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Energy Audit in Households using Machine Learning

Aniruth.R, Suresh Kumar.M, Gokulakrishnan.R, Parthasarathy.M, Krishnan.V.C,

***Abstract:** Maintaining the energy usage with minimal power loss throughout the supply chain is of the major issues faced in many small-scale sectors or even in households of today's world. Even though Power transmission can play a cardinal role in the supply chain, monitoring the transmission lines for energy leakage or any faulty connections is critically important. There have been several measures taken to come up with a better solution but, the problem of finding a consistent method for monitoring the power leakage is still at peril. There are actually many ways of saving the energy by mitigating the usage and preventing the loss of energy due to over usage and wastages, for this a thorough monitoring and study of the usage should be done. If the electricity usage pattern of the concerned is identified, then it will be facile to come up with a solution for the problem at hand. The electricity wastage constituted by all the countries aggregated is found out to be around 8.25%, which is considerately large given that many places around the world does not even have access to electricity. So, there is a need to find a better solution for this problem. After conducting a thorough study on the electricity usage pattern of several households we are proposing a method which is an ensemble of machine learning algorithms, Internet of Things, sensors, Embedded systems. Using an IoT device we've designed we monitoring and collecting electricity usage in households in a time based manner. These collected data is stored in the database and is processed and fed into machine learning algorithm to predict the upcoming month's electricity usage. This predicted data is then fed into another algorithm to provide recommendations to the user to reduce the electricity consumption according to their usage interests. Thus reducing the cost significantly.*

***Keywords:** Embedded systems, Energy efficiency, IoT, Linear regression, Machine learning, Node MCU.*

I. INTRODUCTION

Since using the energy efficiently and maintaining the power with minimal loss from leakage or faulty connections is the predicament at hand, this paper proposes a system pipeline framework which aims at curtailing the wastage and the loss of power in most of the cases. Over usage of electricity and not identifying the energy leakage are the two stems which engender many challenges when dealing with energy usage globally. The users are not aware of the usage and identifying the energy leakage is arduous for the users.

To reconcile this problem, an IOT hardware component (Electron 1.v) is used to sense the power usage data and send it to the database for further processing. A web interface which contains detailed descriptions of the electricity usage has been developed which also provides details about the consumption of electricity by individual devices. To access this web interface the user will be given with a login ID and a password. One of the privileges of using this web interface is that the user will be provided with a predicted cost and units for the upcoming month based on the current month's usage. Initially, the users need to enter all the parameters required for calculating maximum units' usage for each room. This will be stored in the database and fed to the interface. The user will also be given recommendations on the usage reduction i.e. if the user needs to reduce the units consumed by certain units, the user will be given different combinations of methods on the usage reduction.

By comparing the maximum units and the actual consumed units of that month, energy leakage can be detected. If the predicted units and the actual units vary, it will be because of two reasons Energy leakage, Over-usage. If it is over usage then the user will be provided with the above stated recommendations to reduce the usage.

II. LITERATURE SURVEY

Machine Learning for Smart Energy Monitoring of Home Appliances Using IoT [1]: In this method, the authors used Raspberry Pi 3 as the controller, non-Invasive AC current sensor SCT-013-000 to measure the AC current as the IOT middleware. Google Colab is employed for training and testing the Individual household electric power consumption Data Set[4]. This dataset consists of electricity data of 2 million minutes in 1-minute time interval of a single household. The dataset is trained in a Neural Network which is developed using Keras and Tensorflow, where 90% of the dataset is utilized for training and 10% is used for testing. The prediction results for 120 minutes in test set is shown in fig[1].

