International Journal of Trend in Scientific Research and Development (IJTSRD)
Volume 4 Issue 4, June 2020 Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

Prediction of Power Consumption and Leakage Detection

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ABSTRACT

Energy consumption and predictions in the residential buildings play an important role within the energy management and system, as the availability in the demand of energy resources is dynamic. Human beings are unaware of the value of energy consumed by various appliances and therefore the energy resources available for subsequent generation. Each appliances in homes will consume different power consumption in several seasons. Accordingly the bill rate changes.

KEYWORDS: *Phone, Electric Meter, Detector*

How to cite this paper: Vyshnavi B | Selma P. T | Renin Joy | Sheethal M. S "Prediction of Power Consumption and Leakage Detection" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-4 | Issue-4, June 2020, pp.1368-1373, URL: www.ijtsrd.com/papers/ijtsrd31491.pdf

IJTSRD31491

I. INTRODUCTION

The energy resources today are closer to consumers due to sustainable energy resources and advanced technology. The flourishing concern is about the reduction of energy consumption in buildings makes it decisive to predict future energy consumption precisely using an advance predictive model. Microgrid is a power scheme that proposes closer power generation to consumers using renewable resources in rooftop panels at a local energy storages and buildings. By the utilization of renewable energy at the consumer level such as buildings, the consumption will be to get cheaper and cleaner energy resources. However, there will be some energy consumed in buildings from the local grid which has to be adjusted and predicted efficiently to reduce the consumption cost and environmental impacts. Energy consumption in buildings accounts for a large proportion of the primary energy worldwide and plays a vital role in the carbon emission. Hence, prediction of energy consumption at a building level has become a vital topic and it is necessary to develop a reliable optimization predictive model, to lower the energy costs and improve environmental buildings.

Electric consumption also depend upon weather conditions, during summer seasons cooling appliances like fans, air conditioner are used frequently, whereas during winter season it is much low. Some appliances like mixer grinder, iron box cannot be used continuously for a long time whereas appliances like refrigerator are used continuously for long time. User finds it difficult get detailed information about the consumption of electricity of each appliance. Electricity bill will give overall consumption of electricity in one or two month. In this bill consumption of different appliances is not given, it is difficult for the user to find which appliance consumed more electric power.

This helps the users to create a mobile application for electric consumption. the normal user can view electric consumption of each appliances. User can view electric prediction from previous data within a mobile application. User can also have ability to send complaints and its feedback. To implement a effective machine learning strategy using k means clustering and support vector machine to predict energy consumption. Different appliance will consume different electric power. The system will power consumption of each appliance separately. The scope for the project is only going to get better over time and work effectively.

II. PROBLEM DEFINITION

In residential electricity consumption will account for largest proportion in energy consumption. Consumption of energy used in different appliances are different. Many appliances are used in residential building. Some appliances are used regularly, some are not, some are rarely used. User finds it difficult to analysis consumption of different appliances separately. Electricity bill will only give overall consumption of power. User is unaware of which appliance consumed more power, so user find it difficult to reduce the power consumption of appliance in residential building. In residential building appliances are used as per demand. Some appliance can be used for a long time. For instance grinder can used for almost 2 hrs, whereas mixer grinder cannot be used for a long time it can be maximum to a half an hour. Consumption of appliance vary according to climatic conditions. For instance during winter seasons air conditioner are not used. Consumption of also depend on time of day like for night time electric bulb will be used than during day hours. So consumption of electricity vary according to the time of hours of day, climatic conditions etc. Consumption of each appliance makes the user to analysis the consumption of electricity in building and also reduce the consumption.

III. MOTIVATION

Electricity consumption in India is an exponentially growing in residential buildings. As people are using more and more appliances, it has led to an increasing need for effective analysis of electricity consumption. Electric consumption is an important aspects of economy today. Increasing, many appliances are coming in markets, different appliances of different companies are increasing as the demand of user, to get the edge of competitors. For example, refrigerator is a appliance that used in very residential building, this appliance is marketed by different companies. This increase the demand of user, resulting in an increase in the efficiency and performance in energy consumption as a whole.

We are also motivated by electric consumption and relationship between aspects of each appliance and how about consumption of each appliance. Some appliance will consume more electric power than other appliance. For example, iron box consumes more electric power than electric bulb, iron box cannot be used continuously for a long time whereas a light bulb can be used for long time compared to iron box, electric consumption for the two appliance will be different. The factors that affect electric consumption also not always linear in nature, in summer season consumption of air conditioner, fans etc will be more than in summer seasons and also in during day time usage of electric bulb will be much smaller. Electric consumption will depend upon as per the demand of user.

