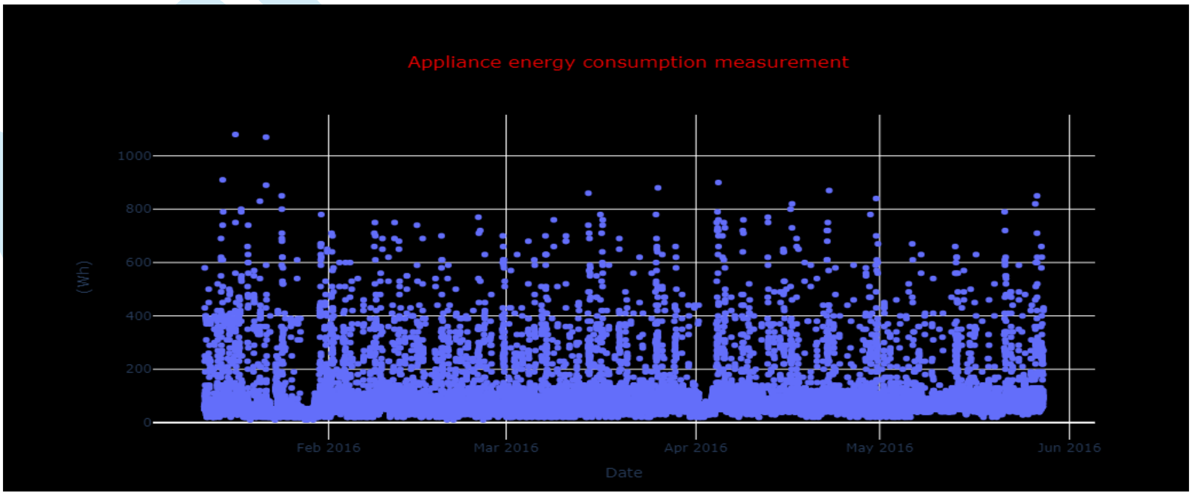


Fig 7. Scatter Plot: Date Vs Wh

(b) <u>Weekend Vs Weekday Demands</u>. The plot of Weekdays Vs Wh (Fig 8) shows the trend in electrical consumption on weekdays for the given time period. The mean demand is around 200 Wh and maximum utilization does not is around 400 Wh to 600 Wh at most. Values beyond 600 Wh appear to be outliers. On the other hand, the weekend demand (Fig 9) in Jan crossed 400 Wh while it is about 400 Wh in April. This indicates that weekend demands seem to be higher than weekdays with seasonal fluctuations.

