International Journal of Engineering & Technology, 7 (4) (2018) 4780-4784

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET
doi: 10.14419/ijet.v7i4.10173
Research paper



Efficient methods for energy saving in smart homes through breakdown the energy consumption

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Abstract

The most crucial issue that affects the consumers, and environment is energy saving. Various home appliances are the primary con-cern in energy savings due to high-energy demand by these appliances. Smart home technologies are a good alternative for energy saving, and comfort for household devices. Buildings (structure and window direction) contribute significantly to overall energy consumption. Studies suggest that providing occupants with energy breakdown per-appliance energy consumption can help to save nearly 15% of energy. However, there are weak practical solutions are present to provide an energy saving breakdown. Current re-search requires hardware in each home and thus cannot be scaled across all households. In this research work, we have presented the techniques for producing energy breakdown in a home without requiring any additional sensing. Therefore, to identify the ener-gy breakdown, we have categorized the appliances in the different classes, i.e., switched-mode based power supply (SMPS), purely resistive, thermostatically controlled, etc. We are proposing a technique for the development of smart appliances that incorporate actuation capabilities and local intelligence for optimal appliance operation. With this proposed approach, the control and knowledge are pushed increasingly to the end device. This proposed approach has been applied to 287 homes from the data set available publically, in which the energy consumption measurement is based on individual home appliances. We have analysed the learned potential factors and found that the energy breakdown performance can improve using the static household properties. These proposed methods are scalable and approximately 42% more accurate compared to the state-of-the-art energy breakdown techniques.

Keywords: *Energy Consumption; Smart Home; Domestic Appliances; Switched-Mode Power Supply; Energy Reliably; Energy Efficiency.*

1. Introduction

In today's life, many household electrical appliances in each house surround us. Without those appliances, we cannot imagine our daily routine or life. In some homes, the number of household electronic appliances will be around 30-40 which is much higher [1]. However, everything that eases our life comes at a specific cost. These household electrical appliances consume a lot of energy per day that cost concerning high-energy consumption bill. The problem is that consumer gets only aggregate energy consumption bill, which shows that how much kWh unit energy consumed during one month. With that bill, consumers are unable to draw the picture that which appliances consume how much of energy so that the energy bill can be reduced [2]. Currently, smart meters are rolled out to know the disaggregate energy consumptions, but due to high cost, most of the houses are unable to install it. Therefore, it requires some way to understand the disaggregated energy bill with existing appliances at low cost.

A recent survey shows that the residential buildings are consuming approximately 20-30% to total energy consumed worldwide [3] and it is expected to increase because of increase in many household electrical appliances and their ownership. Colossal capital is investing by each government in the generation of electrical energy with limited resources [4]. All countries are expecting to reduce the energy consumption from each sector that diminishes to cost. Residential buildings are second most energy consumer in every nation, and it is hard to reduce the energy consumption because of no information on the disaggregate energy bill. If the itemized invoice is generated, the consumer will know that did which appliance consume how much energy and try to reduce the consumption [5]. With real-time information for each appliance, the consumer can reduce 6-15% energy consumption by changing the appliance usage behaviour in the residential sector [6].

Various companies come up with sensors to help the consumers, hardware and software solutions to know the disaggregate energy bill. The most used technique is to install the sensors for each appliance for identifying the real-time energy consumption. The sensor installation is involving high installation and maintenance cost. To overcome this limitation, recently a new technique was introduced named non-intrusive load monitoring (NILM) algorithms. The goal of this technique is to identify the energy consumption of each appliance from aggregate energy bill [7]. This technique uses smart meters but with certain modifications, because it required high-resolution data of 1 min or less and today's smart meter support only 15 min data [8], [9]. Even at some places, the modified smart meters are installed, but due to its very high cost, all the consumers will install it at least soon.

In this paper, we propose a novel approach to find the disaggregate energy consumption without installing any sensors or hardware. Our method requires only the necessary things like area of the house, a number of rooms and persons living in the house, monthly aggregate energy consumption bill, which is readily available. Before proposing this approach, we have monitored one-year data from the similar dwellings that already installed the disaggregated energy consumption data. Based on these houses and the aggregate energy bill, we have proposed our approach to predict the energy consumption by each appliance in the home.

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Because of a high number of appliances in each house, we have designed a model to find the potential factors that contribute most to the energy bill. We have applied our approach to houses that have similar geographical locations, area, and the number of rooms.

