The Standby Energy of Smart Devices: Problems, Progress, & Potential

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***Abstract*—The Internet of Things (IoT) has dramatically expanded the capabilities of everyday devices. These smart devices bring improved convenience, better energy management, and over-the-Internet control, but are also unfortunately reversing an important trend: they are contributing to an increase in phantom standby energy consumption. While many miscellaneous loads have seen steady standby power improvements over time, adding persistent connectivity and advanced features to otherwise simple devices is causing some loads to get worse. This paper provides an analysis of this growing problem, and identifies four primary issues that contribute to the standby energy problem based on a study of commercially available smart devices. Further, it proposes several strategies for addressing these issues, and presents two new systems to illustrate the potential for improvements.**

***Index Terms*—Standby Power Reduction, Miscellaneous Electric Loads, Smart Devices, Internet of Things, Smart Homes, Home Energy Management System**

I. Introduction

Recognizing that buildings are significant consumers of energy, various programs from the US Department of Energy [20], the Ministry of Power in India [8], the Chinese government [51], and other agencies around the world, have led to significant technology improvements and building energy reductions. Much attention has focused on improving large building systems, including HVAC, air handling, and lighting, but more recently improving other energy consumers in buildings, including miscellaneous electrical loads (MELs), has become a priority [49]. These MELs have historically been relatively small contributors to total energy consumption, but as larger systems have improved, the need to improve MELs has become much more pressing [62]. Programs such as Energy Star [16] and European Union energy labeling regulations [9] have contributed to significant improvements in many smaller electrical loads [64].

At the same time that MELs have attracted attention in terms of energy consumption, the Internet of Things (IoT) trend has dramatically expanded the capabilities of many common and ubiquitous devices and appliances. Further, new devices are becoming fixtures in homes. For example, over a quarter of US adults have a smart assistant [58]—a device which in 2013 largely did not exist. This is also not only limited to homes, as commercial buildings have also begun to integrate IoT

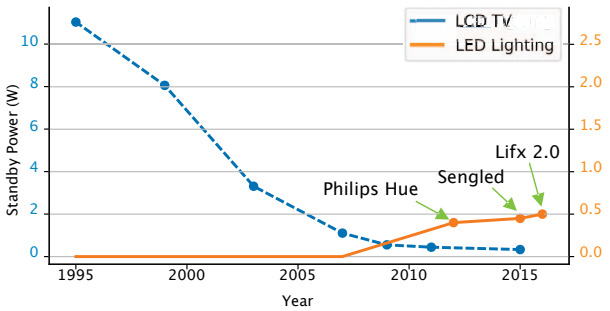


Fig. 1: An example of the contrast between a traditional home appliance with decreasing standby power and a new smart home device. Whereas many appliances like TVs have seen significant improvements in standby power [39], [64] (the blue dots show the standby power rating of LCD TVs over time), smart devices are causing the reverse trend for loads with traditionally zero standby power (e.g. light bulbs, shown in orange).

devices [12] for personalized temperature management, energy management, and other services. This growth in smart devices is likely to continue as IoT devices improve occupant comfort, increase quality of living, and help with energy efficiency, and promise to continue to do so.

As new smart devices are added, and traditional devices are converted, this increase in convenience, functionality, and connectivity comes at a cost: increased energy consumption. Devices which previously had zero power draw when switched off now are always-on and spend most of their time in a standby mode waiting for commands or for an event to happen. Completely new devices increase the number of MELs in buildings, adding additional energy consuming loads. This shift in technology has led to an increase of phantom standby energy consumption (Figure 1). Exacerbating this trend is the IoT gateway problem [70], where many IoT devices require a supporting always-on gateway that also contributes to an increase in standby energy. Despite one purported IoT benefit being increased energy efficiency [19], the proliferation of new IoT devices is having a negative effect on standby energy

978-1-7281-6602-5/20/$31.00 ©2020 IEEE
DOI 10.1109/IoTDI49375.2020.00024

consumption, which at global-scale will be significant.

In this paper we investigate the scope of this emerging problem as traditional devices are increasingly replaced with their smart equivalents, and new smart devices become commonplace. We identify issues with commercially available IoT devices and how smart devices present new challenges for prior work on reducing the energy consumption of MELs. Further, we identify emerging techniques that may help address these new challenges, begin to quantify the improvement they may enable, and highlight areas where further research is needed. Additionally, we prototype new techniques for improving smart device standby power to demonstrate how features of the IoT can help with this challenge.