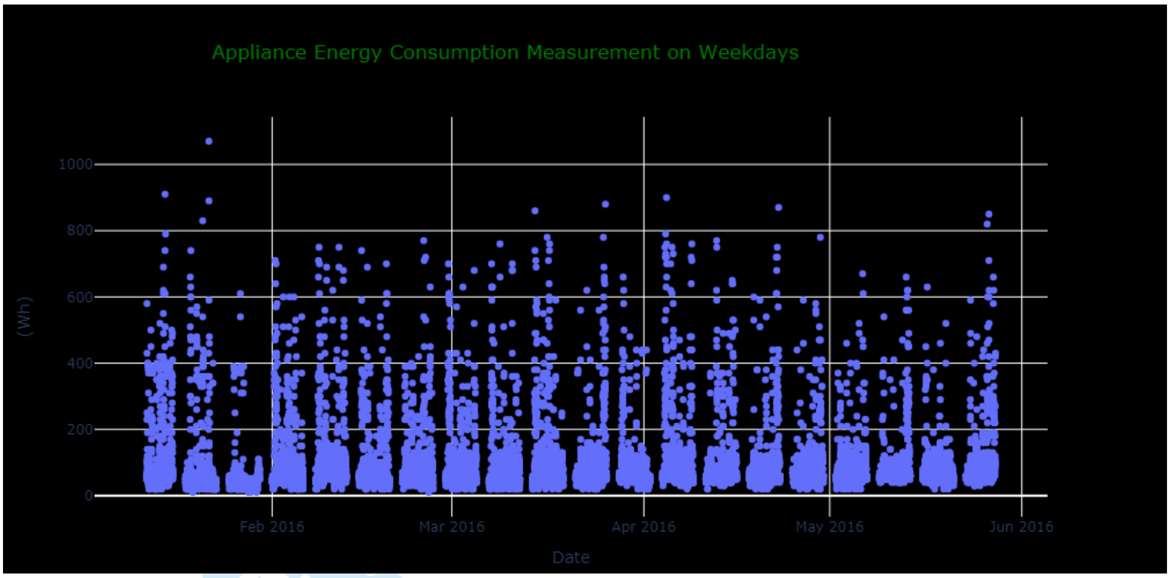


Fig 8 : Weekdays Vs Wh

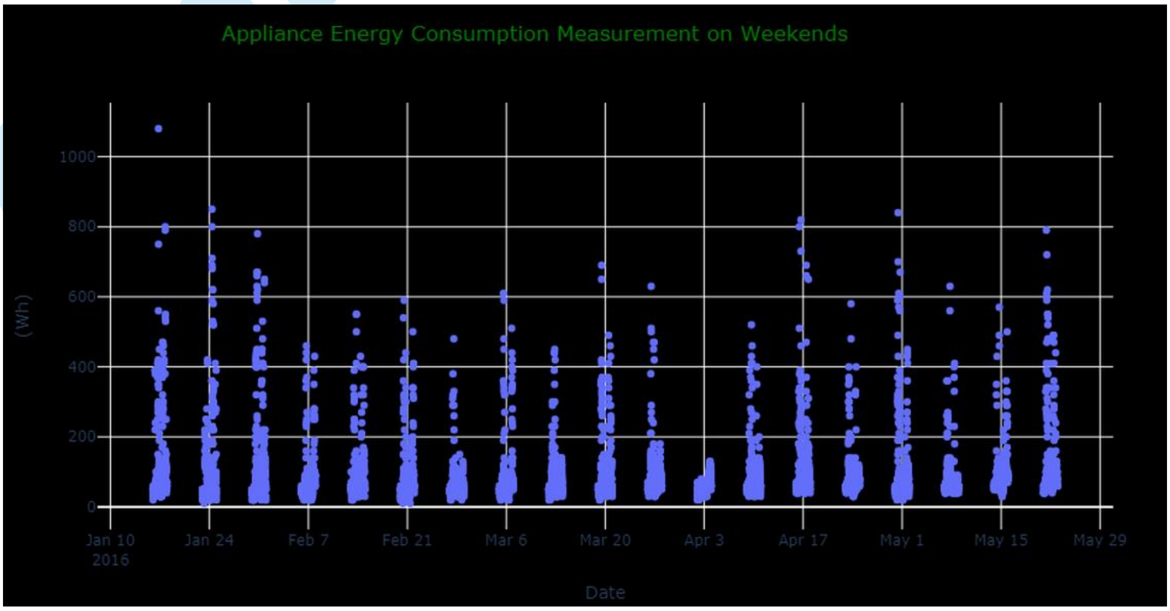


Fig 9 : Weekends Vs Wh

(c) Demand on each day of the Week (Fig 10). The demand is not constant across the week. Weekends definitely have an overall higher average demand. Monday followed by Friday are the days with the highest demand within weekdays.

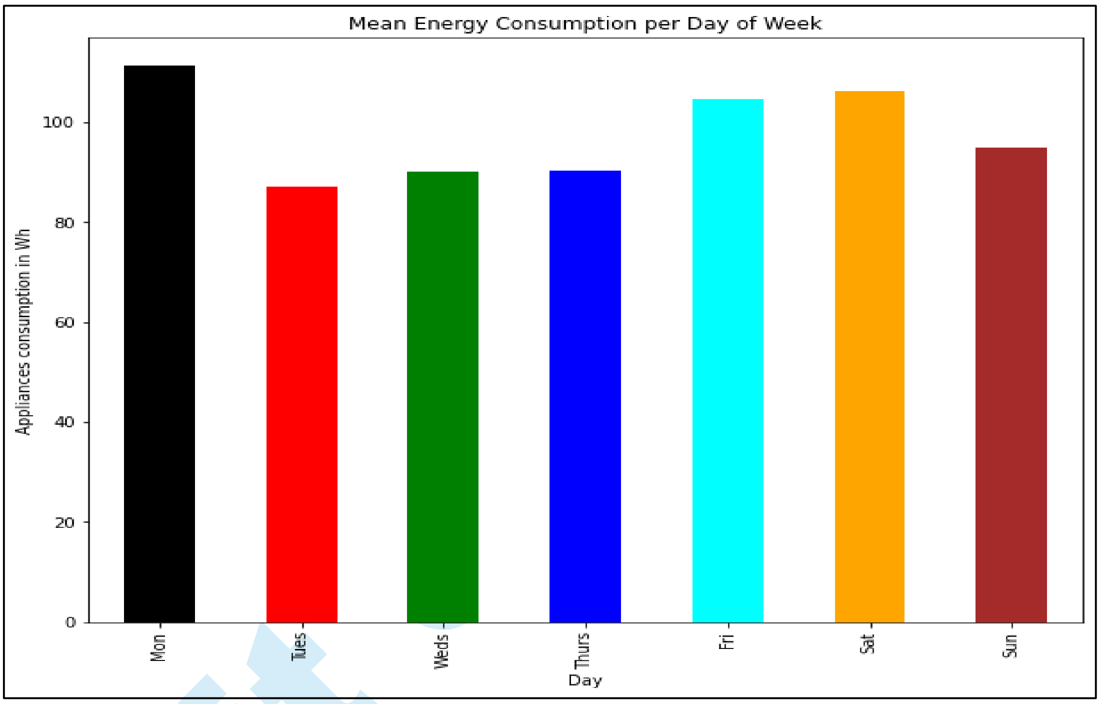


Fig 10. Day wise demand

(d) Demand as per hour of the day (Fig 11). The trend is very clear as the demand increase by around 7.00 AM and then dips around 01.00 PM and rises upto 7.00 PM. Peak demand is in the evening hours. Between 9:00-13:00 the power load is 120-135Wh and after launch reduces again to 110Wh. In the afternoon, the energy consumption ranges from 130-185Wh.