2. Related works

Various techniques are available to measure the appliance-level energy consumption. Most convenient and used method is to install the sensors for each appliance that needs to be measured [10 - 12]. Clark et al. [13] that installed energy sensors on each appliance and perform the computation to determine the energy consumption by each appliance developed Deltaflow system. Temporary sensors were installed to measure the energy consumption by AC installed in the house [14]. However, in later research, it was identified that the temperature sensors are of no use to get the specific energy consumption by the AC. Furthermore, the electromagnetic interference is used to get the energy consumption by appliance [15], [16].

Lighting, fridge and other consumer appliances have extended in each category of residential energy consumption [17], [18]. Non-seasoned consumer appliances are used in every forecasting of energy consumption for the residential sector. Study of energy consumption pattern is mandatory to predict the energy demand according to the area, region, and session. The fundamental problem is that user does not knowof energy consumption by each appliance. If the user gets the higher aggregate bill, then they have no option except to pay without knowing that why they get that much of amount. By providing appliance-level energy consumption along with aggregate energy bill, the user may change its behavior towards usage of energy and will try to optimize [19].

In current research trends, NILM algorithms have been used to get the disaggregated energy consumption data with accuracy. Some algorithms use actual energy consumption, and some use both actual and responsive energy consumption [20], [21]. By the end of 2020, there should be about 830 million electric smart meters installed worldwide [22]. Of these, 438 million will be in China, 132 million will be in the United States, and 27 million will be in the UK.

Another American disaggregation company, PlotWatt, was founded in 2008 and is based in North Carolina. Similarly, to Bidgely, PlotWatt began by selling disaggregation services directly to domestic users using aggregated data recorded by standard home energy monitors. Over the last few years, PlotWatt has focused on offering disaggregation services and other energy analytics to chain restaurants, using PlotWatt's meter hardware [23]. Chain restaurants often have similar appliances installed across the chain, and so it is possible to train a disaggregation algorithm on one restaurant in the chain, and it should be able to disaggregate appliances from the other restaurants in the same chain. PlotWatt's system is installed in some KFC and Dunkin' Donuts restaurants. PlotWatt also offers disaggregation solutions for utilities.

3. Energy consumption in Indian houses

Indian homes energy consumption has been increased three folds since 2000. In 2017, approximately 80% households accessed the electricity in comparison to 55% in 2001 and consumed on average 98 kWh units of energy per month. This monthly energy consumption is third highest in the world but three-fourths of energy consumption in China and tenth of that in USA [24].

In a recent survey conducted by Central Electricity Authority showed that all states of India have increased in energy consumption in past years due to which they demand more electricity from distribution companies, which are shown in figure 1. Some states like Bihar, Jharkhand, Assam shows the consumption of energy (about 13%-18%) in residential areas during past few years. While the metro cities like Delhi, Mumbai consumes much higher kWh units in comparison to another state because of highest household electrification [25].

During a survey conducted in 2014, residential houses consumed 22% energy out of total 883 TWh units consumed in India. The figure 2 shows that the residential energy consumption is the second highest after industrial energy consumption among others [24]. The energy consumption slabs are different for different states of households. Figure 3 shows that around 16-21% of household consume less than 35 units per months. The highest energy consumption for residential is in Delhi. In Delhi, approximately 60% of total household consumes more than 100 kWh units per month that is much higher than other states [25].

A recent study [26] shows the Indian residential energy requirement shortly. The study predicts that by 2020, the energy consumption in residential areas will be around 500-600 TWh which is twofold of energy consumed in 2014. Recently, which appliance consumes the government planned to roll out the smart meters to get the efficient energy consumption so that end user will be aware that how much energy. With his data, the government wants to change the user behavior for reduced energy consumption. Although, the steps are used to get aware of consumers for energy saving it should be taken with a pinch of salt [27, 28].

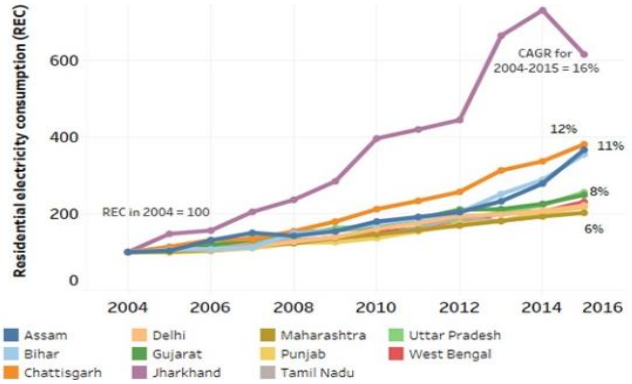


Fig. 1: State-Wide Electricity Consumption Trends in India.