IV. RELATED WORK

Energy consumption of lighting and appliances, and building controls will leads a large impact on heating ,cooling and ventilation demand. Unaware behaviour can add increase energy consumption on building's. User activity and behaviour is major reasons for the larger consumption and used for control of various devices such as artificial light, heating, ventilation, and air conditioning . In this survey of international intelligent buildings research efforts with the theme of energy saving and user activity recognition. This will devise new metrics to compare the existing studies. From the survey, it determine the activity and behaviour and their effect on energy saving potential for every three main subsystems i.e., HVAC, light, and plug loads. The important promising and appropriate activity technologies are recognized and approaches are examined thus it conclude with the principles and context for energy intelligent buildings based on user activity [1].

Demand side management (DSM) plays an important role within the future smart grid by controlling loads in a very smart way. DSM performed via home energy management systems for buildings, provide many consumers enjoy electricity price savings and utility operates at reduced peak demand. Evolutionary algorithms are (binary particle swarm optimization, genetic algorithm, and cuckoo search)DSM model for scheduling the appliances of residential users is presented. The model is simulated in time use pricing environment for 3 cases: 1) traditional homes 2) smart homes 3) smart homes with renewable energy sources. Duplication output show that the proposed model optimally schedules the appliances leading to electricity bill and peaks reductions[3].

Building's energy consumption prediction is a major issue and many studies have been done to improve the energy management of buildings. Prediction of energy consumption in building is important for the energy to build a energy strategy, which could be integrated to building's energy management system. Energy consumption on building uses a prediction model Support Vector Machine (SVM). SVM provides a accurate way for selection of training data. The data selection method based on Dynamic Time Warping is used to train SVM model. To enclose thermal inertia of building, pseudo dynamic model is used to account of information of transition of energy consumption effects and occupancy profile. The output shows that data selection method based on support vector machine to predict the energy consumption of building with a high accuracy in compare to whole data training. Data selection method is a easy way to perform (around 8 minute training time)in contradict to whole data training (around 31 hour for weekend and 116 hour for working days) and admit real control implementation for online system as well[4].

The study presents three modeling techniques for the prediction of electricity energy consumption. The normal regression analysis, neural network and decision tree are considered. Model selection is completed by the root of average squared error. In an electricity energy consumption study, step wise regression model in the understanding energy consumption patterns and predicting energy consumption levels, the choice tree and neural network models appear to be viable alternatives The event of the information mining access for predictive model, different models is in-built a unified platform: to implement various modeling techniques, assess the performance of various models and choose the foremost appropriate model for future prediction[2].

Some of the challenges to predict energy utilization has gained recognition within the residential sector because of the significant energy consumption in recent decades. The modeling of the residential building energy consumption is an underdeveloped for the reduced land robust solutions still now while this research area has become of greater relevance with significant advances in computation and simulation. Such advances include the appearance of artificial intelligence re-search in statistical model development. The Artificial neural network has been emerged as a basic method to handle the difficulty of non linearity of building energy datas and also the robust calculation of massive and dynamic data. The progress or development, validation of such models on one amongst the TxAIRE Research houses has been established. The TxAIRE houses are designed to function realistic test facilities for demonstrating new technologies. The input variables collected from the house data are as followings the quantity of days, outdoor temperature and radiation and also the output variables are house and warmth pump energy consumption. The design which relies on Leven berg-MarquardtandOWO-Newtonalgorithmshad promising results of coefficients of de-termination within 0.87–0.91, which is love prior literature. Further work are explored to develop a sturdy model for residential building application [6]

Energy is that the lifeblood of recent societies. In past decades, the world's energy consumption and related to the CO2 emissions increased rapidly because of the increases in population and comforts of the people. Building energy consumption prediction is crucial for the energy planning, management, and conservation of resources. Data driven mod-els will provide an honest approach to the energy consumption prediction. The studies reviewed the developed data-driven building energy consumption prediction models, with a specific concentrate on reviewing the scopes of prediction, the info properties and therefore the data pre processing methods used, the machine learning algorithms are utilized for the prediction, and performance measures used for evaluation. supported reviews, the present research gaps are identified and future research directions within the area of data-driven building energy consumption prediction are highlighted[5].