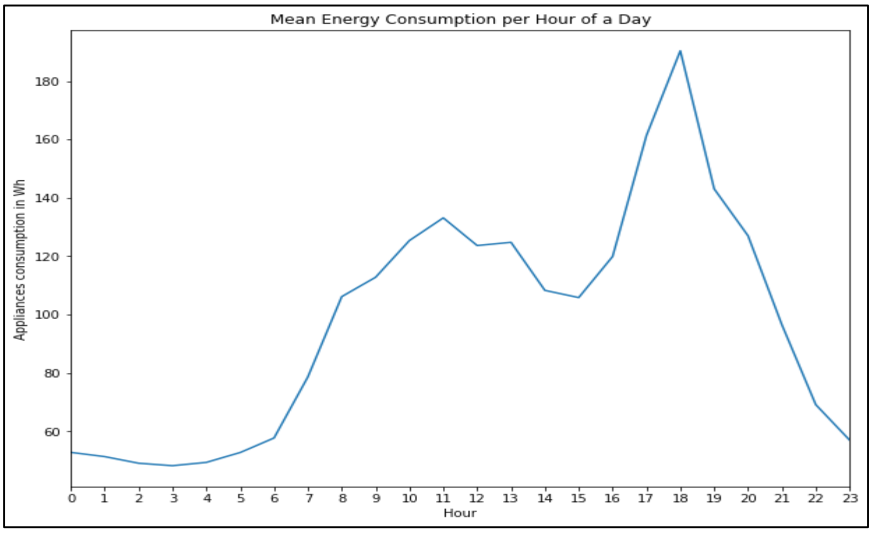


Fig 11. Demand as per hour of the day

(e) Mean consumption per day of the month (Fig 12). The heat map provides insights into the electricity demands across months and weekdays/weekends. It shows that the maximum demands on Sundays occur in Jan. Weekends have a overall higher demand than weekdays and Saturdays have a higher demand across months. Monday is another day which accounts for higher demands across months along with Fridays.

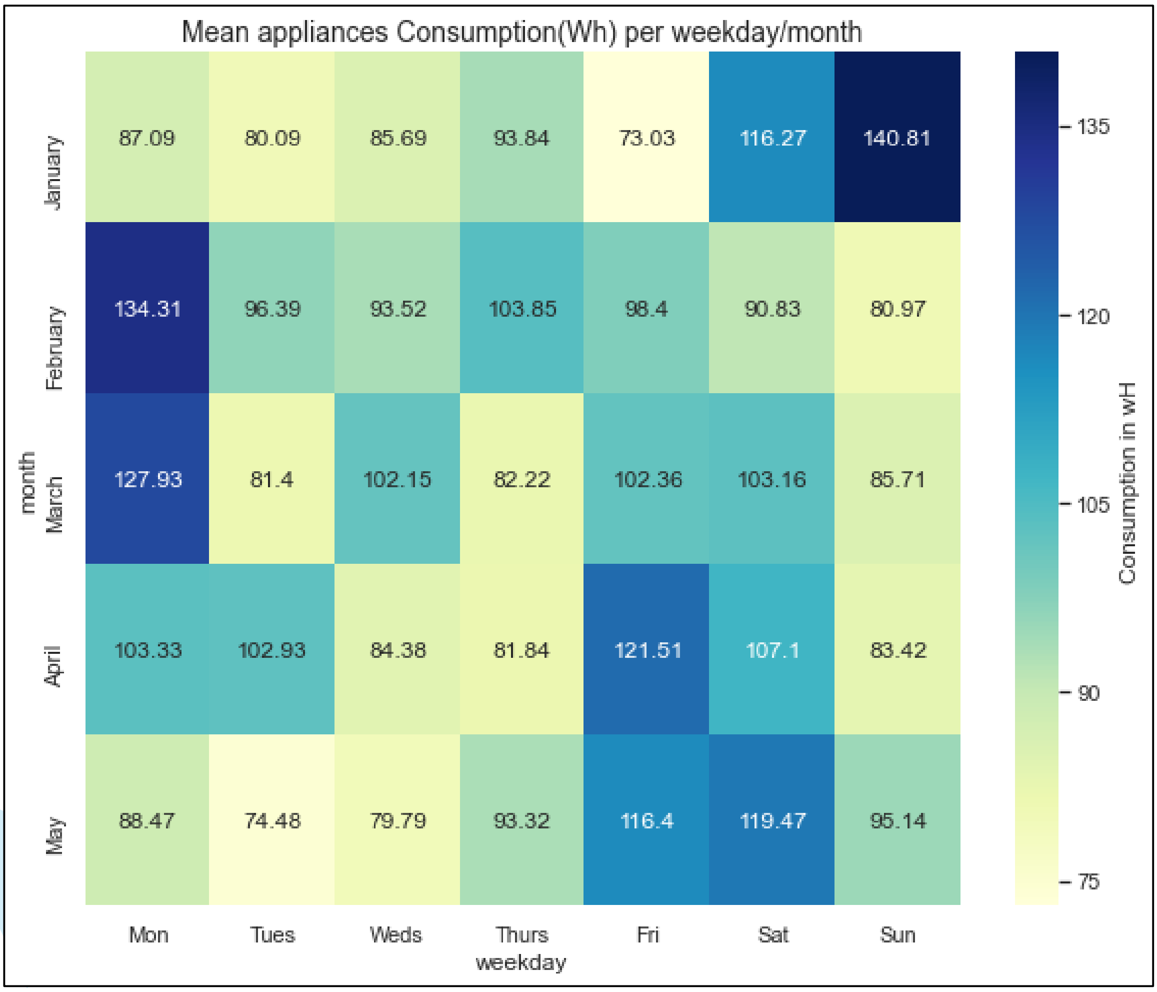


Fig 12. Heat map of Months, Days and electrical demand

5.5.5 **Outliers**. The number of appliances with top 0.1% load values are 21 and they have power load higher than 790 Wh. Mean consumption across the appliances is 97.6949581960983 Wh and the Median is 60.0 Wh. (Fig 13 – Box plot)