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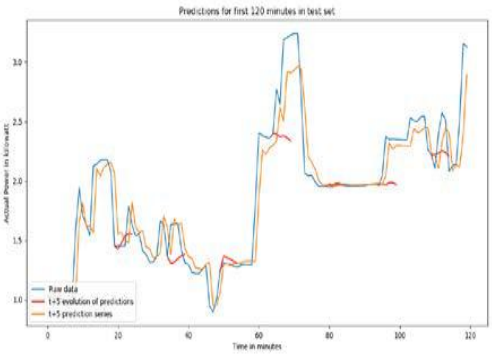
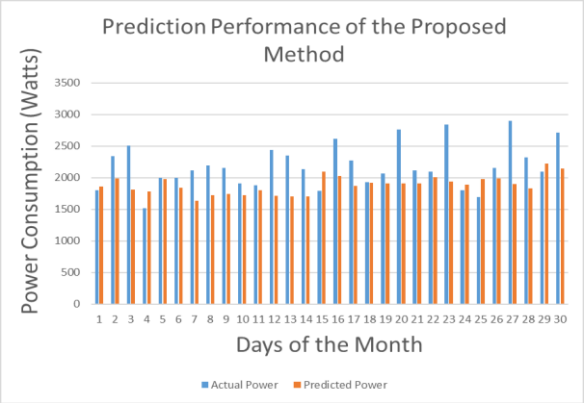
*** Correspondence Author**
Aniruth.R, UG Student, Dept. of Information Technology, Sri Sairam Engineering College, Chennai, India. E-mail: anikrishna3@gmail.com
Suresh Kumar.M, Asst. professor, Dept of Information Technology, Sri Sairam Engineering College, Chennai, India. E-mail: Sureshkumar.IT@sairam.edu.in
Gokulakrishnan.R, UG Student, Dept. of Information Technology, Sri Sairam Engineering College, Chennai, India. E-mail:gokulshyam567@gmail.com



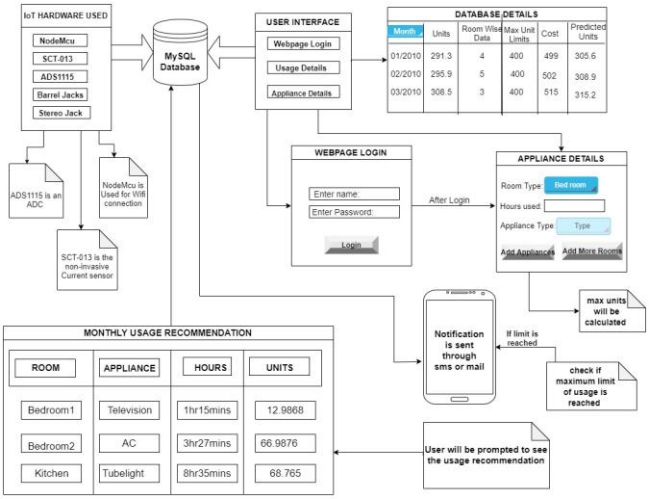
Fig[1]. Prediction results for 120 minutes

Short Term Power Load Forecasting using Machine Learning Models for energy management in a smart community [2]: In this method, the author attempts to predict daily usage of electricity of a household considering parameters such as seasonal, weather, weekday or weekend, summer vacation etc. The author evaluates eight regression models for predicting the daily electricity consumption. By evaluating the eight regression model, the author declares Radial basis function (RBF) kernel as the most suitable model for this prediction. The daily prediction performance of the author's proposed model is shown in fig[2].



Fig[2]. Prediction performance of proposed model

III. MODULES IMPLEMENTATION

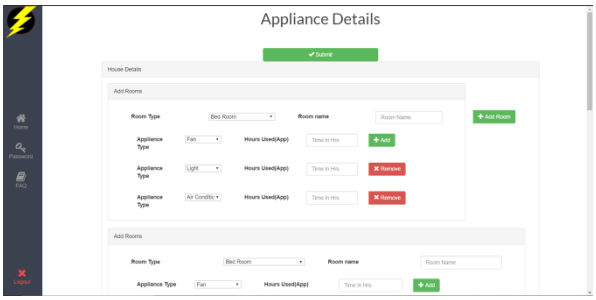


Fig[3]Workflow and Implementation model diagram

In the figure above [3] the implementation and the framework of the model is depicted in a pictorial way. The model has been implemented for effective usage of power and to preclude the loss of power and electricity through leakage and profligated usage. In this model, we have used various modules that include an IOT hardware which is used to sense and send data regarding the usage of power to the respective database. The user interface which is provided with unique user ID and password for each and every user is used for obtaining data like previous months or years electricity usage data and details regarding the household and the electrical components available in the household which is used for meticulously predicting and calculating the maximum usage value and the value that provides us with the details in order to reduce or to abate the usage to effective level. From the data that has been provided prediction is done for the consecutive month or the respective month of the consecutive year accordingly based on the data available. After predicting the respective month's usage data it is segregated into room wise and appliance wise usage data and is checked against the regionally variating tariff value and the maximum value for providing recommendation in case of leakage of current or over usage beyond user's affordability. The recommendation will provide or imbue us with details regarding the appliance based usage reduction and leakage respectively.