V. DESIGN MODULES

A. ARDUINO UNO MODULE

Fig.1. Arduino

Arduino provide an open-source electronics platform for easy-to-use hardware and software. Arduino boards provide to read inputs as light on a sensor, a finger button, or a Twitter message, and turn to an output activating a motor, turning LED, online. The board will give what to do by sending a set of instructions to the micro controller on the board. To do so use the processing based on Arduino programming language (based on Wiring), and the Arduino Software (IDE).

B. ESP-01 ESP8266 SERIAL WIFI WIRELESS TRANCEIVER MODULE

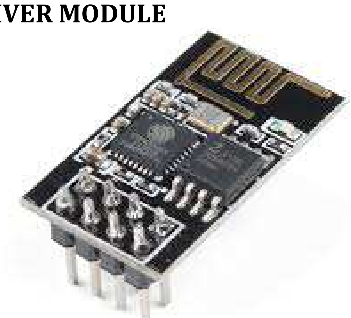

Fig.2. ESP8266

ESP8266 follows 802.11 b/g/n Standards, Wi-Fi Direct (P2P), 1MB Flash Memory ,32 bit CPU with Integrated low power could be used as an application processor, A-MPDU A-MSDU aggregation 0.4ms is a guard interval, Wake up and¡2ms transmit packets, ¡1.0mW of Standby power consumption.

C. RESISTORS

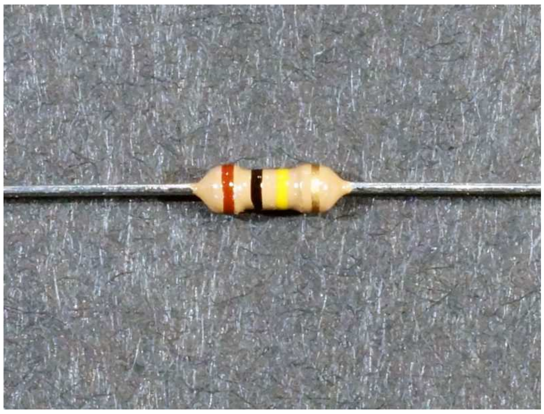

Fig.3. Resistors

It is used to prevent the overflow in the circuit.

VI. PROPOSED SYSTEM

In this project, we propose a mobile application that in which user can predict the values of electric consumption of each appliances in a residential building. User can also use mobile application in order to give reviews and feedback. This uses previous data set of consumption and takes the average of data set consumption and predicts the new consumption. The prediction model will be derived from machine learn-ing techniques like logistic regression provide current usage electric consumption of each appliance and also predicts the consumption it can in future.

VII. DESIGN OF PROPOSED SYSTEM

System basically includes two modules:

A. HARDWARE MODULE

The hardware consist of 3 resistors, pcb board, arduino, ESP sensors, wifi module. The system is connected with hardware device by IP mode and also with wifi username and pass-word which provide a communication between device and system. Power supply provided data are sent to system with help of a electronic device. The voltage will measured device pass the data to system convert into watts and will make a average consumption. In next prediction making this a average consumption along with set of range of values for prediction (like if the value is between 30 to 40 prediction can be 7 percentage ,40 to 50 it will 8 percentage, 50 to 60 it will 12 percentage) will shows the output. We have an application which help us to track the up to date information regarding the energy usage.