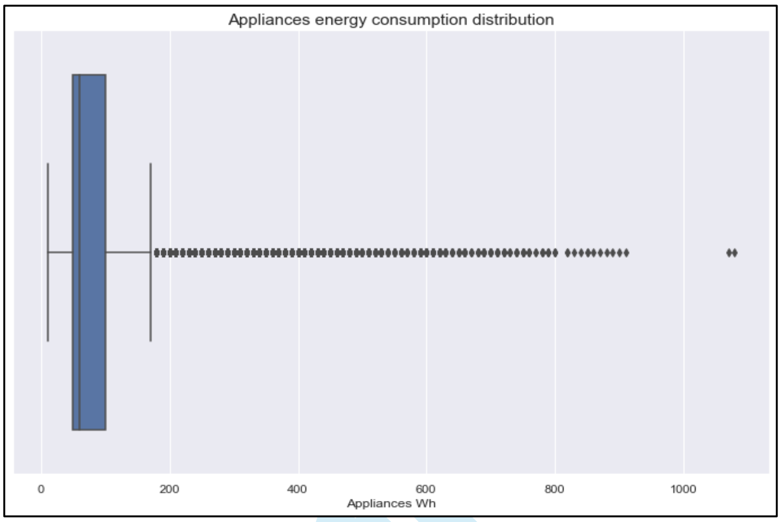


Fig 13. Box plot for Outliers

5.6 **<u>Correlation Analysis – To ascertain factors which affect Energy Consumption by Appliances</u>**.

5.6.1 The outliers are removed so as to ensure identification of correct factors.

5.6.2 <u>Distribution of Variables</u>. After ascertaining the distribution of the variables (Fig 14), it was found that the 'Appliances' column values are not normally distributed hence a log transform of the same was taken.

