International Journal of Energy Optimization and Engineering
Volume 7 • Issue 3 • July-September 2018

Saving Energy in Homes Using Wi-Fi Device Usage Patterns

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ABSTRACT

Reducing power usage in the residential sector is a global problem. Appliances used for space heating, cooling, and lighting are the primary sources of home energy consumption, increased costs, and CO_2 emissions. Such devices are a significant source of energy wastage if they are left on and not being used. This article proposes a solution to reduce energy wastage in smart homes. The solution consists of a method to detect the presence of resident activities in the household based on Wi-Fi devices. It presents a model for identifying the Wi-Fi devices that are similar in usage compared to the resident's appliances using machine learning techniques. In addition to displaying the device usage charts, this solution helps in automatically turning off such appliances when they are not in use. A controlled experiment is conducted to evaluate the performance of the solution. The results indicate that this approach can significantly reduce energy wastage in the homes.

KEYWORDS

Energy Reduction, Human-Machine Interaction, Machine Learning, Smart Home, Wi-Fi

1. INTRODUCTION

According to a study (D&R International Ltd., 2012), 45% of the energy used within the residential sector is for space heating, 18% is for water heating, 9% is for space cooling, and 6% is for lighting. These four factors make up 78% of the total energy usage in most homes, so a good place to focus energy saving efforts is heating, cooling, and lighting. The same study also predicts that there will be a 13% increase in energy consumption between 2009 and 2035. According to Gardner and Stern (2008) and Armor (1995), direct energy usage by households accounted for approximately 38% of overall US CO_2 emissions, or 626 million metric tons of carbon in 2005. These emissions equal about 8% of global emissions, which is larger than the emissions of any country except China. Reducing power consumption in the residential sector is a global problem (Ueno et al., 2006). Studies show 20% to 30% of energy usage can be saved by turning appliances, lighting, cooling, and heating devices off when residents are away from home (Lu, 2010).

Motion sensors or occupancy sensors are used in indoor spaces to control appliances. If no motion is detected, it assumes that space is empty, and thus the sensors do not light the space. These sensors can be manually programmed to turn "off" after a preset time interval. A paper by Garg and Bansal (2000) presented the design of a smart occupancy sensor that saves 5% more energy compared to fixed delay motion sensors. The system learns the variations in residents activity levels based on the time of the day. Based on this knowledge, it varies the delay and turns "off" the lights earlier based on how long a resident is likely to stay in a given room (Torunski et al., 2012). In the paper (Lu et al., 2010), the authors presented the concept of a smart thermostat that sensed occupancy statistics in a home to save energy through improved control of the heating, ventilation, and air conditioning

DOI: 10.4018/IJEOE.2018070103

(HVAC) system. They demonstrated how to use wireless motion sensors and door sensors to sense occupancy and sleep patterns in a home, and how to use these patterns to save energy by automatically turning off the home's HVAC system.

In the commercial sector, recent research was performed in detecting the building occupancy and implementing the energy-saving strategies. The MIT Enernet study (Vaccari, 2009) demonstrates the campus-wide Wi-Fi network activity data shows building occupancy and the information could be utilized in implementing lighting and ventilation strategies across the campus. According to Ouf (2017) and Li (2012), Wi-Fi networks can be used to analyze occupancy at a higher level of accuracy and minimal cost. The paper (Thanayankizil, 2012) explores the methods to detect the office building occupancy using soft sensors such as ID badge scanning systems, Wi-Fi access points, online calendar.

In the residential sector, more research will be needed to make the systems simpler, unobtrusive, and deterministic. Otherwise, they will simply be ignored. New solutions are needed to save energy without requiring daily thought or the intervention of residents. The growth of Internet of Things (IoT) encompasses a wide variety of sensing devices such as smart phones, and through their collaborative operations, billions of such devices will realize the vision of smart homes, smart cities, and beyond (Reinhardt, Christin, & Kanhere, 2014). A smart home can now include app controlled light bulbs, smart plugs, robotic vacuum cleaners, smart coffee makers that synchronize to a morning alarm clock, electronic locks. Programmable smart plugs provide the ability for residents to turn off appliances from a smart phone or tablet and create on/off schedules and rules (Page, 2017). Through Wi-Fi residents can access IoT devices with a smart phone or tablet via a home router (Monnier, 2013). The diffusion of Wi-Fi enabled devices is expected to grow to 3.4 devices and connections per capita by 2020, up from 2.2 per capita in 2015 (Cisco Systems Inc., 2016). These Wi-Fi devices are good indicators of a resident's presence or activity in a home.