In particular, through our analysis of many commercially available IoT devices, four primary trends have emerged that contribute to the IoT device standby energy problem. First, over a decade of research into optimizing the low-power operation of wireless embedded sensing systems is not adequately being applied to commercially available smart devices. Similarly, improvements in low power hardware are not being leveraged for these devices. Second, the supporting hubs or gateways that smart devices often require and that are typically vendor- or device-specific are always-on and multiply the standby power problem. Third, smart devices often operate logically in groups of several related devices, and power optimization strategies are limited in how they understand and exploit these groupings. Fourth, smart devices have different operational patterns than traditional MELs, and house-wide prediction and control algorithms must consider these differences. Understanding the changing burden that smart devices place on reducing standby energy consumption is essential for developing effective techniques for future improvements.

In a study of 40 smart devices, ranging from smart lighting to doorbells with cameras, we find that many smart devices draw over a Watt when in standby mode, with some drawing over 5 W while not being used. This becomes particularly problematic for certain smart devices, like digital assistants and wireless video streaming devices, which actually consume more total energy doing very little in standby than in active mode when they are actually used.

Based on this understanding of current devices, we propose several strategies for improving future devices. While market considerations are difficult to fully consider, the proposed roadmap highlights some of the disconnect between research and practice, and identifies areas where future research is likely needed. These strategies are based on recent work in related areas, observations from the presented analysis, and new trends accompanying the IoT. In some cases, the change to a world of very connected things presents new opportunities for addressing the standby energy challenge, and we develop two new systems to illustrate the potential for improvements. The first uses a network of connected devices to proactively force a MEL into a lower power mode. The second leverages the network affects of related devices to improve a machine learning approach for predicting when a MEL will be used. Accurately predicting usage times will enable aggressive standby power reductions without user inconvenience. Together, these prototypes show how system-level improvements can reduce the energy wasted on IoT standby mode. However, they are just a start, and many more advances are needed. This paper attempts to highlight the growing problem in this area, and serve as a call-to-action for new research to further reduce the energy footprint of the Internet of Things.

II. Related Work

Current approaches on reducing standby power in smart homes focus on three directions.

Increase Awareness of Wasted Energy. Providing energy consumption data to users can raise their awareness of the wasted energy in their household. Several approaches have focused on this direction. One proposed approach is an augmented reality system to display power draw data on a user's smartphone when the camera is pointing at a device [34]. Another approach allows smart devices to "talk" to users on the social media, and have the device post its energy use periodically to inform the user [50]. These approaches help to increase awareness of standby energy, but leave reducing it to manual intervention by the user.

Standby Reduction on Individual Devices. Many approaches have focused on reducing standby power issue for smart devices. Gerber et al. highlighted technologies to eliminate standby power consumption in electric loads, including burst-mode, sleep transistors, and optical wake-up radios [31]. This survey reinforces that this is a pressing problem, and complements what we propose in this paper, as it focuses on low-level hardware while we consider more systems-level issues. Other work targets specific hardware improvements, including reducing leakage current [55], [59], reducing operating voltage [59], optimizing microcontrollers [57], [60], and including ultra-low power radios [53]. These improvement can help future devices and suggests that future hardware improvements will reduce standby power, but integrating new components into full smart device systems remains a challenge, and will not fully solve the problem.

Energy Management Mechanisms for Smart Homes. One of the major directions is to use an energy management system to control loads in smart homes to reduce standby energy. One approach is controlling loads based on user location and the assumption that devices not near users can be shut completely off [36], [43]. Location is determined by localizing a user's smartphone which users are expected to carry with them. This reduces the convenience of the system, and location may not be a good control signal with new smart devices. Other works propose control systems based on usage profiling and prediction [26], [45], [65], however, these approaches do not directly consider smart devices. Other control systems for avoiding peak-time electricity rates show very promising results [63], but do not consider the consistent energy cost of the control system itself. Smart plugs and other IoT devices can enable these control systems, but their standby power must also be considered in the larger system.