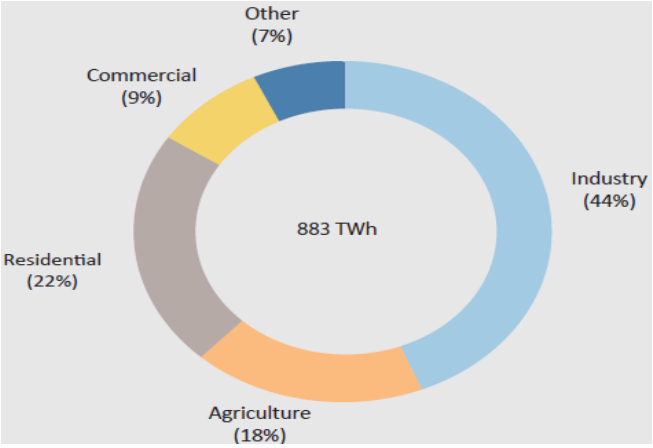


Fig. 2: Energy Consumption by Each Section of India in 2014.

4. Proposed model and approach

We need to design a matrix to find the disaggregate energy consumption on aggregate energy bill based on appliance level energy consumption. The goal of our approach is to predict the energy consumption by each learned appliances in a house, which does not have disaggregated energy bill. To achieve this goal our aim is not to use the traditional submetering or sensing approach for each home. The basic idea of our approach is the essential features of a house as an area, a number of rooms, the number of persons living in the house and the aggregate energy bill. To predict the disaggregate energy bill from aggregate, the one-year appliance wise

energy consumption data has been collected from homes which have to submeter. Based on submetered data and overall energy consumption details, the potential factors are learned which is shown in figure 4.

From all energy features available at test house, we have learned the potential factors to identify the disaggregate energy consumption. The possible factors used in measuring disaggregate energy.

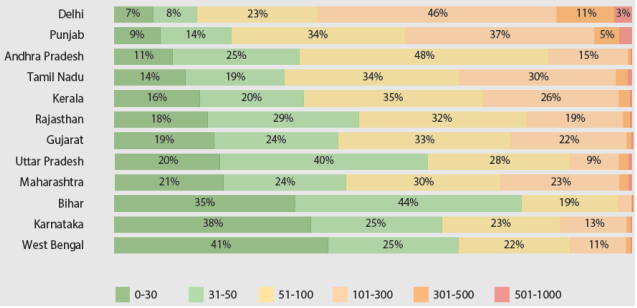


Fig. 3: KWH Unit Energy Consumption Across Different States in India.

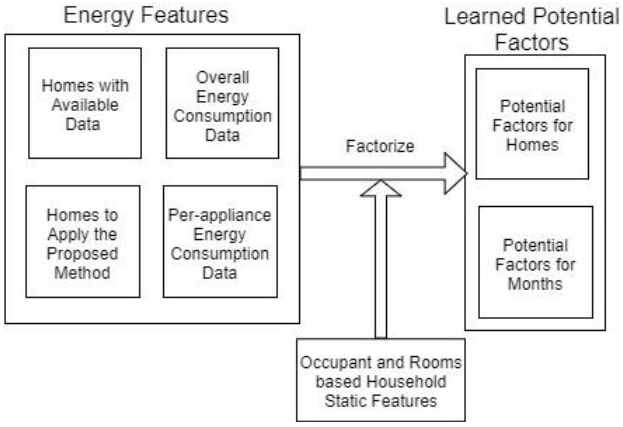


Fig. 4: Detailed Proposed System Diagram to Predict the Energy Consumption by the Individual Appliance in Smart Homes.

Consumption are a fridge, washing machine, CFL and LED lights, dishwasher, iron, television, internet router, fan, cooler, room heater, AC, microwave oven, vacuum cleaner, geyser, phone/laptop charger, and toaster.

The goal of our approach is to find the appliance wise energy consumption. To achieve the goal, we have taken some characteristics of the house like area in sq ft, no of persons living in the house, their occupations, no of rooms especially in urban areas to compute the energy consumption. We have also used the annual and monthly electricity bill that is generated by Uttar Pradesh Power Corporation Limited.

We have categorized above state appliance into two broad categories, i.e., firm, and flexible appliances. Firm appliances are needed to run all the time without any scheduling such as fridge, internet routers. Flexible appliances are required to be scheduled to run at a different time within 24 hours.