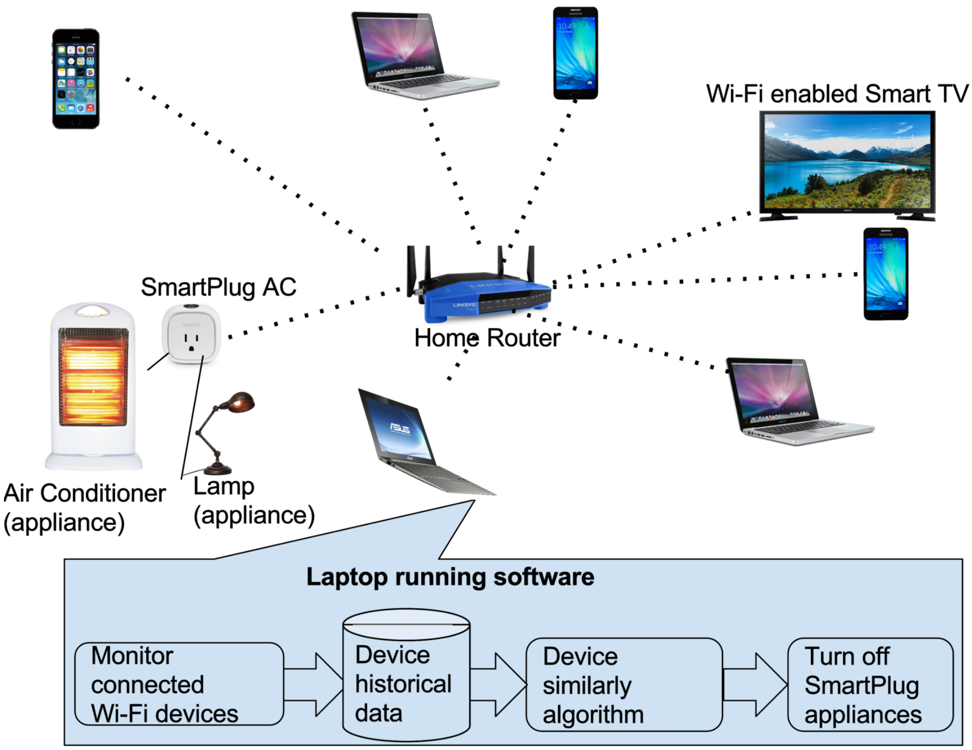
In this paper, the author proposes a solution to save energy by turning off the appliances that are not currently being used through machine learning, based on a resident's usage of Wi-Fi devices. The rest of the paper is structured as follows. Section 2 describes the proposed setup in a typical household. Section 3 illustrates the method for detecting the presence and activity of the residents and the mathematical representation of the collected data. Section 4 shows the model for finding the devices that exhibit similar usage pattern as the appliances and section 5 explores methods to reduce energy wastage by turn off unused appliances. The experimentation and results come under Section 6. Limitations are described in Section 7, and finally, Section 8 appraises the conclusion.

2. SOLUTION SETUP AND OVERVIEW

A typical household consists of a home router, Wi-Fi enabled devices, such as laptops, smart phones, smart TV, and appliances, such as air conditioner(s) and lamps, as shown in Figure 1. A Wi-Fi enabled smart plug is connected to a power outlet and to the appliances (e.g., air conditioner and lamps) in a room. The Wi-Fi smart plug provides software application programming interface (API) to monitor the power state and energy consumption of the appliance, and to control its power (turning it "on" or "off").

The software on the laptop periodically scans the Wi-Fi devices connected to the home network and also collects the power status and energy consumption of the smart plug(s). The collected data are inserted into a database for analysis. From the collected data, a machine learning similarity algorithm is used to figure out the Wi-Fi devices that have similar usage patterns as the appliances. Based on the similarities between the appliances and the Wi-Fi devices, the appliances are turned off automatically by the software via the smart plug when the corresponding Wi-Fi devices are not connected to the home network. The next sections discuss this approach in detail.

Figure 1. Setup that shows home router, Wi-Fi devices, a smart plug, and appliances connected to the smart plug, and software running on a laptop



3. TRACKING THE WI-FI DEVICE USAGE

A home area network (HAN) is a local computer network that aids communication among devices within a household. Wi-Fi is a common technology with extremely high adoption rate, used in HANs, smartphones, laptops, and many other electronic devices. Almost every new electronic device, be it a Smart TV, laptop, game console or a smart phone, comes with installed Wi-Fi technology. The Internet Protocol (IP) is the leading communications protocol that facilitates communication among HAN devices (Lobaccaro, Carlucci, & Lofstrom, 2016).

Each device on an HAN is identified with an IP address. It consists of four sets of numbers from 0 to 255, separated by a decimal, such as 192.168.1.20. The dynamic host configuration protocol (DHCP) protocol running on the home router assigns or leases an IP address to each Wi-Fi device that is connected to the network (Droms & Lemon, 2002). When residents walk into the home, their smart phone connects to the HAN. During the time they stay at home, the smart phone will be reachable on the home network. When they leave home, the smart phone disconnects from the network and, hence, will not be reachable on the HAN. Similarly, when residents power on a laptop, it will be reachable on the home network. The reachability of these Wi-Fi devices on the HAN is a good indicator of the residents' presence or activity in the home.