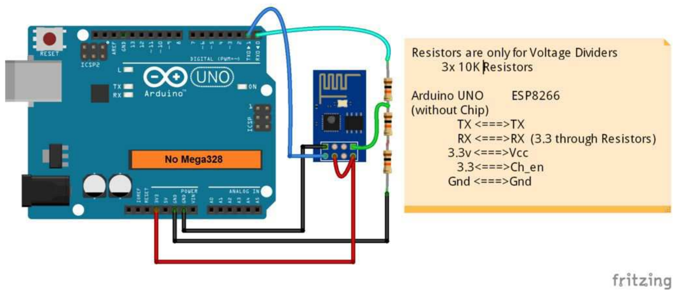

Fig.4. Connections

B. SOFTWARE MODULE

```
#include < Arduino:h >
#include < ESP 8266W iF i:h >
#include < ESP 8266W iF iM ulti:h >
#include < SocketIoClient:h >
#define USESERIALSerial
ESP 8266W iF iM ulti W iF iM ulti;
SocketIoClientwebSocket;
#include < ArduinoJson:h >
DynamicJsonDocumentdoc(2048);
Stringjson;
//currentsensorinit
constintsensorIn = A0;
intmV perAmp = 185;
    double Voltage = 0;
    double VRMS = 0;
    double AmpsRMS = 0;
void event(const char * payload, size_t length)
{
USE_SERIAL:printf("gotmessage : %s"; payload); g
}

void setup()      {
pinMode(A0, INPUT);
USE_SERIAL.begin(115200);

USE_SERIAL.setDebugOutput(true);
USE_SERIAL.println();
USE_SERIAL.println();
USE_SERIAL.println();

for (uint8 t t = 4; t > 0; t)         {
USE_SERIAL:printf("[SET U P ]BOOT W AIT %d:::"; t);
USE_SERIAL:flush();
delay (1000);

WiFiMulti.addAP("D-Link", "bh4802888561");
while (WiFiMulti.run() != WL CONNECTED)
delay (100);
}

webSocket.begin("192.168.1.7",3080);

void loop()       {
webSocket.loop();
webSocket.on("response", event);
Voltage = getVPP();
VRMS = (Voltage/2.0) *0.707;
AmpsRMS = (VRMS * 1000)/mVperAmp;
float Wattage = (220*AmpsRMS)-4;
Serial.print(AmpsRMS);
Serial.println(" Amps RMS ");
Serial.print(Wattage);
Serial.println(" Watt ");
doc["AMPS"] = AmpsRMS;
doc["WATTAGE"]= Wattage;

serializeJson(doc, json);
const char* message = json.c_str();
Serial.println(json);
webSocket.emit("data", message);
delay(2000);
json = "";
}
float getVPP()

{
float result;

int readValue;
int maxValue = 0;
int minValue = 700;

uint32 t start time = millis();

while((millis()-start time) < 1000)          {
readV alue = analogRead(sensorIn);

if (readValue > maxV alue)
{
        maxValue = readValue;
}

if (readValue < minV alue)
{
        minValue = readValue;
}

//Serial.print(readValue);
//Serial.println(" readValue ");
//Serial.print(maxValue);
//Serial.println(" maxValue ");
//Serial.print(minValue);
//Serial.println(" minValue ");
//delay(1000);

result = ((maxValue - minValue) * 5)/1024.0;
return result;
}
```