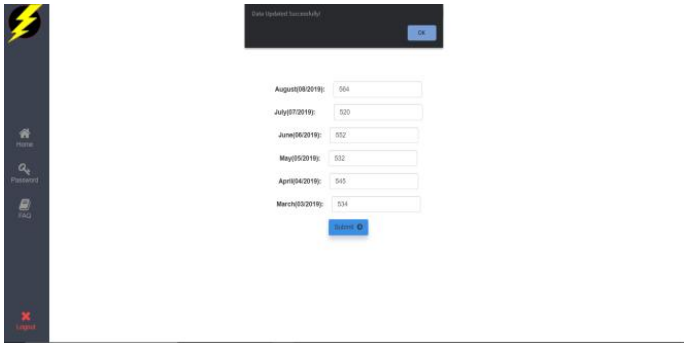
IV. USER INTERFACE

All Electron 1.v models are assigned with a unique Node ID and the user's meter ID is assigned to this Node ID. Thus the data collected from Electron 1.v is sent to the server. The login ID for each user is their meter ID. As soon as the user logs in, they are prompted to provide their room details.



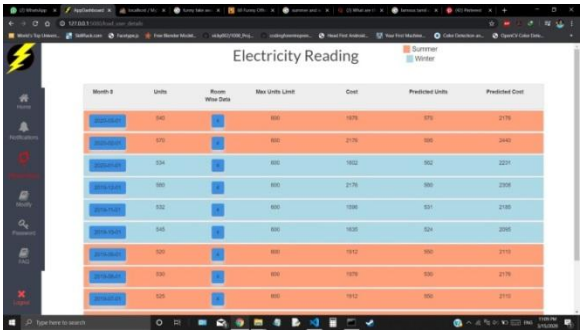
Fig[4]. Appliance Details Interface

As seen in fig[4], the user is prompted to provide the appliances' details and maximum hours of usage of each appliance in an interactive user interface. This interface contains all the room types & appliance types commonly used in all households. Using these details, the maximum electricity consumption per device is calculated and aggregated to find the maximum electricity consumption per day of that house hold and this can be split to find the maximum consumption per room. These data are also used to calculate various parameters which are required to predict the electricity usage. These parameters include maximum usage in each room, aggregated usage in all rooms, cost calculations etc. Then the user is prompted to provide previous 6 months electricity usage data.



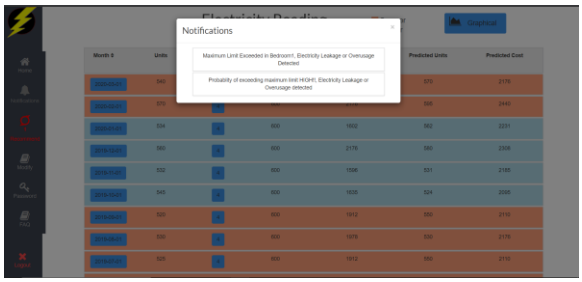
Fig[5]. Monthly Usage Data Input Interface

The past 6 months electricity usage units collected are used to predict the current month's electricity usage and also the cost. The appliances' details and electricity usage details collected from the above mentioned user interfaces are stored in the database for future references and calculations. Thus, the initial setup phase is complete. Now the user is redirected to the dashboard.



Fig[6]. Web Application Dashboard

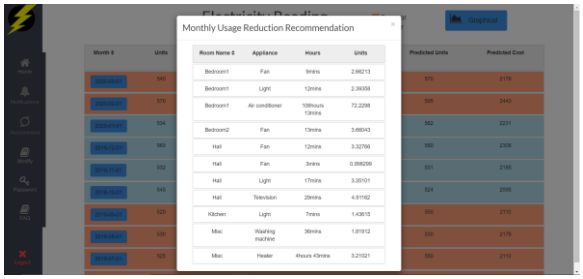
User's electricity consumption details are presented intelligibly in Web Application Dashboard fig[6]. Here, users can view day, room wise consumption for each month. Predicted cost and predicted units are also presented which enables the user to be aware of their electricity consumption. By using applications of IOT, real-time data updates are made possible, allowing us to inform the users when the consumption exceeds the maximum limit or about to exceed maximum limit. This notification allows users to take immediate action to reduce usage or to perform energy audit to detect leakage. Room wise appliances data obtained from user are used to identify the exact room where the probability of energy wastage is high. Thus the laborious task of identifying electricity leakage location in the house hold can be simplified significantly.