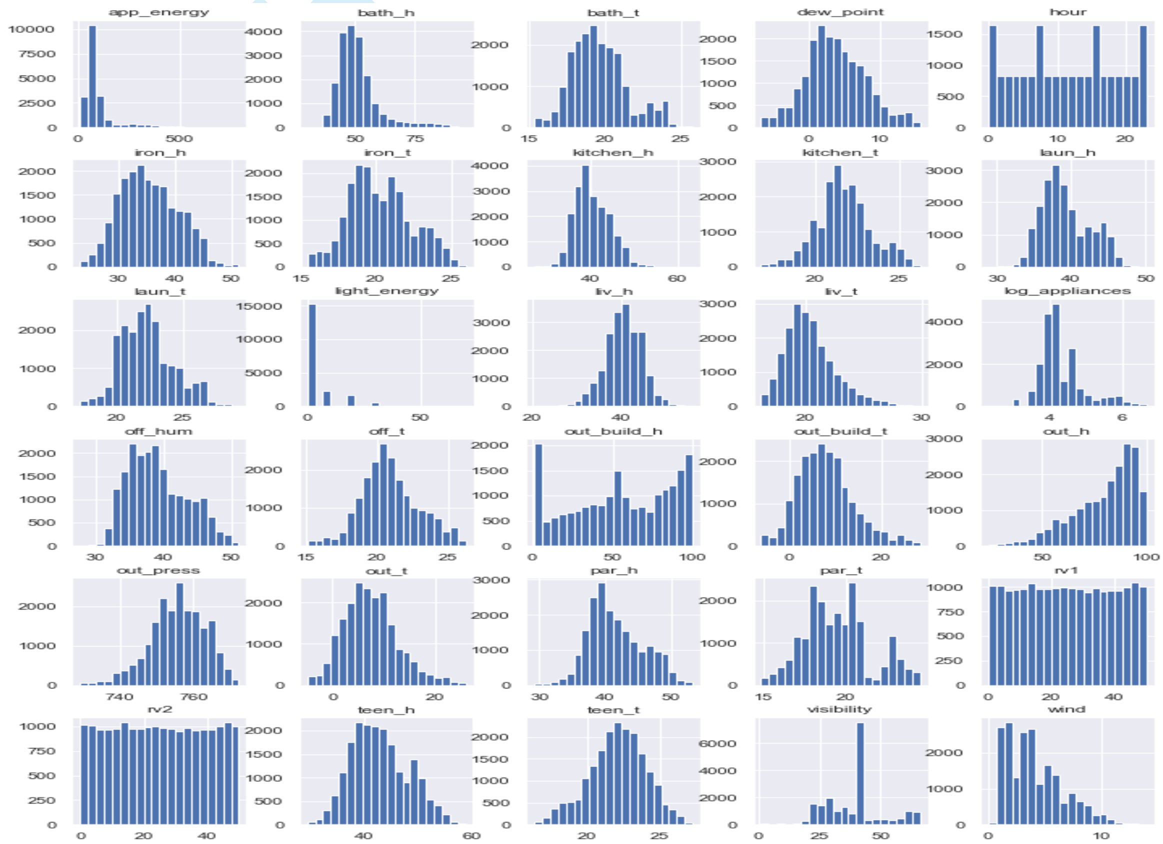


Fig 14. Distribution of Variables

5.6.3 Log Transform of 'Applicance (app_energy)" carried out inorder to enable determination of Pearson's Correlation.

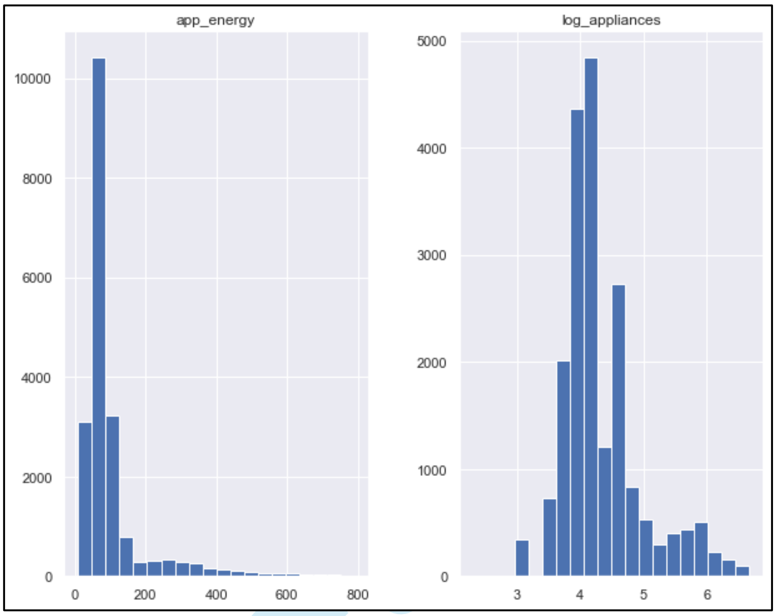
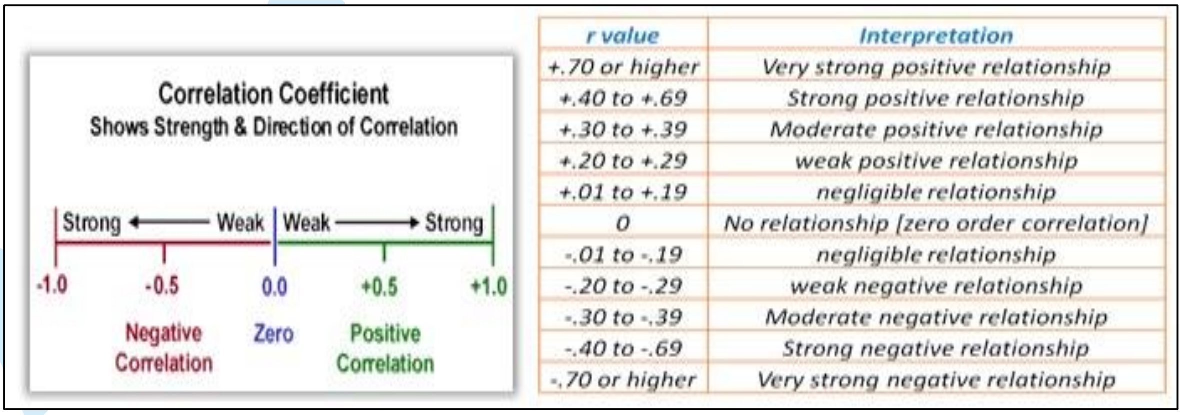


Fig 15. Log Transform of Appliance feature

5.6.3 <u>Correlation</u>. Pearson correlation coefficient is a measure of the strength of a linear association between two variables and is denoted by r. It provides a measure of the relationship between variables. The value is between -1 to +1. The interpretation of the values is as follows:-



r value	*Interpretation*
+.70 or higher	*Very strong positive relationship*
+.40 to +.69	*Strong positive relationship*
+.30 to +.39	*Moderate positive relationship*
+.20 to +.29	*weak positive relationship*
+.01 to +.19	*negligible relationship*
0	*No relationship [zero order correlation]*
-.01 to -.19	*negligible relationship*
-.20 to -.29	*weak negative relationship*
-.30 to -.39	*Moderate negative relationship*
-.40 to -.69	*Strong negative relationship*
-.70 or higher	*Very strong negative relationship*

Fig 16. Pearson's Correlation Scale interpretation

5.6.4 <u>Dataset Correlation Values</u>.

(a) The variables do not have a strong correlation with consumption of electricity by appliances as indicated in the correlation heat map (Fig 17). Positive weak correlations exist with lights (value - 0. 20). Negligible positive correlation exists with kitchen temperature (value – 0.06) and humidity (value-0.09); living room temperature (value-0.12); outside building temperature (value-0.12) and outside temperature (value-0.1). Negative correlations exists with outside humidity (value: -0.16) and outside building humidity (value: -0.09).