VIII. RESULT AND ANALYSIS

A. EXPERIMENTAL SETUP

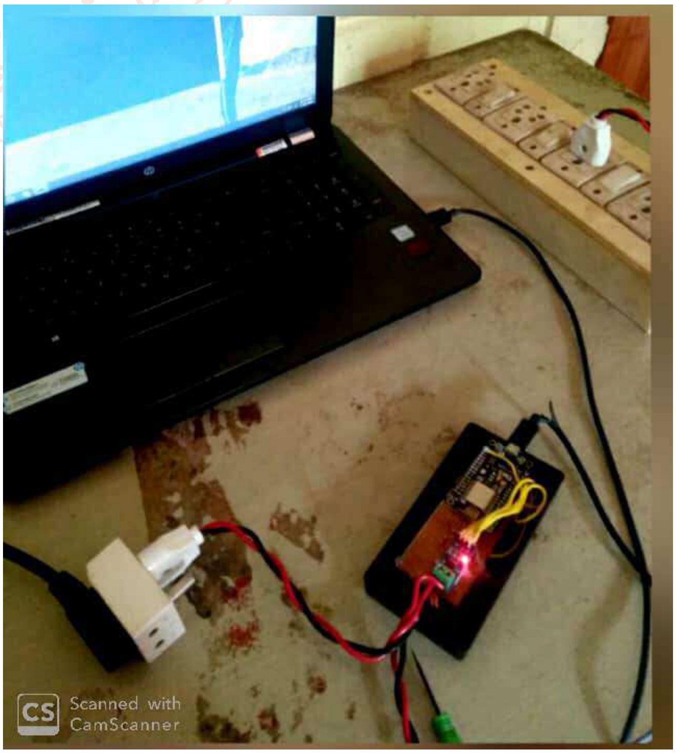

Fig.5. Experimental Setup

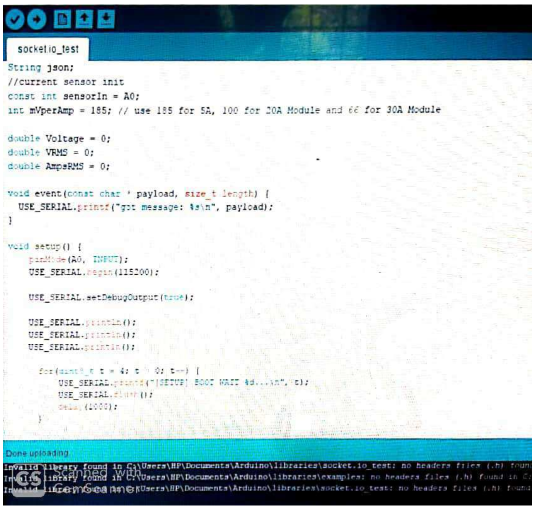

Fig.6. Execution Phase 1

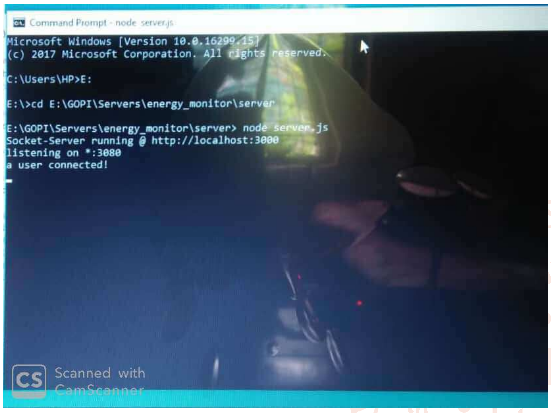

Fig.7. Execution Phase 2

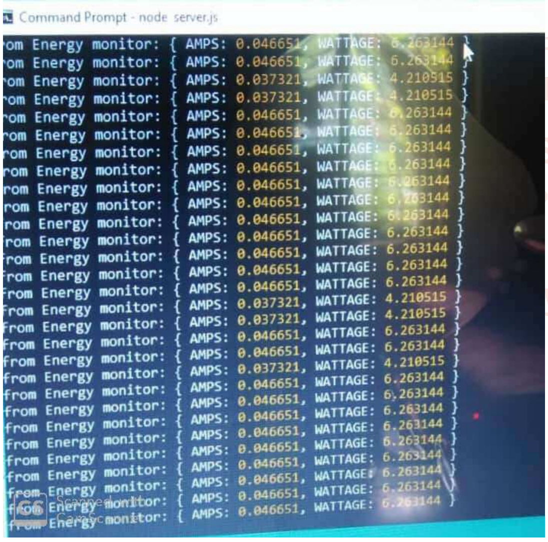

Fig.8. Execution Phase 3

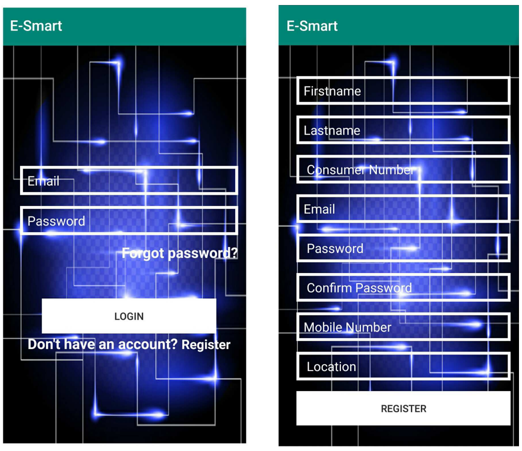

Fig.9. Application (a)