Fig[7]. Over usage or leakage notification interface

As seen in fig[7], the notifications inform wastage or over usage in a particular room precisely.

In certain states, the cost for electricity consumption is almost double than the cost for usage below a certain limit. Thus to restrain the consumption, recommendations are sent to user at the start of the month. This notification recommends user to reduce usage hours of a particular appliance to reduce electricity consumption below the limit. These recommendations allow the users to save electricity cost each month. Since there is a considerable reduction in cost users will tend to follow these recommendations as shown in fig[8].



Fig[8]. Usage Reduction Recommendation Interface

In case the user wants to modify his appliances details, another user interface is provided. Notifications are send periodically to modify the appliance details to improve predictions, calculations and recommendations.

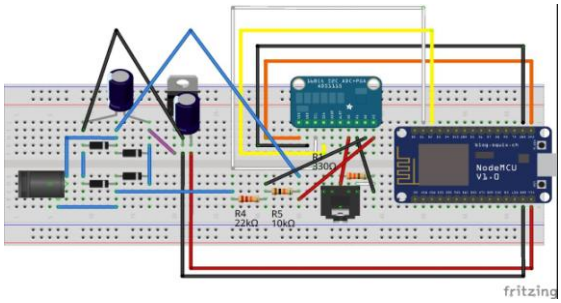
V. IOT HARDWARE

The IoT part is concerned with sending real time data which contains the data about the consumption of electric power of every device in the household to the server. The usage of electric power of the necessary devices is read by using various IoT components. The data collected from the IoT components is cardinal for performing calculations and predictions involving machine learning algorithms. This data can be collected in two methods, either collecting the total power usage from the energy meter or collecting the power usage room wise (acquiring the power consumption of each and every device for better accuracy). The components play a vital role in collecting the data of electricity consumption. The figure [9] below is the outlook of the actual device. The IoT components which are necessary for acquiring the power consumption are wired in this Electron 1.v model. The 3D model of internal components arrangements of Electron 1.v is shown in fig[11].

Fig [9] 3D Model of Electron 1.v Device

In order to measure the voltage and current consumed in the households the SCT-013-000 is used. SCT-013-000 is a Non-Invasive AC current sensor which means that it is a current transformer that can be used to measure AC current upto 100amps. Current transformers (CTs) are sensors used to measure alternating current. The main reason why SCT-013-000 is preferable is that it is small in size and it can be easily clipped straight on the live or neutral wire (energy meter in most cases) without having to do any high voltage electrical work. The wiring starts with passing the primary winding (live or neutral wire, in some cases the energy meter's wire) through the opening of the SCT-013-000 Current transformer. The output of the SCT-013-000 can be sent through connecting the 3.5mm plug in the CT to a barrel jack. Once the current sensor is clipped in the energy meter's wire, it will start measuring the current. Once the wiring is done, the current coming from the live wire will be outputted through the 3.5mm plug. The output of this component is the 3.5mm plug which makes it easier to use a barrel jack for the connections. The 3.5mm plug is connected to the DC connector (barrel jacks).We need to convert the analog values of the current and voltage digitally because the server can handle only digital values.

Even though NodeMcu has an inbuilt ADC, external ADC is used because the inbuilt ADCs in these microprocessors are not reliable and not very accurate and the signal is weak. The circuit model representation of the proposed Electron 1.v is shown in fig[10].