III. Standby Power Challenges

New technologies and regulations have led to significant reductions in the standby power of various wall-powered loads. For example, LCD TVs saw greater than a 90% reduction over two decades of improvements. However, a different technology trend, the Internet of Things, is pushing loads in a different direction: actually increasing standby energy over time. Consider smart lighting: traditional bulbs draw zero power when off, however, today's smart lighting remains connected and in standby mode when not providing any illumination. Figure 1 shows the differences in the trends of TVs and lighting.

Adding radios and intelligence to everyday things poses a pressing challenge for the IoT community to not undo prior efforts in standby energy reductions in buildings. We start by identifying some roots of this issue to understand what new problems smart devices introduce. Then, we highlight promising trends and related technologies that might help address this issue.

To show the challenges in standby power of smart devices, we provide a detailed analysis of commercially available IoT devices, explain the difference from traditional non-smart devices, and identify four primary emerging challenges that IoT devices present. These include: research progress in low-power embedded systems is not being applied to commercial smart devices, gateway redundancy multiplies standby power, automatic standby power optimization in a household is limited without logically grouping devices, and control and prediction algorithms are not designed for the operational patterns of smart devices.

A. The Standby Power Gap

Unlike many appliances which draw zero power when switched off, smart home devices often keep several components on while the device appears to be off. For example, a traditional light switch is purely mechanical and does not have any standby power when turned off. In contrast, smart switches like the Geeni smart switch [11] have a standby power of 250 mW when the load is off. This standby power in the off state is mostly used to keep the device reactive and "smart" when it is not in use. To better understand the standby energy consumption of smart devices, we consider common smart home appliances and measured their standby power, as shown in Table I. The minimum we measured was 170 mW, and several devices consume well over 1 W while appearing to be completely off. Next we further investigate the causes and effects of this standby power draw.

1) Standby Power Adds Up: In some cases, the standby power of a single device is relatively insignificant, however, a smart home might use dozens of these devices. The standby energy consumed by these devices adds up, and can surpass the potential energy waste of misusing legacy devices (e.g. leaving the light on). To demonstrate the significance of standby power of smart devices, we consider two examples.

First, we consider smart lighting, a popular application with many products [6], [7], [14]. According to a recent study by the U.S. Department of Energy, a residential household has an average of 67 light bulbs [3]. Philips Hue, a popular smart light bulb, has bulbs which each draw 0.4 W in standby mode, and hubs which draw 3.84 W on average and can support 35 bulbs. If all 67 of the light bulbs are replaced by smart bulbs, this lighting system would consume a total of 724 Wh each day in standby energy. To contextualize this, we compare the standby energy of the smart lighting to the energy wasted by

Device Name	Off Mode (W)	Standby Mode (W)
Google Home	3.32	3.32
Amazon Echo Show	0.17	7.36
SmartThings Hub	1.35	1.52
Philips Hue Hub	1.63	1.63
Amazon Fire TV 4K	2.62	2.62
Google Chromecast	1.69	1.69
Sony PlayStation 4	0.17	6.31
Xbox One S 1 TB	0.28	24.50
Geeni Smart Socket	0.25	0.25
Edimax Smart Socket	1.43	1.43
Geenie Smart Socket	0.25	0.25
Sony X800E Smart TV	0.42	23.80
Bose Wave SoundTouch Speaker	3.48	6.92
Amazon Cloud Camera	1.84	1.84
Nest Hello Wireless Doorbell	1.88	1.88
Awair 2nd Edition Air Quality Sensor	1.17	1.17
Philips Hue Bulb	0.40	0.40
Keurig K40 Coffee Maker	3.26	4.12

TABLE I: Standby power of popular smart home devices. "Off Mode" is when the device is explicitly turned off using an on-device interface. "Standby Mode" is when the device is not actively being used. Devices without a power button or other power control have equal off and standby power draw. Please see Appendix A for more information on all tested devices.

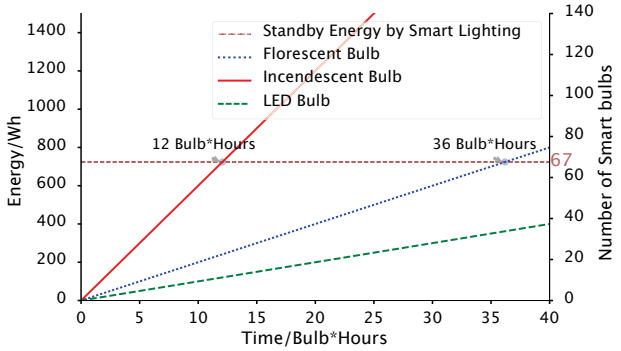


Fig. 2: Comparison between the standby power used by smart lighting (when the bulb is off) and leaving existing lighting types on. An average house with all smart bulbs (67) consumes 724 Wh per day in standby energy, equal to leaving incandescent, florescent or LED bulbs on for 12, 36 or 72 hours, respectively. That is, smart lighting providing no illumination and only waiting for a command is equivalent to just leaving on three LED bulbs.