Appliance_energyConsdaywise()
Inputs:
x = Time of day in hours
y = all days of a particular month
m(x,y) = the value of energy consumption in x hour of y day.
max = maximum consumption value of day
min = minimum consumption value of day
n(y) = minimum value of energy consumption of a particular day.
Temporary variable.
SV = value when appliance not in use.
Procedure:
x ← 1
y ← 1
repeat for all days in the chosen month
max ← m(x,y)
min ← m(x,y)
if (max <m (x+1, y)) then
max ← m (x+1, y)
if (min> m (x+1, y)) then
min ←m (x+1, y)
x ← 3
repeat until 24 hours of a day
if (max <m (x-1, y)) then
max ←m (x-1, y)
if (min >m (x-1, y)) then
min ← m (x-1, y)
if (m (x,y) = = 0 and m(x-1, y) > 0 and m(x- 1,y) = = m(x-2,y)) and if (n(y) < m(x-1, y)) then
n(x) ← m (x-1, y)
else if (m (x, y) = = 0 and m (x-1, y) = = 1 and m(x-2,y) > 0 and m(x-2,y) = = m(x-3,y)) and if (n(y) < m(x-1, y)) then
n(y) ←m (x-2, y)
x ← x+1
if (min > 0) then
x ← 1
repeat until 24 hours of the day
if (m (x, y) = = min and m (x+1, y) = = min) then
n(y) ← min
if (max > 0 and (n(y) / max) > 0.07) then
n(y) ← 0
SV← n(j)

The calculation of appliance not in use is essential as this value may mislead the calculation of disaggregate energy consumption data for a particular period.

The below algorithm is the procedure to find the number of similar homes based on no of persons living in the house. Other features like the area of house and number of rooms are fixed for our approach. In this procedure, we have found the energy consumption by each appliance for one full calendar month. For a particular month, the energy consumption of each appliance is combined to calculate the aggregate kWh unit consumption. The result is compared with the aggregate units mentioned in the bill generated by the electricity board. We have taken the precision of errors by 10%. If consumed unit difference greater than 10%, then the value has been stored to check the error precision. Based on the above computation, we have applied the same procedure on test homes to find the disaggregate energy consumption details for each mentioned appliance.

applevel_energy ():
Input:
N ← No of rooms
area ← Area of the house in Sqft
n ← No of persons living in the house
features ← N, area, O
appliances ← List of the most impacted appliance
monthly_bill ← Aggregate energy bill of each month from Jan to Dec
AEC ← Appliance wise energy consumption details (kWh)
Procedure:
z ← 0
x ← 0
count ← 1
house ← 0
// Identify the no of houses according to the no of persons living in the house
for each house in test data with no of persons living in the house
x ← similarity_index[n][house]
// Find the month wise energy consumption by each appliance for similar homes.
Repeat until the count is less than or equal to 12.
for all similar x
for each appliance in appliances
y ← y + AEC [appliance]

if combined no of kWh units of appliances (y) same as monthly_bill
then continue
otherwise
find the difference between y and monthly_bill.
if unit difference is greater than 10%
store the value of x in z.
if $z \neq 0$
find the percentage of difference, and that will be counted as percentage error.
Print percentage error with a value of x.

Our approach can currently only make accurate predictions for homes in a particular region with a similar area of house and no of rooms. In other words, the train and the test homes should come from the same region.

5. Results and discussions

Now, we will discuss the potential learned features from our approach. Figure 5 shows the potential learned features over monthly energy consumption for all the homes where sub-meters are available to get the disaggregate energy data. Our result shows that which appliance consumes how much energy month wise. It also shows that we can find the disaggregate appliance wise energy consumption from the aggregate bill. There is no hardware or sensors required to see the disaggregate energy consumption details if the user uses our approach. For a possible feature like a geyser, the highest energy consumption is during winters. That means the impact of a geyser on the aggregate energy bill is in winter that is 0.89 and 0.74 respectively in December and January months. In this paper, we do not include the analysis of this impact on the aggregate bill. Furthermore, like fridge do not have a particular month for high impact on total energy bill because of its constant use irrespective of weather or season. This type of potential features are most useful in clustering houses and find the disaggregate energy consumption data from aggregate data. Month-wise distribution of energy consumption is shown in Figure 6.
Households use the services provided by these appliances most in the evening between 7-10 p.m., with the use of lighting and TV dominating. As shown in figure 7, 59% of all households reported they used lighting in the previous evening and 33% of households watched television in that time slot.

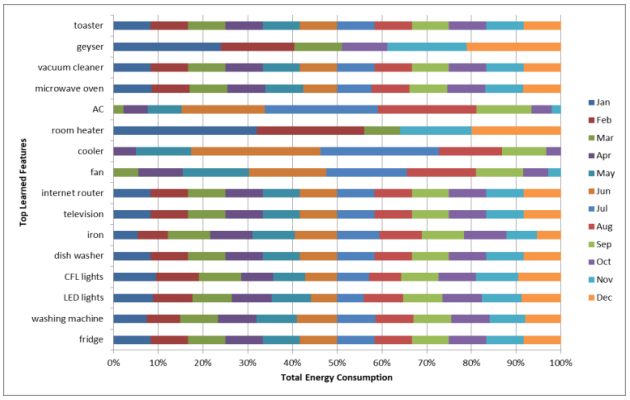


Fig. 5: Potential Learned Features Over Monthly Energy Consumption.