Fig[10] Internal circuit representation of Electron 1.v

Since we are dealing with current values which involve high accuracy for predictions the inbuilt ADCs are inaccurate and not very reliable. ADS1115 comes in handy to solve the inaccuracies. ADS1115 is precise, low power, 16-bit analog-to-digital converters (ADCs).Typically the digital output of an ADC is the two's complement binary number proportional to the input but there are also many other possibilities. Since the conversion of analog to digital involves quantization of the analog input, it is very important to introduce a small amount of error or noise. So, in every cycle when the ADC gets the analog signal it will convert it into a digital value. The outputted analog value from the SCT-013-000 is passed to the analog pins of the ADS1115 as input. The SCL and SDA pins in the ADS1115 pins are serial clock and serial data pins. In order to send a large sequence of data, serialization is implemented. The SCL pin in the ADS1115 is the clock signal which will synchronize the data transfer between the devices on the I2C bus and it's generated by the master device. The SDA pin is the serial data pin which carries the data. The NodeMcu will receive its input from the SDA and SCL pins. NodeMcu is used to send the data collected from the current sensor. The utilization of NodeMcu makes it easier for the connections and to code using the Arduino IDE. NodeMcu has an inbuilt WiFi module. This is used to send the data to the server.

Fig[11]3D model Internal components of Electron 1.v.

The NodeMcu should be powered externally or DIN -rail transformer can be used to provide the power to the NodeMcu. The HTTP request method: POST is the desired protocol used for sending the data from NodeMcu to the database. Using a DIN- rail transformer real power can be measured as long as loading power-factor issues are calibrated. When sampling the AC voltage care has to be taken to avoid overloading the ADC.

VI. IMPLEMENTATION OF PREDICTION MODULE

The application that has been proposed is used for auditing and predicting the usage of electricity by using specific high efficiency techniques based on the user data available. The application module can be divided into the following, based on the data provided by the user. If the data for the quantity of power consumed by a household provided by the users is less than for a year, then the prediction model is implemented in a way such that the prediction is done based on the monthly segregation of data. If the given data is for more than two years the prediction is carried out by considering various parameters which includes seasonal based variations, daily humidity and temperature data, holiday count in order to improve and make the system attain efficacy in its prediction and calculation of the electricity usage for the future terms respectively.

Fig [12] Seasonally Differentiated Usage Data

Consider the figure [12], in that figure we can see that various seasons are differentiated based on the colors of the bars representing the rows accordingly. Hence the prediction will be based on the data available and parameters like temperature, seasonal variation of data is considered from previous years data.

The dataset for the prediction is obtained from the user using the interface as shown in the figure [5] and following it, the data that is needed for training the regression model is obtained and the training is conducted in such a way that the prediction is done separately for each month which includes the climatic seasonal variation on its own which is derived from the previous years reading respectively. The prediction model that has been implemented performs prediction for two basic usage period respectively. One of it is based on the prediction of usage of electricity for a regular time period for every month and the other part of the module where prediction is implemented is for the cost that is incurred based on the units consumed by the household as shown in the figure [13].

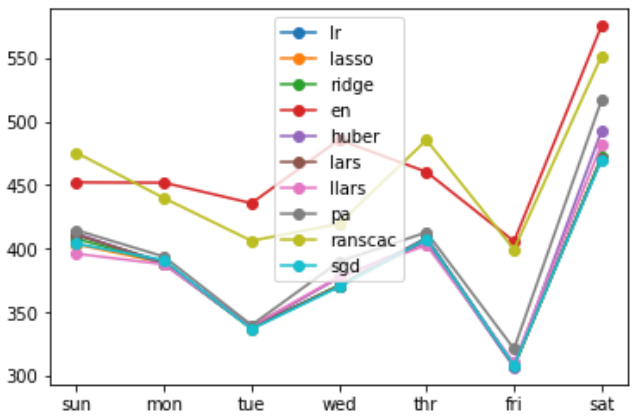
id	meterId	month_date	units	rooms	max_limit	cost	pred_units	pred_cost
1	1001	2019-09-01	520	4	600	1912	550	2110
2	1001	2019-08-01	530	4	600	1978	530	2176
3	1001	2019-07-01	525	4	600	1912	550	2110
4	1001	2019-06-01	580	4	600	2308	600	2440
5	1001	2019-05-01	585	4	600	2308	595	2440
6	1001	2019-04-01	555	4	600	2110	580	2308
7	1001	2020-03-01	540	4	600	1978	570	2176
8	1001	2020-02-01	570	4	600	2176	595	2440
9	1001	2019-12-01	560	4	600	2176	580	2308
79	1001	2020-01-01	534	4	600	1602	562	2231
80	1001	2019-10-01	545	4	600	1635	524	2095
81	1001	2019-11-01	532	4	600	1596	531	2185

Fig[13] Monthly usage database representation

The machine learning model that has been used for prediction is linear regression model, which has been considered to be appropriate for this prediction after having compared eight different algorithm models which provide similar plot for the usage prediction as shown in the graph [14].