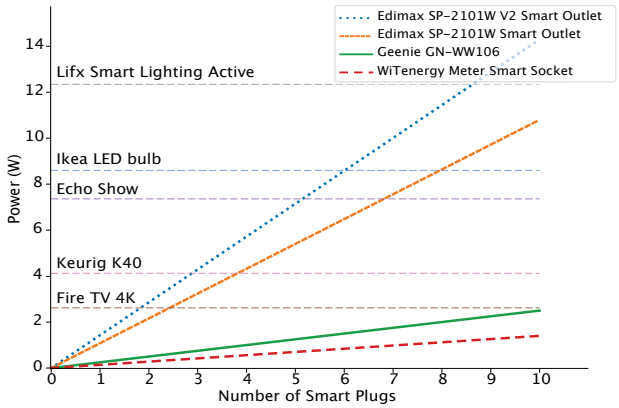


Fig. 3: Standby power draw of different smart plugs compared with smart devices in active mode. Using smart plugs can surpass the potential energy waste of misusing non-smart devices.

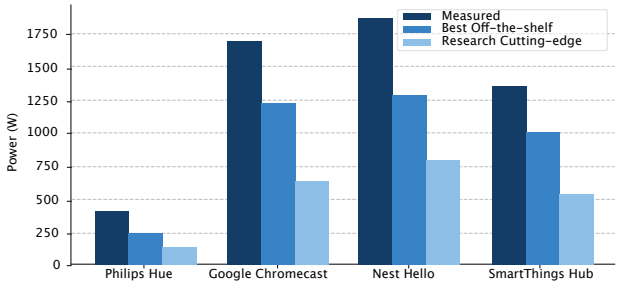


Fig. 4: The comparison of standby power if the major circuit components in smart devices are upgraded to the best-in-class versions both commercially available and published in recent research papers. The gap indicates that current commercial devices are not leveraging the best available technology.

leaving traditional lights on, as shown in Figure 2. A smart home with all smart bulbs consumes the same energy per day as leaving three 60 W equivalent LED bulbs on continuously. If the smart lighting was installed to reduce energy waste, it would have to displace 36 bulb-hours of unnecessary fluorescent light use per day just to break even on standby energy. This study indicates that using smart devices does can result in more energy consumption compared to legacy devices.

We see a similar effect with smart plug-load control devices, where the standby energy of multiple smart plugs exceeds the standby energy of certain loads, as shown in Figure 3. For example, with just three Edimax V2 smart plugs [15], providing wireless control consumes more energy in standby than simply leaving a traditional appliance, in this case a Keurig coffee machine, on.

2) Commercial Devices Lag Best Practices: The broader research community has made significant progress on creating very low power wireless IoT devices. However, current products on the market are not exploiting the results from cutting-edge research. We study the energy consumption of off-the-shelf

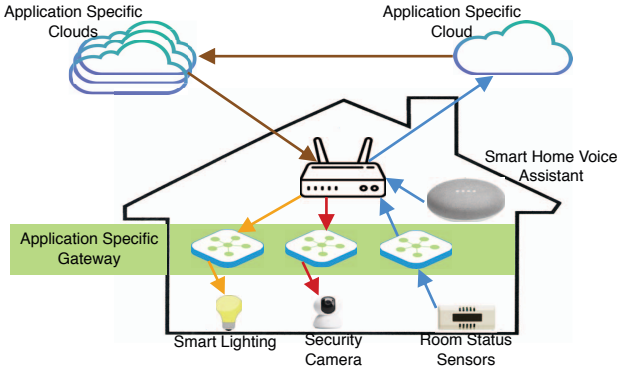


Fig. 5: The gateway problem for smart devices. Devices from different manufacturers often cannot join the home network through existing gateways, even with the same radio. Using redundant gateways result in extra standby energy consumption.