A ping sweep is a network tool to probe the devices on the HAN. The ping sweep sends a set of Internet Control Message Protocol (ICMP) ECHO packets to a network of devices and sees which ones respond. The reason for this is to determine which devices are alive and which are not. One common tool for conducting ping sweeps is fping, which takes an IP address range and sends ECHO packets to them. The tool fping sends one ECHO packet to one IP address and then continues quickly to the next IP address. This method efficiently scans the home Wi-Fi network and lists all the IP addresses of the devices that are up and accessible on the HAN (Teo, 2000). The example below shows a partial list of IPs that were reachable at the time of running the command:

```
$ fping -g 192.168.1.1/24
192.168.1.1 is alive
192.168.1.103 is alive
192.168.1.116 is alive
192.168.1.137 is alive
192.168.1.140 is alive
192.168.1.141 is alive
192.168.1.144 is alive
. . .
```

The IP address cannot reliably be used to uniquely identify a device, because the device may get a new IP address based on a variety of conditions, such as lease expiry and router power cycle. Since IP addresses are subject to change, for a given device, over time within an HAN, the media access control (MAC) address of a device is used. A MAC address is unique for every device. The arp network software utility gives the MAC address for the corresponding IP address (Kozierok, 2005). The unique MAC address of a device is what will be stored in the database, instead of its IP address. The following example shows a partial list of IPs and their MAC addresses at the time of running the command:

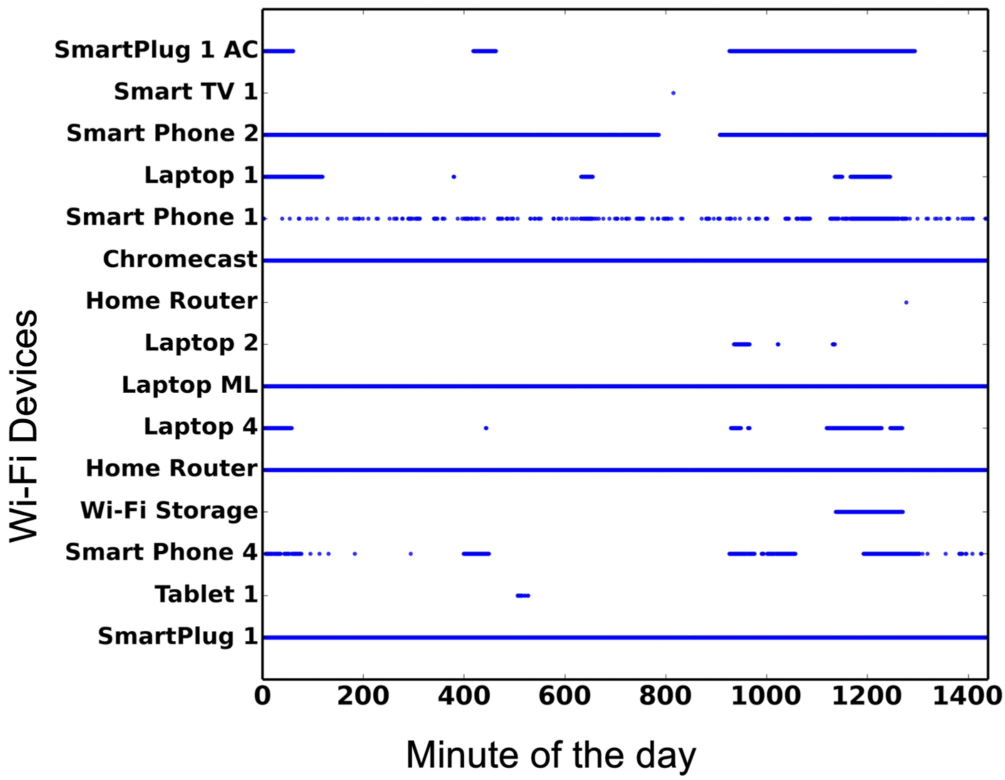
```
$ arp
Address HWtype HWaddress Flags Iface
192.168.1.144 ether 20:56:27:b4:a5:89 C wlan0
192.168.1.141 ether 90:90:a9:fa:c2:15 C wlan0
192.168.1.146 ether 50:bb:3a:1a:e7:d5 C wlan0
192.168.1.140 ether 44:91:82:d9:61:91 C wlan0
192.168.1.143 ether 44:bc:0c:67:97:bc C wlan0
192.168.1.142 ether ac:ad:f8:2b:aa:8d C wlan0
192.168.1.116 ether s6:8d:12:18:6e:98 C wlan0
192.168.1.103 ether ac:bc:32:c4:01:27 C wlan0
192.168.1.1 ether 90:c1:c0:b2:be:c4 C wlan0
192.168.1.102 ether 18:e8:56:43:49:18 C wlan0
192.168.1.139 ether 96:94:26:05:12:0b C wlan0
...
```

A software program runs the fping and arp programs every minute, collects the devices that are connected to the home network, and stores the information in a database. For ease of readability, each MAC address is mapped to the device name. For example, 96:94:26:05:12:0b corresponds to the device Smart Phone 4. Figure 2 shows the device status for the entire day in the experimental setup on February 16, 2017. Noticeably, Wi-Fi devices Chromecast, Laptop ML (running software), Home Router, and SmartPlug 1 are up throughout the day. SmartPlug 1 AC shows the power status of the appliances that are connected to the SmartPlug 1.

3.1. Device Interval Status and Transition Points

As the previous sections mentioned, the software scans the home network every minute and finds the connected Wi-Fi devices and the appliances power status. All the collected data are stored in the database. The software aggregates these data every 15 minutes. If a Wi-Fi device is visible for any minute in the 15-minute interval, it is marked as “on” (1); otherwise, it is marked as “off” (0) during that 15-minute interval. Certain smart phones, when they are not being used, go into standby mode, disconnect from Wi-Fi, and periodically wake up and connect to Wi-Fi. Such devices are detected

Figure 2. Wi-Fi device and appliance power status data collected on February 16, 2017



during the wake-up time. Figure 2 illustrates Smart Phone 1 exhibiting this behavior. The interval aggregation helps in accurately determining the presence of a smartphone in the home.