Thus the usage of linear regression ameliorated the system's complexity.

In this prediction model that we have implemented, the prediction is done based on the following basis, when the data provided is less than for an year, the data used for training the dataset and the output predicted is based on cumulative accumulation of the previous months data for predicting the consecutive month that follows the provided months respectively.



Fig[14] Usage prediction values for various machine learning models

Once the unknown month's actual data is obtained it is added to the dataset that is used for training the system effectively. In this case, the prediction is done based on the usage data available for the previous months excluding factors like seasonal variations and official holiday that includes the public factor into account.

VII. ALGORITHM

The below algorithm is for the case where the data available is less than for an year. Previous_months_data represents the list that contains previous month's data and k represents the total number of months available for training the system respectively. consumed = previous_months_data

k = number_of _months

x = array(consumed[0:k-1])

y =current_month_predicted_data

Initialize X_train, X_test, y_train, y_test to x, y based on the test size=k-(k-1) and random_state=4.

Here x represents the input parameter provided and y represents the output parameter respectively. test_size represents the size of the testing data for the learning model and random state is the weight that has been provided in order for narrowing down the predicted value to be accurate and effective. Thus when the data provided is not sufficient for yearly prediction the following is performed effectively.

When the prediction is done for yearly dataset prediction is done in a way such that for each month the above mentioned algorithm is followed in dividing the dataset but the dataset is arranged in such a way as shown in the table below.

TABLE FOR ELECTRICITY CONSUMPTION FOR TWO YEARS

2018

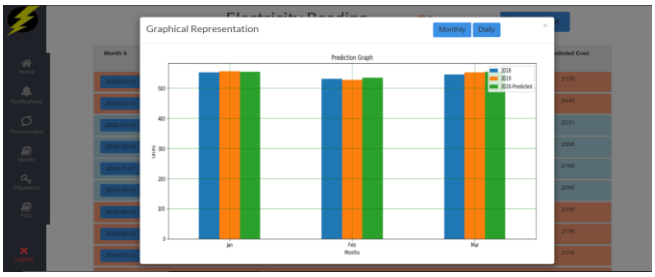
Month	Season	Holiday Count	Electricity Usage
January	Winter	5	552
February	Summer	5	531
March	Summer	7	546
April	Summer	6	554
May	Summer	5	579
June	Summer	5	549
July	Summer	5	544
August	Summer	6	546
September	Summer	7	552
October	Winter	5	534
November	Winter	7	548
December	Winter	6	542

2019

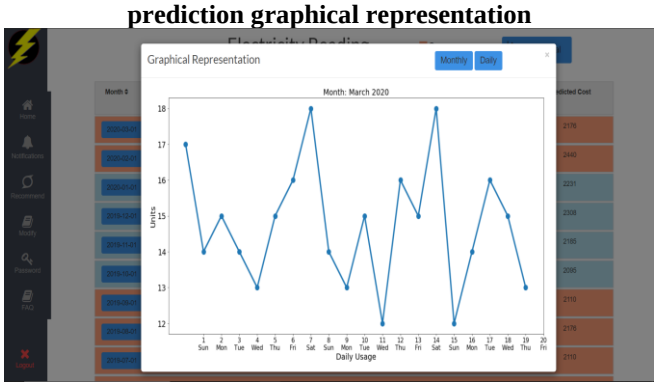
Month	Season	Holiday Count	Electricity Usage
January	Winter	4	556
February	Summer	4	528
March	Summer	7	552
April	Summer	6	551
May	Summer	5	570

June	Summer	6	554
July	Summer	4	542
August	Summer	7	553
September	Summer	6	550
October	Winter	7	549
November	Winter	5	541
December	Winter	6	547

Thus with the data available we can predict the following year's corresponding month respectively. The holiday count will be reflected in the month's usage prediction effectively which has been provided in order to emphasize its usage as a parameter which affects the usage prediction effectively which is shown in the graph [15a]. Daily usage of the household is also presented to the user as shown in graph [15b].