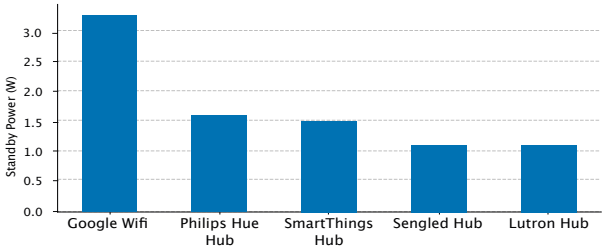


Fig. 6: The standby power of several commercial gateways. Having five different gateways consumes the same energy as playing an Xbox One for 5 hours.

devices based on their primary components and the cutting-edge research products, and estimate the standby energy consumption of several smart home appliances if all components are replaced with best off-the-shelf and cutting-edge research options. The results are shown in Figure 4. Replacing all with best off-the-shelf products can reduce the standby power by 25% to 35%, and 55% to 70% cutting edge research components are used. There is a clear gap between the measured power and the estimate with best off-the-shelf components, indicating that current commercial devices are not leveraging the best available technology. There is a larger gap between the measured power and the estimated result using cutting-edge components, which provides an approximate lower bound for these devices in the future.

With mains-powered IoT devices, power draw may not be a priority for manufacturers, who instead focus on advances in features and performance. That is, despite the opportunity existing for more efficient devices, these improved hardware components may not be readily included into power unconstrained IoT devices without regulatory incentives (like Energy Star) or functionality enhancements.

B. Gateway Redundancy

Many IoT devices require a gateway to bridge the low power radios used by the wireless nodes to an existing

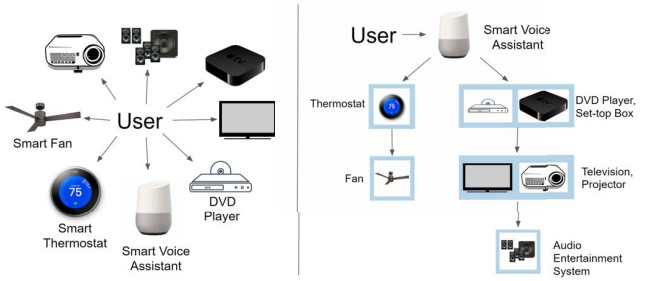


Fig. 7: The network of smart devices under different users. Logically grouping smart devices is a major challenge, as different users have different usage patterns resulting in different device networks.

network. Both wall-powered and battery-powered devices use gateways, for example, Philips Hue [7], Sengled [14], Lutron [18], and SmartThings [13] all use hubs. These gateways provide application-specific services like network connectivity, in-network processing, and user interface functions to IoT devices [70]. A new device from a different manufacturer often cannot join the home network through existing gateways even when using the same radio, due to vendor silos and application layer differences, as shown in Figure 5. These gateways typically stay in idle mode while connected to devices, and draw a certain amount of standby power continuously. Figure 6 depicts the standby power of several popular gateways in smart homes, ranging from 1.2 W to 3.5 W.

The standby energy from these gateways can become significant in reasonably equipped smart homes where devices often come from different vendors. For example, a home with smart lighting, home security, garage door monitoring, and smart lock systems from different vendors can consume up to 240 Wh per day in standby energy for the gateways for those systems, similar to playing an Xbox One for five hours. This lack of shared gateways is the standard today, and with the difficulty of creating a full line of IoT products, the incentives of collecting and controlling data, and the diversity of connectivity options, it seems smart houses will have heterogeneous IoT systems in the future as well. In that case, the energy waste due to redundant gateways will continue to grow as users adopt more smart home systems.

C. Network of Devices

Reducing the standby power of appliances is an active area of research [31]. Prior work has shown that it is beneficial to look at appliances from a network perspective, where devices frequently used together are controlled as a group [45]. Standby energy reduction can be achieved by turning off a device when all correlated devices are turned off, instead of keeping the device in idle mode wasting energy. A centralized hub is required to collect device states, group smart devices logically, and deliver control signals to control smart devices. Commercial products like Currant [10] use smart plugs attached to each device to gather device power data and control device to turn on/off. However, due to the lack of ability to group devices,

Project	User Presence	Usage Prediction	Peak-Time	Control Energy	Smart Devices
BuildSys'18 [36]	✓			✓	
IEEE SMC'13 [43]	✓	✓			
Energy Build'13 [26]		✓			
IEEE PerCom'16 [45]	✓	✓			
UCAml'14 [65]		✓			✓
IEEE Access'16 [63]		✓	✓		

TABLE II: Existing home energy management systems. Current approaches focus on different aspects, with very few of them targeting on smart devices. More advanced management systems considering all aspects are required to optimize power savings.

the system still analyzes and suggests energy savings for single devices.