A transition point is where an appliance power status changes, i.e., from "on" to "off" or from "off" to "on." Figure 3 illustrates this concept and shows sample data of a device status over time intervals. The power of the appliance transitions from "off" to "on" at interval 5 and from "on" to "off" at interval 10.

A device status can be represented as a vector, where each element represents the device up status (1) or down status (0) during that interval. Table 1 shows the status vector for each Wi-Fi device.

Since the device status data are extracted in the form of vectors, similarity measures can be used to find the devices that exhibit a similar usage pattern as the SmartPlug 1 AC power status. The next section will discuss this in detail.

4. MODEL FOR IDENTIFYING RELATED DEVICES

This section examines the approach for identifying devices and appliances that are related to each other. The notion of similarity between devices is explored and quantified using various metrics, to find the Wi-Fi devices that are similar in usage to the appliances.

Figure 3. Wi-Fi devices status over time intervals

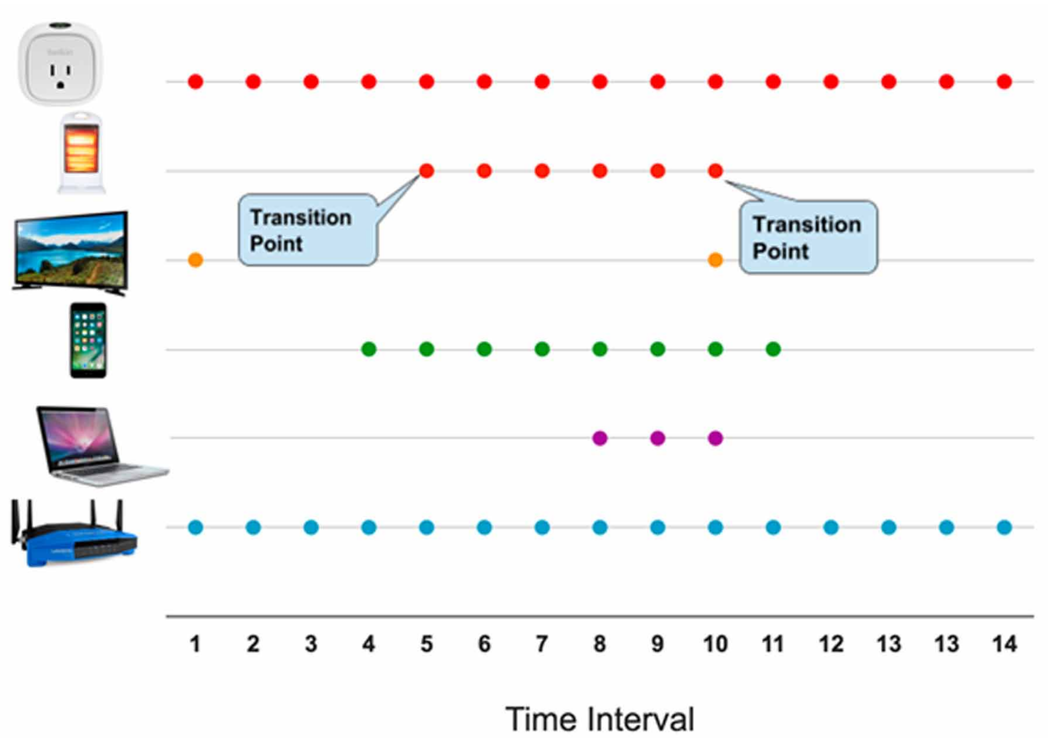


Table 1. Wi-Fi device status vectors corresponding to Figure 3

Wi-Fi Device	Device Status Vectors
Appliances	[0,0,0,0,1,1,1,1,1,1,0,0,0,0]
Smart Plug	[1,1,1,1,1,1,1,1,1,1,1,1,1,1]
Smart TV	[1,0,0,0,0,0,0,0,0,1,0,0,0,0]
Smart Phone	[0,0,0,1,1,1,1,1,1,1,1,0,0,0]
Laptop	[0,0,0,0,0,0,0,1,1,1,0,0,0,0]
Router	[1,1,1,1,1,1,1,1,1,1,1,1,1,1]

4.1. Device Usage Similarity

Similarity learning is an area of supervised machine learning in artificial intelligence. A similarity measure is a real-valued function that quantifies the similarity between two objects. Various learning algorithms implicitly or explicitly rely on a notion of distance (or similarity) between the objects of the data set. If the data are in the form of vectors or matrices, or have been transformed by feature extraction to such structures, then various distance and similarity measures can be used. (Abou-Moustafa, 2016).