Fig[15a]. Yearly data based corresponding month's usage prediction graphical representation



Fig[15b]. Daily usage data graphical representation.

Then based on the units the cost is calculated respectively based on the tariff proposed regionally. The general algorithm is as follows,

If (units < 500):
    cost = units *1.5
else if (units > 500):
    cost = units *3.0

The maximum usage of electricity for a month is performed sequentially in the proposed way. The usage time period for each appliance present in a room is considered as a parameter along with the approximate time period for which a particular appliance is used in a particular room which is then used to find the units consumed by the particular appliance respectively.

After calculating the units consumed by each appliance in a particular room, they are summated in order to sum up for the total units of electricity that can be consumed by that particular section of the household per day respectively. Following the above, calculation is performed for all the rooms available in the house.

Following which the summation of all those individual room consumption values is performed. Thus the maximum units that could be consumed by a particular household for a day is calculated.

By using the above calculated data, we can multiply it with the number of days in a month, following which we will be able to obtain the month's maximum consumption value for a particular household respectively.

VIII. ALGORITHM

if i is not equal to the length of the array d, then do
Initialize room_name to d('room name')
if j is not equal to the length of the list room in d , then do:
initialise app_details to be empty.
initialise app_type to contain d('room appliance type') from the list d.
initialise app_hours to contain d('room appliance hours) from the list d.
Append room_name to app_details list.
Append app_type to app_details list.
Append app_hours to app_details list.
If (app_type==type_1), then do:
initialize unit_app to be
(app_hours_1)/time_required_per_unit_a1
else (app_type==type_2),then do:
initialize unit_app to be
(app_hours_2)/time_required_per_unit_a2
end.

In the above algorithm d represents the array of rooms along with their appliances. Room name is the new list which contains the type of rooms available in a household. app_details contain details regarding the particular appliance respectively. The above algorithm is used to find the consumption of electricity by each individual appliance in the household respectively which is summated in order to obtain for the total household and for each room accordingly.

IX. FORMULAE USED

For calculating the maximum usage of an appliance in a particular room is:

$$au = \frac{ah}{ta}$$

Where, au= Units consumed by an appliance per day.
ah=maximum duration for which an application is used per day.
ta= total amount of time in hours which is required for an appliance to consume one unit of current.

$$rwu = rwa + au$$

Where, rwu = total units consumed in a particular room per day.

After obtaining the room wise usage data it is multiplied by the number of days in a month.

$$mru = rwu * ndm$$

mru = the maximum units consumed by a room in monthly basis.

ndm = number of days in a month

After obtaining the monthly usage for a particular room the total usage for the whole house is obtained by summating all the total monthly units consumed by all the rooms respectively.

Thus the maximum units that can be consumed by an household for a month is calculated and is displayed room wise as well as in monthly basis as shown in the below figures[16] and [17].

meterId	month_date	name	current_units	predicted_units	max_pred_units
1001	2019-09-01	Bedroom1	131	143	150
1001	2019-09-01	Bedroom2	85	102	110
1001	2019-09-01	Hall	164	188	190
1001	2019-09-01	Kitchen	43	62	70
1001	2019-09-01	Misc	107	116	120

Fig[16]. Room Wise data representation

id	meterId	month_date	units	rooms	max_limit	cost	pred_units	pred_cost
1	1001	2019-09-01	520	4	600	1912	550	2110
2	1001	2019-08-01	530	4	600	1978	530	2176
3	1001	2019-07-01	525	4	600	1912	550	2110
4	1001	2019-06-01	580	4	600	2308	600	2440
5	1001	2019-05-01	585	4	600	2308	595	2440
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80	1001	2019-10-01	545	4	600	1635	524	2095
81	1001	2019-11-01	532	4	600	1596	531	2185

Fig[17]. Month Wise data representation

Thus, we can find appliance percentage of the total units consumed as well as the predicted units based on the following formula used.

$$uap = (\frac{uam}{mlr}) * 100$$

Where, uap=percentage of total units consumed by appliance in a room.

uam= total units consumed by that appliance.

mlr= total units consumed by the particular room.

$$urp = (\frac{urm}{mlh}) * 100$$

Where, urp= percentage of total units consumed by room in the household.

urm= total units consumed by that room.

mlh= total units consumed by the household respectively.