(b) A correlation carried out with the log Transform of the appliances values indicates similar weak correlations with lights (value - 0.26), kitchen temperature (Value: 0.16), living room temperature (value : 0.21), laundry room temperature (value-0.168), outside building temperature (value-0.198) and outside temperature (value-0.17). Negative correlation exists with outside building humidity (value: -0.17) and outside humidity (value: -0.22).

(c) Pressure, wind and visibility do not seem to have a relationship with energy consumption by appliances.

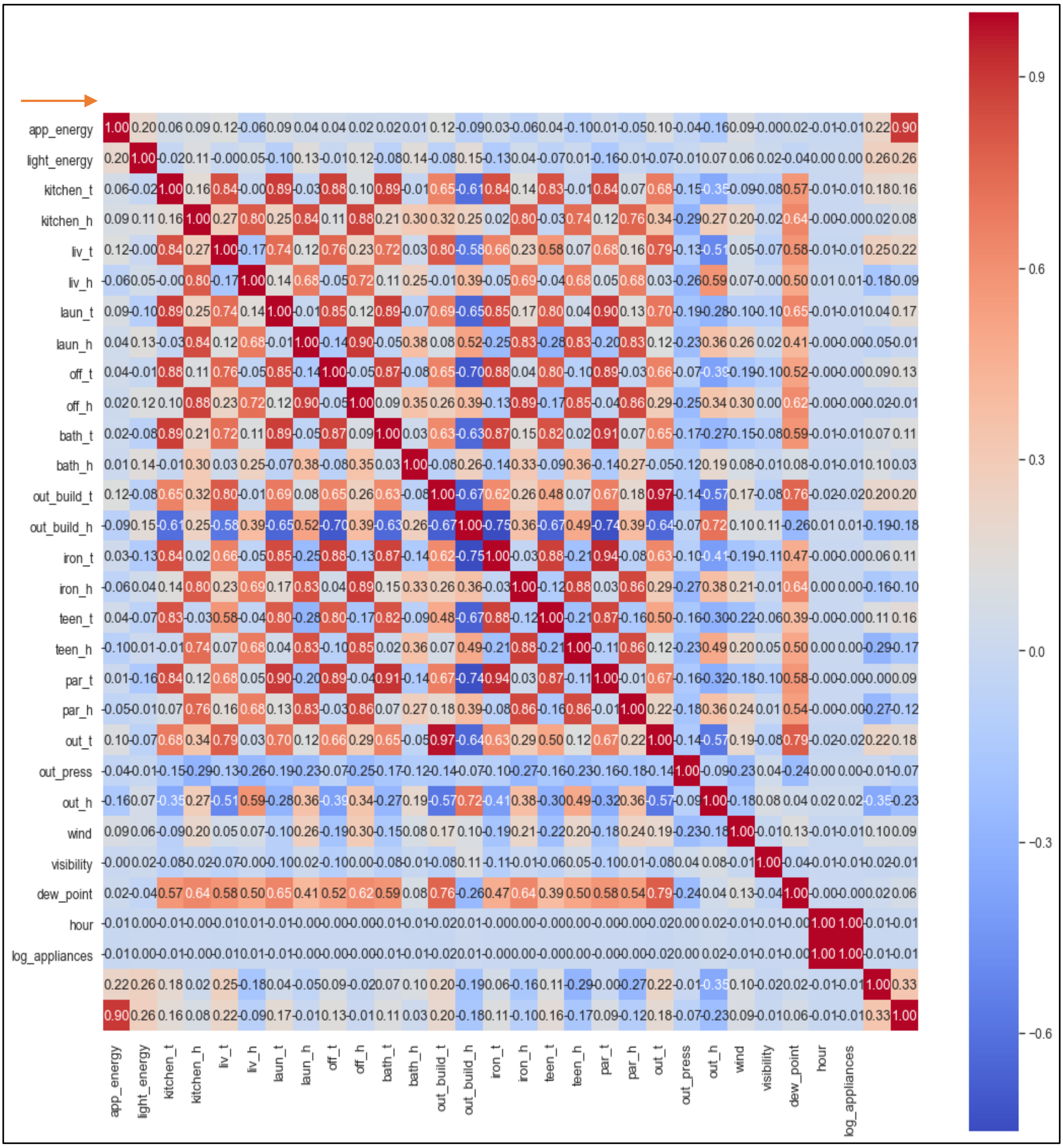


Fig 17. Correlation Matrix

6. **Inference**. The inferences drawn and objectives achieved from analysis of the dataset have been summarized.

6.1 Study energy consumption behavior of consumers in a small household.

(a) Consumption by Electrical Lights. Majorly the consumption of electrical energy by lights used in the house ranges between 10 to 40 Wh. The use of energy efficient lights can further reduce this consumption.

(b) Demand per Day. The Demand per day is never below 200 Wh across the the entire time period. Jan shows some outliers wherein demand has crossed 1000 Wh, probably due to heating appliances being used. . End of Jan and beginning of May show some reduction in demand. Mean of the electrical demand appears to be about 400 Wh for the house for the time period under study.