Considering the device status vectors are the points in the space V .of 2^d .vectors, there are two common ways to define the notion of distance between two vectors, namely the Euclidean distance and Manhattan distance. The Euclidean distance (ED) is the straight-line distance between two points in Euclidean space. The ED $D: V \times V \rightarrow \mathbb{R}$ .is given as follows (Dubey & Saxena, 2017):

$$D\left(p,q\right)=\sqrt{\left(\mathrm{q}_1-\mathrm{p}_1\right)^2+\left(\mathrm{q}_2-\mathrm{p}_2\right)^2+\ldots+\left(\mathrm{q}_\mathrm{n}-\mathrm{p}_\mathrm{n}\right)^2}\ .$$

$$D\left(p,q\right)=\sqrt[2]{\sum_{i=1}^{n}\left(q_i-p_i\right)^2}\ .$$

where p and q are two feature vectors each having dimension n, defined as $p = \{p_1, p_2, p_3, \ldots p_n\}$ and $q = \{q_1, q_2, q_3, \ldots, q_n\}$.

The Manhattan distance, also known as taxicab metric, is the shortest distance a car would have to drive in a city block structure to get from point p to q. The Manhattan distance is given as follows:

$$D\left(p,q\right)=\sum_{i=1}^{n}\left|q_i-p_i\right|\ .$$

The Manhattan distance counts the number of dissimilarities among the vectors (Chang et al., 2006). It is clear that smaller the distance D(p,q), in any of the above metrics, the greater the similarity between the vectors.

A more appropriate notion of metric in this scenario, to that of the computation of the distance between objects, is the determining of similarity function S(a,b) that compares the two vectors a and b. This function S should be symmetrical i.e. S(a,b) = S(b,a), the value will be large when a and b are somehow "similar" and should constitute the largest value (close to 1) for identical vectors. Cosine similarity is one of the techniques that is used for similarity measure. Cosine similarity for two nonzero vector CS: $V\times V \rightarrow [-1,1]$ is defined as follows (Dubey & Saxena, 2017):

Let α, β be two vectors: α = {p1, p2, p3 ...} and β= {q1, q2, q3 ...}
Let "*" denote a scalar product between two vectors. Then cosine similarity between α, β is given by:

$$CS=\frac{\left(\alpha*\beta\right)}{\left(\left|\alpha\right|\times\left|\beta\right|\right)}\ .$$

$$\alpha*\beta=\left(p_1*q_1+p_2*q_2+p_3*q_3+\ldots\right)=\sum_{i=1}^{n}p_i*q_i$$

$$\left|\alpha\right|=\sum_{i=1}^{n}p_i^2$$

$$\left|\beta\right|=\sum_{i=1}^{n}q_i^2$$

In the above equation, CS is cosine similarity, |α| and |β| are the magnitudes of vectors α and β respectively.

If the angle between the two vectors is nearly zero, then the similarity between them is highest. The cosine similarity is a representative similarity measure, while the Euclidean distance, Manhattan metric represent dissimilarity measures (Dubey & Saxena, 2017). This paper uses cosine similarity to find Wi-Fi devices that have similar usage patterns as the appliances.

The cosine similarity of appliances is computed with all the other devices at its transition points by considering four intervals on both sides of the transition point. For example, the device status vector of appliances for transition point 5 is [0,0,0,0,1,1,1,1] as shown in Figure 3. The cosine similarity of appliances with all other devices using the corresponding device vectors is shown in Table 2.

Similarly, the device status vectors of appliances at transition point 10 are [1,1,1,1,0,0,0,0] as shown in Figure 3. The corresponding cosine similarity with all the other devices is shown in Table 3.

Two devices are considered similar if they exhibit the same visibility status for at least 1 hour 45 minutes in a 2-hour period, i.e., seven out of eight 15-min intervals. This corresponds to the threshold value of 0.89. All devices that have a cosine similarity of at least 0.89, at any transition point, are similar on the appliances. From Tables 2 and 3, appliances are similar to Smart Phone and Laptop, as the similarity is at least 0.89 at any transition point. This helps in deciding when to turn off the appliances; when the Smart Phone and the Laptop are not connected to the home network, the software automatically turns off the appliances.

5. REDUCING THE ENERGY WASTAGE

This section describes the methods to save energy using manual and automatic approaches.

5.1. Manual Intervention Using Device Usage Charts

The Wi-Fi device status charts, as Figure 2 shows, provide useful information that can be acted upon manually to save energy. The chart shows the devices and appliances uptime over a period. Some devices are constantly up, such as the Chromecast. From this alert, the residents can manually turn off such devices when they are not using them.

Table 2. Cosine similarity (CS) of appliances with all other devices at transition point 5

Wi-Fi Device	Device Status Vectors at transition point 5	CS
Smart TV	[1,0,0,0,0,0,0,0]	0.00
Smart Phone	[0,0,0,1,1,1,1,1]	0.89
Laptop	[0,0,0,0,0,0,0,1]	0.50
Router	[1,1,1,1,1,1,1,1]	0.71
Smart Plug	[1,1,1,1,1,1,1,1]	0.71

Table 3. Cosine similarity (CS) of appliances with all other devices at transition point 10

Wi-Fi Device	Device Status Vectors at transition point 10	CS
Smart TV	[0,0,0,1,0,0,0,0]	0.50
Smart Phone	[1,1,1,1,1,0,0,0]	0.89
Laptop	[0,1,1,1,0,0,0,0]	0.87
Router	[1,1,1,1,1,1,1,1]	0.71
Smart Plug	[1,1,1,1,1,1,1,1]	0.71