Thus by applying the above mentioned formulae and prediction model the units consumed per house hold is calculated which is then used for providing recommendation in order to reduce the usage as per user's convenience. The formula which is used for finding out the units that has to be cut down from the usage in order to be efficient and lucrative is given. After obtaining the percentage of units consumed for an appliance in a particular room, the maximum units that can be consumed by the particular appliance can be calculated in advance. Thus if the predicted value surpasses the tariff based recommended value, the following is performed to find out the excess usage of units and will be provided for the user as an recommendation in order to reduce the usage and cost respectively.

$$uc = \frac{ah}{th}$$

Where, uc= Units consumed by an particular appliance

ah=maximum duration for which an application is used per day.

th= total amount of time in hours which is required for an appliance to consume one unit of current.

$$ec = ta - tm$$

Where, ec= The consumption of unit which has to be reduced

ta=predicted maximum units consumed

tm=maximum units consumption above which tariff is doubled.

$$ru = ec * urp$$

Where, ru=units consumed in a particular room

urp= percentage of total units consumed in a room in the household.

$$ac = ru * uap$$

Where, ac=units consumed by appliance in a room.

uap =percentage of total units consumed by appliance in a room

The usage time period that has to be cut down in order to reduce the consumption to the safe level is obtained as follows,

$$rt = ac * trc$$

Where, rt = reduction time in hours

trc = time in hours for appliance to consume one unit.

The reduction time is converted to hours and minutes and presented to the user in recommendation message box.

Thus, by using the above formula we can provide recommendation to the users as depicted in fig [8].

X. CONCLUSION

Hence the model that has been developed and proposed here, in order to make the usage of electricity to reach efficacy will buttress the users with features to reduce the wastage of power effectively. The system that has been proposed can be made further effective by modifying and implementing it based on each region's tariff system respectively. The above provided recommendation service and model framework can be further developed in order for efficient transmission of power through the grid by improving this model with deep learning techniques in order to predict the usage and consumption of power in each grid and transmitting the excess power consumed to other grids or sub grids which require excess power respectively. This model can also be improved to detect leakage and over usage location in a city.

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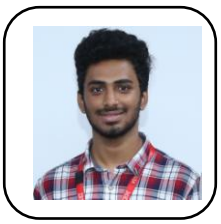
AUTHORS PROFILE

Aniruth. R is presently a Senior UG student at Dept. of Information Technology, Sri Sairam Engineering college, Chennai. He has 2 International Technical publications. He has completed 2 internships in Augmented reality in reputed companies. He is interested in Machine learning, Deep learning, Data science, Web development, Android Development etc.

Suresh Kumar. M has 19 years of experience in the field of Teaching and Research and is currently working as a Associate Professor, Information Technology Department, Sri Sai Ram Engineering College, Chennai. He received his Ph.D degree under Information and Communication Engineering, Anna University in Web Service composition. Also his research area includes Web Service, Cloud Computing, IoT, Machine Learning, Semantic Web and Cyber Security. Around thirty numbers of peer reviewed International Journal and Conference publications are there in his credit.

Gokulakrishnan. R is presently a Senior UG student at Dept. of Information Technology, Sri Sairam Engineering college, Chennai. He has 2 International Technical publications. He has pursued numerous courses in Coursera to augment his knowledge. He has completed 2 internships in reputed companies. He is interested in Machine learning, Deep learning, Data science, Web development, Android Development etc.



Parthasarathy. M is presently a Senior UG student at Dept. of Information Technology, Sri Sairam Engineering college, Chennai. He has 2 International Technical publications. He has completed 2 internships in Augmented reality in reputed companies. He has pursued numerous courses in Coursera to augment his knowledge. He is interested in Machine learning, Deep learning, Data science, Augmented reality, Web development, Android Development etc.

Krishnan. V. C is presently a Senior UG student at Dept. of Information Technology, Sri Sairam Engineering college, Chennai. He has 2 International Technical publications. He has won many inter-college coding competitions. He's a passion driven tech enthusiast who's interested in web and android application development. He has worked and has interest in Python, C, Java Object oriented programming, React, React Native etc.