(c) Weekly Trend. Demand is maximum on Mondays and Fridays during weekdays across the year. However, demand on Sundays and Saturdays is high during winter and summer months. Weekend demand reduces when temperatures outside are moderate in the months of Feb, Mar and Apr, which may indicate that occupants prefer to remain indoors in winter and outdoors in moderate temperature months.

(d) Daily Trend. Demand on an average day increase by around 7.00 AM and then dips around 01.00 PM and rises up to 7.00 PM. Peak demand is in the evening hours. Between 9:00-13:00 the power load is 120-135Wh and after launch reduces again to 110Wh. In the afternoon, the energy consumption ranges from 130-185Wh.

(e) Top Electrical Loads. The number of appliances with top 0.1% load values are 21 and they have power load higher than 790 Wh. Mean consumption across the appliances is 97.69 Wh and the Median is 60.0 Wh. These 21 appliances are the biggest consumer of electricity and may include air conditioners and central heating. These need to be focused upon to reduce electrical consumption.

6.2 Analyze the appliance energy consumption relation with factors such as temperature, humidity, wind speed and atmospheric pressure as prevalent inside a house.

(a) The factors of temperature, humidity, wind speed, dew etc., do not have strong correlation with consumption of electricity by appliances. However, temperature and humidity are the major attributes affecting the energy consumption of appliances.

(b) Positive correlations exist with temperature in various rooms of the house primarily kitchen, living room and laundry room. Also consumption is weakly affected by temperature outside the building and the general prevalent temperature.

(c) For the indoor temperatures, the correlations are high as expected, since the ventilation is driven by the air conditioner/ heating unit and minimizes air temperature differences between rooms.

(d) Negative correlation exists with outside building humidity and general humidity prevalent. Thus humidity effects consumption inversely.

(e) Pressure, wind and visibility do not seem to have a relationship with energy consumption by appliances.

6.3 **Linear Regression**. A linear regression model was developed to predict energy consumption. The features utilized in the model were 'light_energy', temperature and humidity in all rooms of the house; inside and outside the building as well as temperature, pressure and humidity values as prevalent.