Research in this area has presented a more advanced method to group devices by tasks [45], however, this system is designed based on knowledge of each device and preset rules, and lacks the flexibility to work on different devices and different rules. Logically grouping smart devices is a major challenge, as different users have different patterns to use these devices. Figure 7 depicts an example of the same devices grouped differently by different users.

With the development of IoT, a new opportunity appears as various IoT systems encourage users to indirectly express device networks. New frameworks like IFTTT (if this, then that) [2] allow users to customize triggers and actions for devices, providing user-specific relationships between devices. Smart assistants support the notion of "recipes", where individual commands can affect multiple devices. Although approaches like this still require users to manually group devices, these new systems may provide new sources of logically grouped smart devices. Standby power control algorithms need to improve to incorporate this valuable source of information.

D. Control Systems Issues

Home Energy Management Systems (HEMS) can help reduce the standby energy of loads by switching them completely off when no users are present to use the loads. This often requires predicting when a load will be used to ensure it is available for the user. Table II lists several recent HEMS systems and their various capabilities. While these can help with standby energy, they typically only consider traditional, non-smart devices, and smart devices can have different operational patterns due to non-human-present updates and a continuous power draw when turned to idle or off. In fact, many of today's smart devices did not exist when some of these HEMS approaches were developed! Additional development is needed to ensure these HEMS are suitable for smart devices.

Additionally, most of the HEMS control algorithms either require users to manually input information [29], or rely on continuous power measurement from smart plugs attached to devices to understand device states [36], [43], [63]. They ignore that the control system itself consumes energy, and that metering causes standby power draw. This creates a new problem as the energy consumed by the control system can be larger than

Components	Current	Best Off-the-shelf	Cutting-edge
AC-DC	75 mW	22 mW	1 mW [42]
MCU Sleep	2.7 uW	1.08 uW	0.009 uW [54]
MCU Active	540 uW/MHz	228 uW/MHz	28.2 uW/MHz
BLE (TX: 0dBm)	TX: 24 mW RX: 26.1 mW	TX: 12.5 mW RX: 17.2 mW	TX: 5.2 mW [47] RX: 2.6 mW
WiFi (TX: 0dBm, 54OFDM)	TX: 693 mW RX: 346 mW	TX: 554 mW RX: 190 mW	TX: 325 mW [40] RX: 162 mW
Zigbee (TX: 0dBm)	TX: 77.4 mW RX: 55.5 mW	TX: 28.5 mW RX: 36 mW	TX: 5.4 mW [48] RX: 3.8 mW
LED (800 lm)	5W	3.5 W	N/A
Temperature Sensor	19.8 uW	13 uW	N/A
IR Sensor	14.19 mW	9 mW	N/A
LDO Voltage Regulator	0.28 W	0.21 W	N/A

TABLE III: A per-component breakdown of power requirement for each chip in an IoT system. For each major circuit component, we compare what is found in teardowns of existing devices, what is easily available from chip suppliers, and what is published in recent circuits research. Adopting new chips into current existing products could significantly reduce standby power.

the waste energy of devices in standby. To address this, new methods of device state measurement are needed, and HEMS frameworks need to consider the cost of running the HEMS.

IV. Emerging Technologies and Directions

Progress towards an "Internet of Everything" has provided great gains in connectivity, control, and the ability to program traditionally "dumb" devices, but, as we have shown, contributed to an increase in wasteful standby power. Luckily, evolving IoT technologies bring new opportunities to solve the standby energy problem in smart devices. We identify three key directions for improvement: reducing the standby power on individual devices, removing redundant hardware, and leveraging network of devices and home energy management systems. Further, we quantify the potential improvement of emerging technologies that show promise in this area. These specific recommendations may not be immediately viable for commercial applications, as new systems-level research is still required to reduce the complexity and cost of building more energy efficient IoT devices.