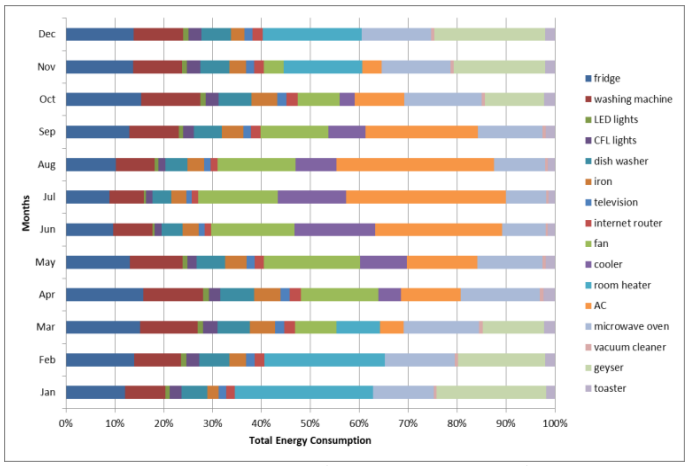


Fig. 6: Month-Wise Distribution of Energy Consumption for Potential Features.

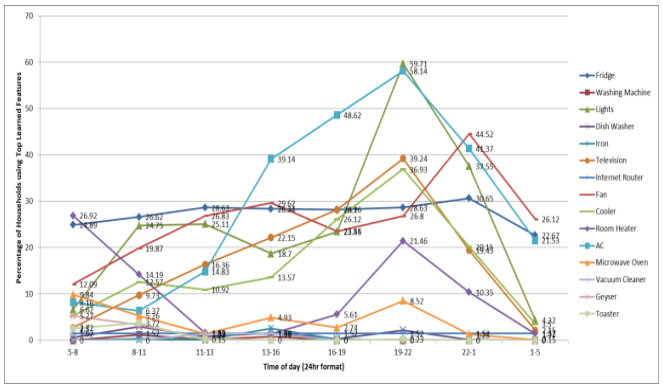


Fig. 7: Hourly Energy Consumption by Potential Features.

Fan usage peaked during the night, whereas a small number of fridges, on the other hand, were switched off during the night to save on the electricity bill.
These numbers indicate that not all households use lights in the evening, turn on fans while sleeping or always keep the fridge on. In discussions, some residents reported that their work did not allow a '9 to 5' schedule where they spent the evening at home; others said they did not turn on lights as the street and hallway lights were enough to illuminate the homes. Appliances can be categorized according to their sessional or regular impact on aggregate energy consumption bill. The regular impact appliances are not affected by any session like fridge, and they consume the almost same amount of energy in every session. While the seasonal alliances like geyser impact the energy consumption bill during a specific season only. Therefore, for those appliances, we need to add the particular variations of their energy-consuming properties.

6. Conclusions and future recommendations

We realized that a great deal of energy breakdown literature could not be scaled today to all homes. This is because current energy disaggregation solutions require specific hardware or sensors to be installed in each home. Even though Indian government is planning to roll out the smart meters all across, these smart meters often sample at low rates, which makes most of the NILM literature impertinent. Against this background, we chose to develop scalable energy breakdown solutions that do not require any hardware to be installed in a house with aggregate energy bill only. We started to collect the disaggregate energy consumption data without investing any expenditure and scale up to predict the monthly energy consumption by each appliance to contribute in the aggregate energy bill. To do so, we have changed the way to predict or compute the disaggregate energy consumption from the monthly average energy bill. Our approach uses only the readily

available data like the number of rooms, a number of persons living in the house, area of the house and aggregate monthly energy bill to predict the appliance level energy consumption. Not only is our approach more scalable, but it is also more accurate than state-of-the-art methods.

Our approach currently faces the challenge of the availability of static information (metadata) along with the power data. Very few public datasets survey such information. Future dataset owners should try to obtain as much static household properties as possible. Our current work on making energy breakdown more scalable works only for homes in the same geographical regions. If we can learn the properties of different regions that cause differences in energy consumption, we can make energy breakdown more scalable. We are currently looking into transfer learning methods for scaling energy breakdown across multiple geographies.

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