6.3.1 Model Evaluation. The model was tested and gave the following results:

(a) Average Error : 0.3828 degrees

(b) Variance score R^2 : 15.10%

(c) Accuracy : 91.33%

6.3.2 Predicted Values. The graph of predicted versus test values is given below.

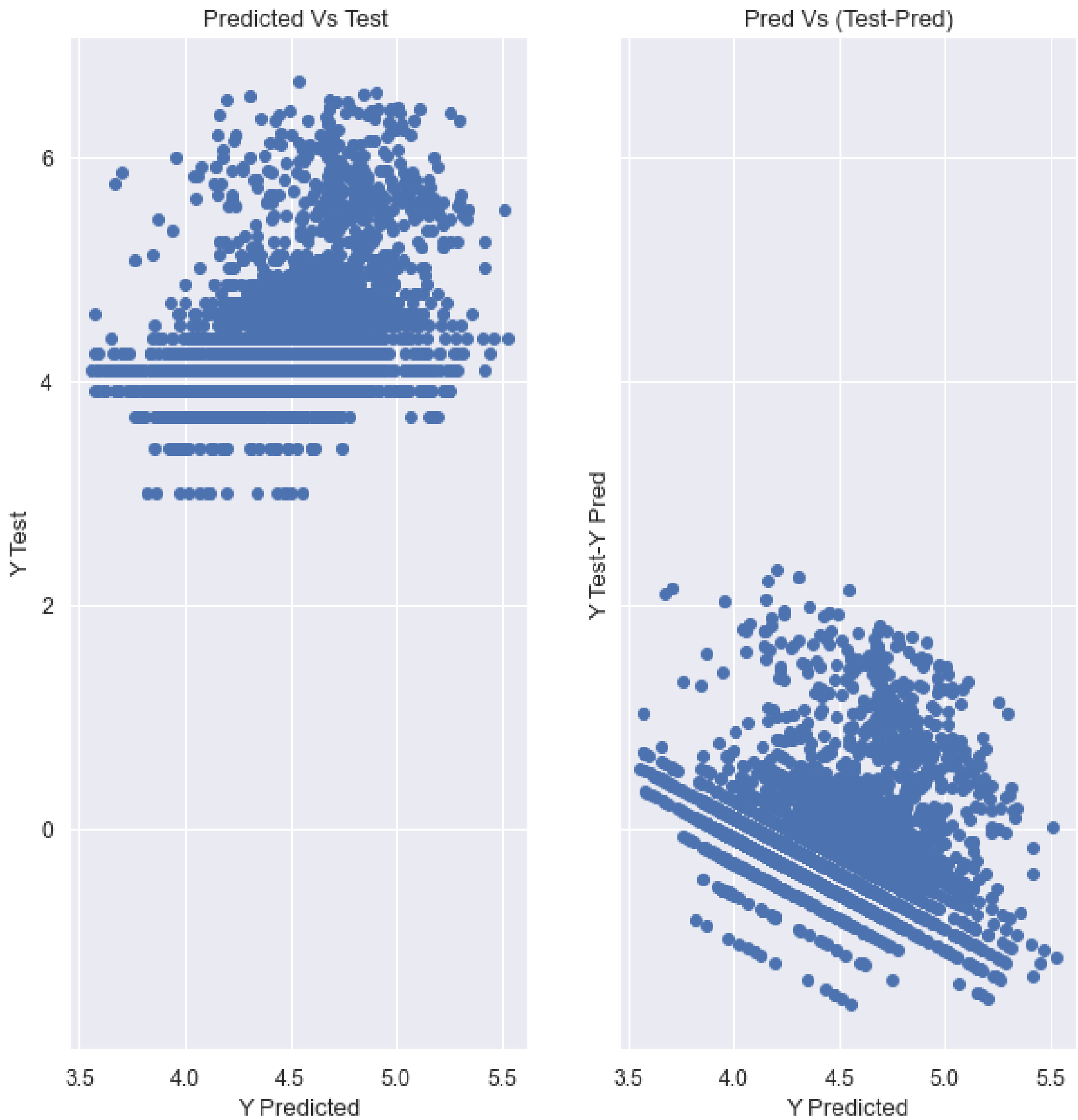


Fig 18. Graph of Predicted Vs Test Values

6.3.3 Coefficients and Plot of Actual Versus Predicted Values.

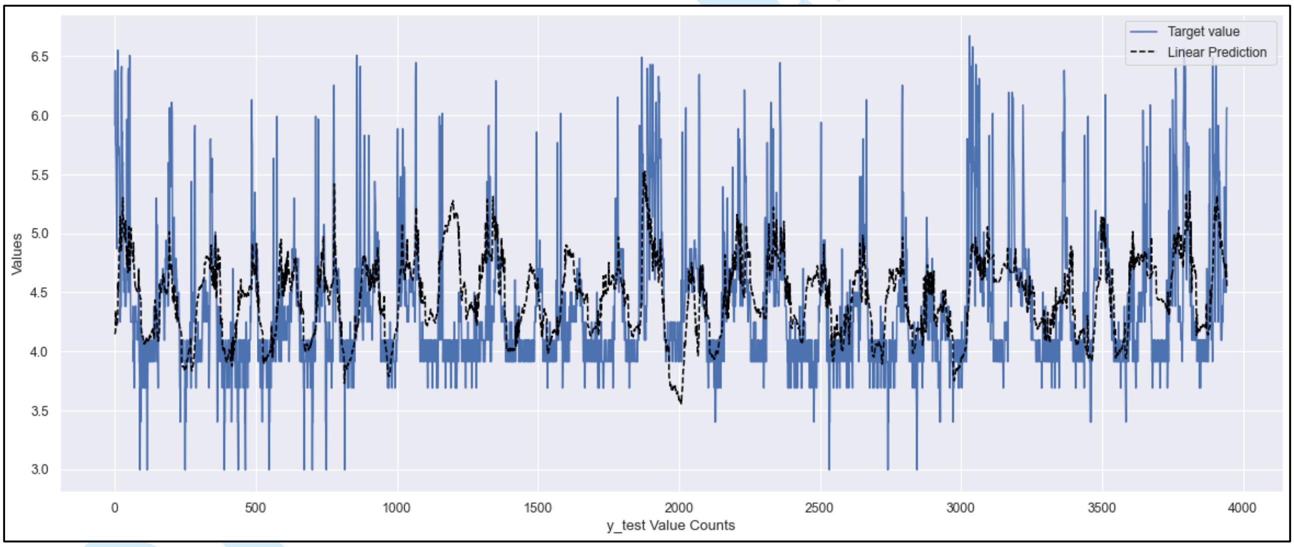
(a) Coefficients. The coefficients of the model are as follows:-

```
In [271]: y1_pred = lin_model.predict(X1_test)
          y1_coef=lin_model.coef_

          print(y1_pred)
          print('---------------------------')
          print('The coefficients of the linear model are:\n', y1_coef)

[4.14441154 4.1605023  4.17104737 ... 4.73641258 4.65895403 4.55263956]
---------------------------
The coefficients of the linear model are:
 [ 0.13743951 -0.03921942  0.31272162 -0.12193921 -0.26992663  0.25950259
  0.15041749 -0.03082231 -0.08351263 -0.00900891  0.01608426  0.26876034
  0.08070377 -0.04112035  0.01496829  0.1659954  -0.23588592 -0.11167002
 -0.02004697 -0.15330683 -0.0089717   0.01038214  0.07487808]
```

(b) The Plot of Actual Versus Predicted Values is as follows:-



6.3.4 Inference.

(a) The linear model gives an acceptable prediction model for the dataset.

(b) The Coefficient of determination (R^2) score is low indicating that the model does not fit a large percentage of the plot.

(c) It can be inferred from the model that the energy consumption relies on temperature and humidity even though the values are weakly correlated. This is intuitively also true.

(d) Linear model is not the best model for this dataset to predict energy consumption.

7. **Conclusion**. A study of the Appliances energy dataset has revealed various aspects. It provides basic inputs on the pattern of energy consumption. A large number of factors influence energy consumption including temperature and humidity. A study in Indian conditions would definitely provide very valuable insights into energy consumption. This study could be for different economic strata of households in India within both urban and rural settings.

Earmarking of major energy consuming appliances also need to be highlighted in the dataset for a future study.

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