A. Adoption of new chips

With the natural improvement of low-power hardware, adopting new chips into current existing products could significantly reduce standby energy. A per-component breakdown of power is shown in Table III, which lists the power requirement of currently used, best off-the-shelf, and recent research versions of each chip in an IoT system have achieved. To quantify the improvement of using better chips, we simulate replacing one or more components with best off-the-shelf products. Figure 8 shows the results for several IoT devices. Replacing the radio chip could have a standby power reduction of 40 mW to 120 mW on average. Replacing the memory could result in a reduction of 50 mW to 100 mW.

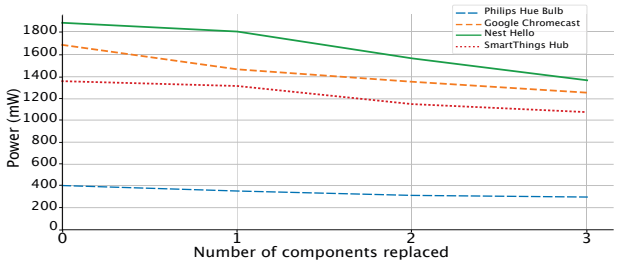


Fig. 8: The standby power of replacing one or more components with best off-the-shelf products in several IoT devices. Replacing each component could reduce standby power by 5 mW to 200 mW depending on the device.

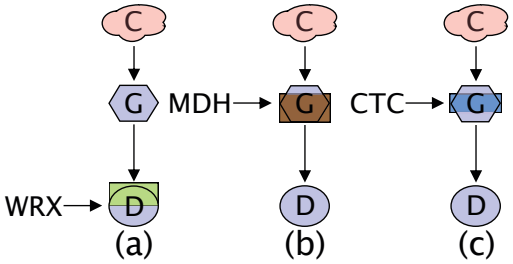


Fig. 9: Three different approaches for addressing the redundant gateway problem for embedded device connectivity. Wake-up receivers (WRX) can enable existing gateways to coordinate many devices. Gateways with multiple radios and improved software stacks can mask device heterogeneity (MDH) and consolidate gateways. Using Cross-Technology Communication (CTC) can allow an existing gateway to communication with unmodified devices.

The research community has also indicated several directions for reducing component-level standby power. A major direction is reducing leakage power, by either reducing leakage current, lowering the supply voltage, or using transistors to disconnect modules. For example, a method using extensive power gating shows a 15% reduction in standby power of a 2.4 GHz phase-locked-loop [55]. A recent study by Gerber et al. [31] also examines the promise of cutting-edge technology for reducing or eliminating the standby power of smart devices. The study highlights burst mode power supplies, sleep transistors, and optical wake-up radios as potential low-level circuits that can help future devices. Simply developing low power solutions is not sufficient, however, they need to actually be incorporated into devices. This may require new systems and architectures that can effectively leverage the circuits, or new development strategies that simplify incorporating lower-power components into existing devices.

B. Wake-up receiver

A common feature of IoT devices is that most devices wait for a wireless event before executing. Thus, devices maintain a network connection to wait for control instructions. The energy consumption of radios is a large portion of the total energy

due to the need for frequent network synchronization [53]. To reduce the radio standby power, ultra-low-power wake-up receivers listen for a predetermined wake-up packet before waking up a higher-power radio [52], [68], [69]. Figure 9(a) illustrates a wake-up receiver integrated into the common IoT architecture. Current research on wake-up receivers attempts to balance the trade-off between high sensitivity and data rate for low-power operations, and help reduce the standby power of non-active radios to sub-50 uW level, which is 100X less than conventional WiFi radios [23], [33], [66]. For a LIFX bulb, replacing the WiFi radio with a 45 uW wake-up radio [23] would reduce the standby power by 35%, from 480 mW to 310 mW. To fully leverage the benefit of wake-up receivers, all smart home devices could add them into their system, enabling a single gateway to control multiple devices from different manufacturers and reducing the standby energy of multiple gateways. A software communication protocol taking advantage of the wake-up on radio functionality is also required to embed in commercial gateways to effectively use the wake-up receivers.

C. Mask device heterogeneity

One possible solution to remove the need for redundant gateways is to enable a single gateway to support multiple communication protocols, and hence multiple devices. Gateway software can mask the heterogeneity between devices to create a unified resource description that can be shared among IoT applications and devices, as shown in Figure 9(b). Multiple systems take this approach [27], [28], [41], [56]. These facilitate the communication between previously incompatible IoT devices, creating a device network and consolidating the gateways, but require gateways with multi-radio capabilities. For a household with five hubs, using this technology could reduce the standby power of gateways by 70%, plus the savings in hardware cost. Despite these benefits, heterogeneity masking approaches have gathered little traction, and future work is needed to make these approaches usable for real systems.