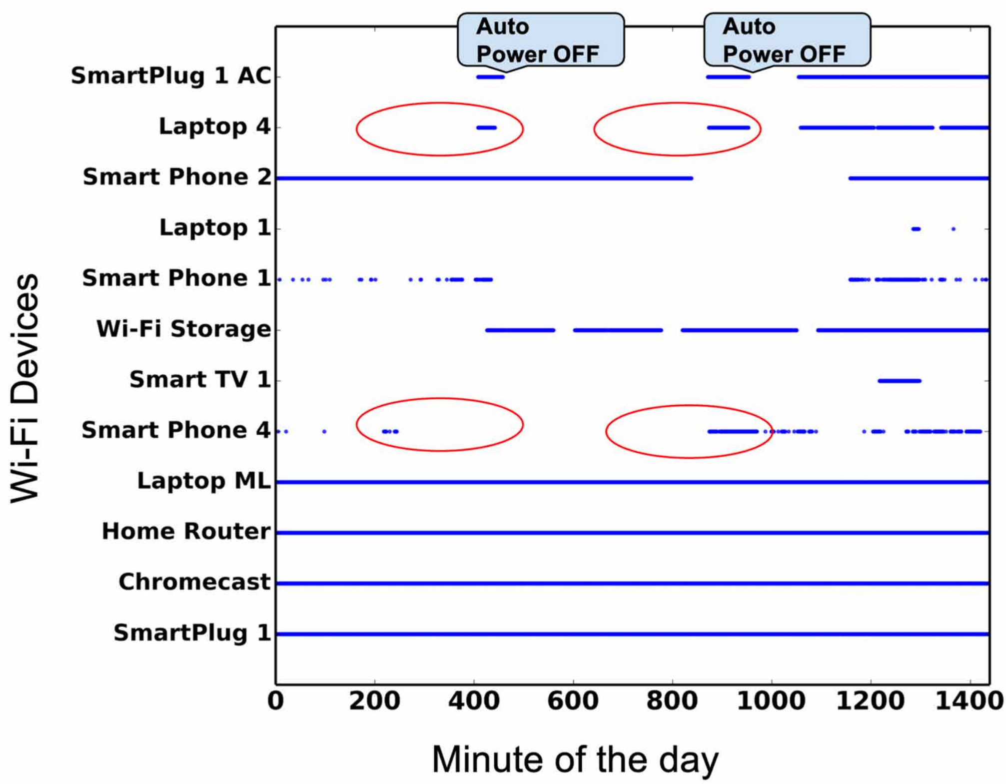
5.2. Automatically Turning Off the Appliances

The Laptop ML runs software that performs ping sweep of the Wi-Fi devices connected to the home network, and collects appliance power status of the Wi-Fi-enabled smart plugs, every one minute.

Using the cosine similarity algorithm, the software learns the devices that are similar to the power status of the appliances. The following parameters are used in the software: a) Cosine similarity threshold value of 0.89; and b) Similarity learning is updated continuously based on the previous three days of data. In order to reduce false positives, when the software automatically turns off the appliances that are connected to the smart plug, it starts a hold-off period of one hour (i.e., it will not automatically turn it off again for the next one hour). Once the software deduces upon which Wi-Fi devices an appliance is dependent, these devices will serve as an indicator of when the Wi-Fi-enabled smart plug should be turned off.

Figure 4 shows a sample device usage chart in the experimental setup. It demonstrates how the software automatically powers off SmartPlug 1 AC when similar or dependent devices are not connected to the home network. For example, if both Smart Phone 4 and Laptop 4 are not connected to the home network for a period of 15 minutes, because the resident left the house with these devices, the software powered down the appliances (SmartPlug 1 AC) through Wi-Fi SmartPlug 1.

Figure 4. SmartPlug 1 Air Conditioner is turned off when Laptop 4 and Smart Phone 4 are not connected to the home network for a period of 15 minutes



6. EXPERIMENTATION AND RESULTS

A controlled experiment was conducted to evaluate the performance of this approach in three different homes during different periods. The Home 1 consisted of four residents, 14 Wi-Fi devices, and WeMo Switch Wi-Fi enabled smart plug (shown in Figure 4 as Smart Plug 1 AC) is connected to a power outlet and to the appliances (air conditioner and lamps). The Home 2 consisted of three residents and 9 Wi-Fi devices. The smart plug is connected to a power outlet and to the appliances (lamps) in a room. The Home 3 consisted of three residents and 10 Wi-Fi devices. The smart plug is connected to a power outlet and to the appliances (air conditioner) in a room.

In each household twenty consecutive days were used for experimentation. In the treatment group, the software and the residents turned off the appliances to reduce energy consumption. In the control group, the appliances were turned off by the residents only. During these twenty days, at the beginning of the day, the software randomly choose whether to apply the treatment or not. The experiment is double-blind since the residents were not aware of the treatment applied. Each day energy consumption of the appliances, measured using the smart plug, was recorded along with the applied treatment as shown in Figures 5, 6, 7 for Homes 1, 2, 3 respectively. Figure 8 shows the combined results of all three homes for comparison.