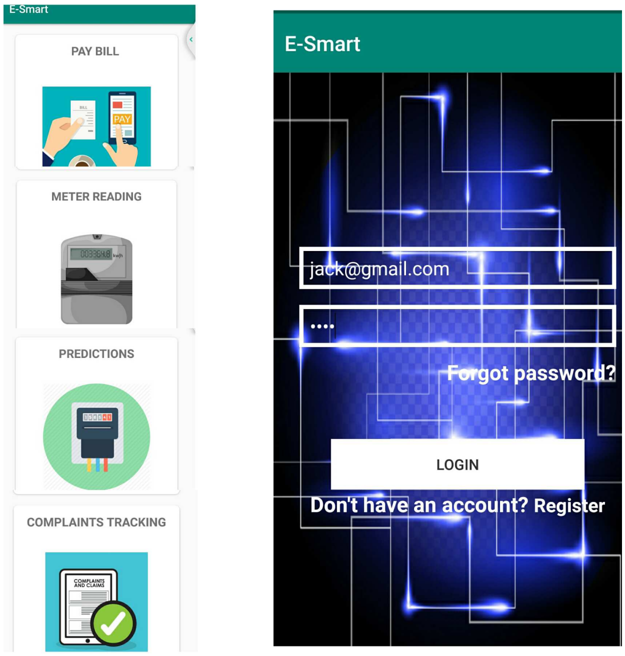

Fig.10. Application (b)

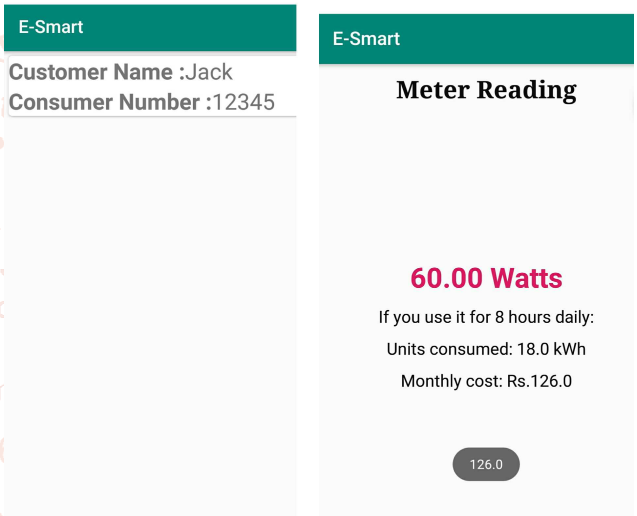

Fig.11. Application (c)

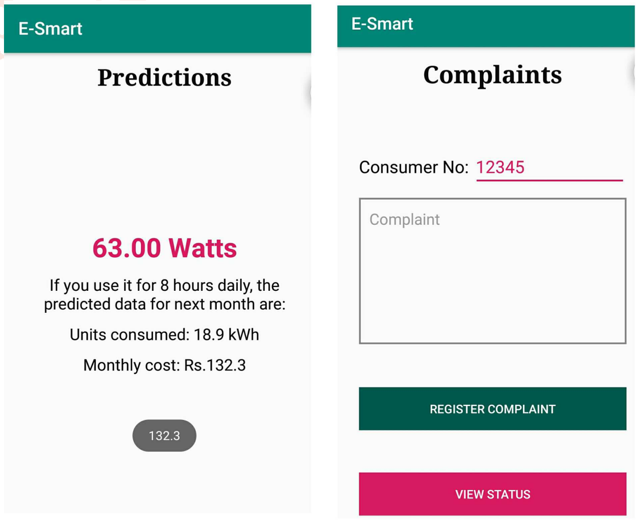

Fig.12. Application (d)

IX. CONCLUSION AND FUTURE WORK

Implemented methodology has provided very interesting and valuable results. The load estimation process provided good results in the analysis of the sensitivities has revealed itself effective for finding the most relevant variables. The overall quality of the results support the adequacy of the adopted approach. The implemented tool both can be used for the energy efficiency classification of buildings. The choice of prediction model becomes the important influence factors how to improve price forecasting accuracy. Level consumption of appliances are directly measured so that the lifestyle of the household is easier to identify, which further assist in the forecasting. Based on this realization, rather than serving only aggregated energy data a way is implemented propose to in- put all available major appliance energy sequences to train the predictor. In real-world applications, the energy consumption load in buildings features a relationship with several underlying factors, like temperature, humidity, work time, holidays, occupants can provide more information about the energy consumption variability and uncertainty. Thus, the proposed approach is modeled to handle multiple input parameters and large data non-linear prediction. If these factors considered, the proposed model may result to better prediction accuracy. Data acquired is processed using logistic regression in order to predict in an accurate way. The customer could check the predicted bill according to their usage in the previous months. The user can check their usage in appliances and accordingly reduce the consumption. The project will help in developing an awareness among the people towards the usage of electricity. The user can track their usage through smartphones. The scheme is based on machine learning and processing of data. All the output testing is done many times and errors are corrected. We believe that the project will bring a helpful hand for society and check their usage of electricity consumption and reduce if necessary.

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