Table 4 shows the summary of the energy consumed in the three homes and the corresponding energy savings.

The data shows this approach accurately tracks the resident activity. It continuously learns similar devices without requiring daily manual intervention such as setting up of the devices and policies. The energy savings vary depending on the resident's usage of appliances, e.g., residents who turn off appliances proactively, the kind of appliances, amount of time residents spend at home. Regardless, the results show energy savings in all the three homes and a significant reduction in the energy wastage.

Figure 5. Daily energy consumption in Home 1

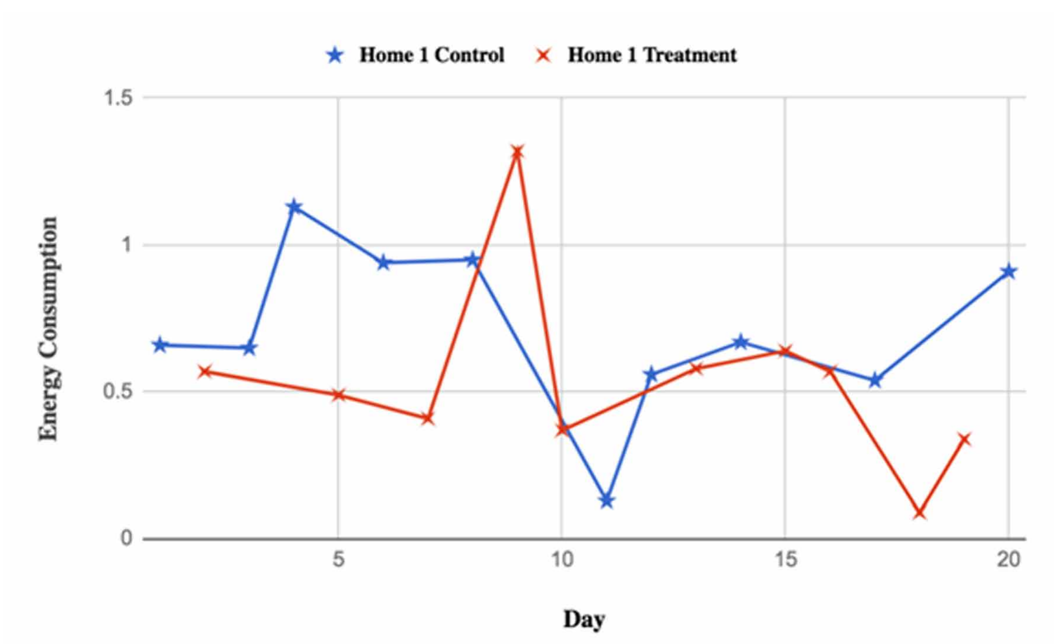


Figure 6. Daily energy consumption in Home 2

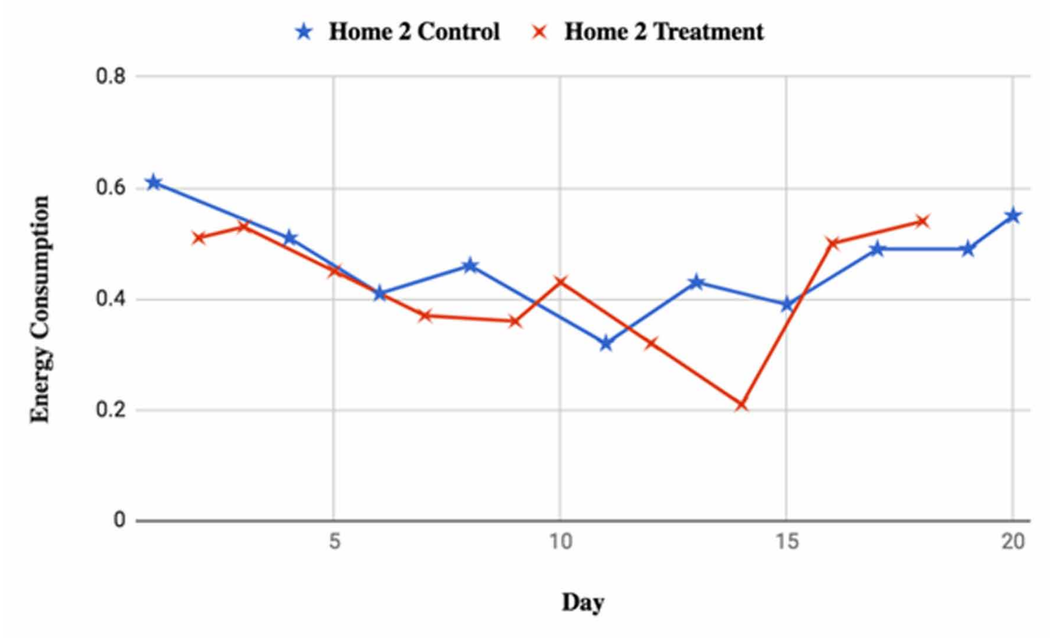


Figure 7. Daily energy consumption in Home 3

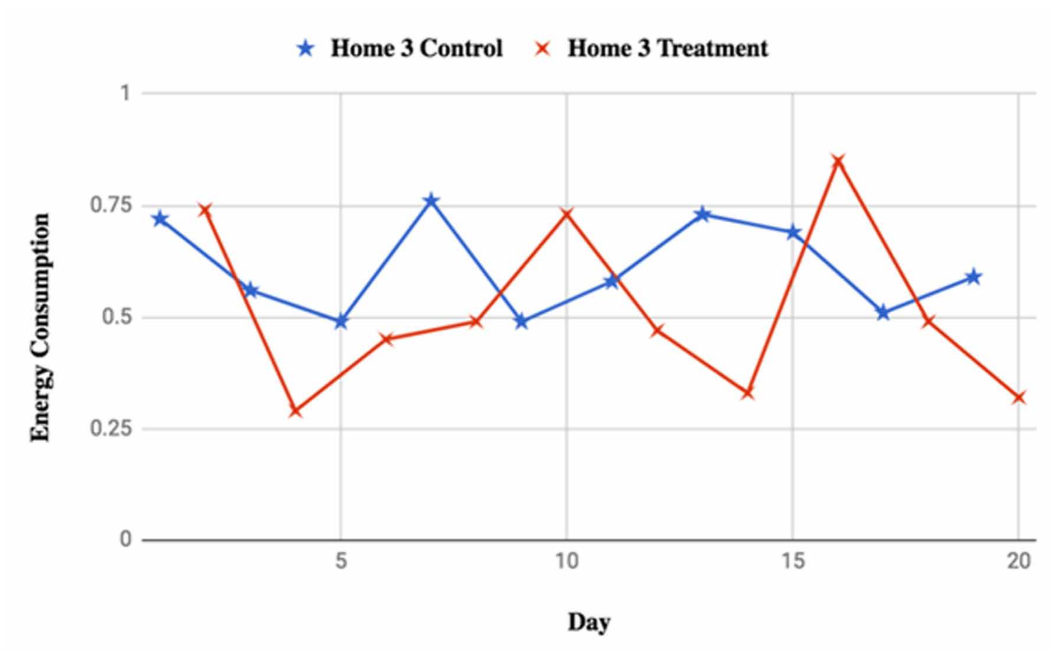


Figure 8. Daily energy consumption in Homes 1, 2, 3

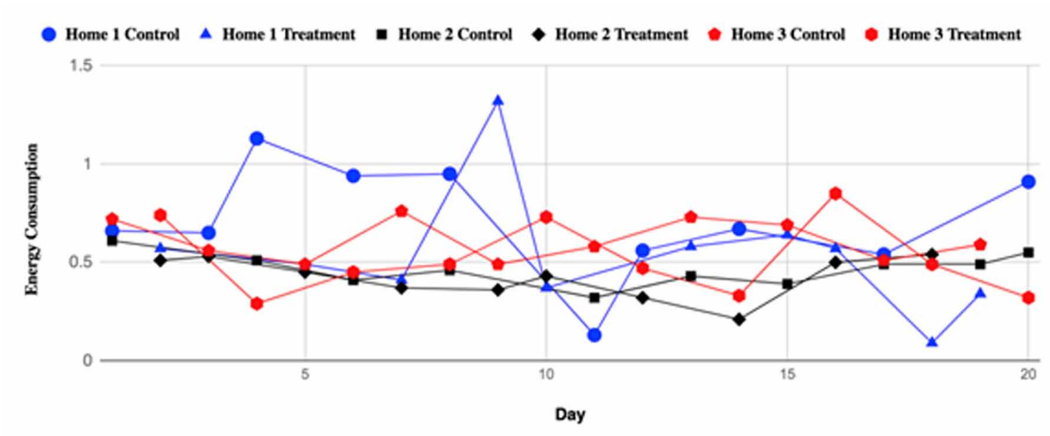


Table 4. Energy Consumption in three homes

Home	Control Group	Treatment Group	Savings%
1	7.14	5.38	24.65
2	4.66	4.22	9.44
3	6.12	5.16	15.68

7. LIMITATIONS AND FUTURE WORK

This paper examined the approach to powering off appliances that were not in use; however, it did not explore approaches to power-on the devices. Since the resident's arrival times were not known, a key challenge was to decide whether and when to preheat the room. This might be possible by finding similarity of the power status of the appliances with the geo-location of the smartphones, home network connectivity of the devices, and weather data. Also, the probability of a resident being home can be estimated using the Hidden Markov Model (HMM), as explained in (Lu et al., 2010). Another limitation of this work is that the laptop, which runs the software, needs to be on all the time. This requirement can be satisfied by running the software on the existing embedded devices that are on all the time in the homes, such as a home router. A further area of research is investigating new methods to conserve energy in public environments, such as schools and libraries.

8. CONCLUSION

In this paper, the author presented a new approach to automatically turn off appliances that were not in use, to save energy in residential homes and reduce carbon emissions. The approach consisted of detecting the Wi-Fi device and appliance power status every one -minute using network software utilities in the home network. From the collected data, one can continuously ascertain the Wi-Fi devices that impact the power status of the appliances using the cosine similarity algorithm. The appliances were turned off when the corresponding Wi-Fi devices were not detected in the home network. This approach was evaluated by performing a double-blinded experiment for twenty consecutive days in three different homes. The results indicate that this approach can result in significantly reducing energy wastage.

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