D. Cross-technology communications

Cross-Technology Communication (CTC) helps break the barrier between communication standards and can also help reduce redundant gateways as shown in Figure 9(c). IoT devices use different wireless standards, commonly, WiFi [21], IEEE 802.15.4 [22], and Bluetooth [32], and although they can use the same spectrum, these standards are incompatible and typically require different hardware radios. CTC resolves this by enabling different radios to talk directly. For example, FreeBee enables connections between WiFi and Zigbee, Bluetooth and WiFi, and Bluetooth and Zigbee [37]. Esense [30] and WEBee [44] enable a connection between WiFi and Zigbee. Xbee uses cross-decoding to connect Zigbee to BLE [35]. These approaches can enable existing single-radio gateways to provide connectivity to a range of devices, eliminating the need for redundant gateways. However, CTC has not been shown as a general purpose communication technique for arbitrary workloads, and further improvements are needed to enable a single generic gateway.

E. Context-aware device network

Reducing the overall standby power draw by controlling devices as a network is an effective approach [63]. Within a network, standby energy on individual devices can be saved by turning off the device when all the correlated devices are off. However, identifying and logically grouping devices to a network is still a challenge. One possible direction is a context-aware device network, where device relationships are identified based on human tasks. CASPRE [45], an approach that groups appliances with respect to task execution, and Energy-Prone Contexts [67], an approach that groups actions to individual devices, both help auto-discover device networks. Alternatively, frameworks like IFTTT [2], Google Home Routines [17], and Smart Things [1] provide a new chance to discover network of devices, as programming tasks and events consisting of multiple devices inherently exposes relationships between devices. These user-provided device groups can then likely be used to improve control algorithms that help manage standby energy use in home settings. However, these algorithms also need to consider how to effectively control smart devices which are not exclusively used only when a user is present.

F. Cloud computing alternatives

The IoT has largely increased the amount of data generated by individuals, with estimates indicating an average person and smart home generate 1.5 GB and 50 GB of data, respectively, each day [61]. This increased data results in an increase in energy to collect, store, process, and report the data. New techniques for the cloud, and at the edge, are needed to mitigate this.

One direction is serverless computing, which dynamically matches applications to machine resources on the cloud. This mechanism enables efficient scaling for varying workloads, while reducing the overall energy cost. As an example, Barcelo et al. propose a comprehensive IoT-cloud service optimization framework and demonstrate an 80% power reduction for certain applications [25].

Another direction is offloading some tasks to execute on edge resources near the IoT devices. Tasks that do not require large data processing and storage could save the energy costs of transmitting to the cloud, and instead run on energy-efficient edge computers. However, a low density of devices, or algorithms suited for a large number of data streams, may cause edge computing to be more energy intensive than the cloud approach. Considering energy as an optimization parameter for edge computing may be necessary. For example, Zhang et al. present an energy-efficient computation offloading mechanism, and demonstrate energy reduction on various applications [71].

Many IoT user interfaces require a cloud backend to handle control operations. For example, a user may change a thermostat setting using a phone app, but the app communicates with a cloud backend and the backend sends a message to the thermostat. This incurs both transmission and datacenter energy

costs, but has proven to be more reliable and simpler to implement. If, instead, the user interface can be provided by local gateways or devices themselves, the energy cost would be reduced. New tools, frameworks, and protocols are needed to aid creating local user interfaces for IoT systems.

V. Preliminary Improvements

In this section, we demonstrate the feasibility of achieving standby energy reduction by applying some emerging technologies. The first approach reduces standby power by intelligently disconnecting a device from power. We target a sophisticated device with multiple power modes and where fully disconnecting it from power (as with a smart plug) can result in significant disruption for users as well as reliability issues for the device itself. Often, sophisticated loads remain in a high-power standby state before going into the off state to ensure the device is ready for further interactions and to provide a better user experience. Our proposed prototype leverages a single gateway to communicate with multiple devices from different vendor silos to quickly and safely completely shut the device off once a user is finished with it. This reduces the time unnecessarily spent in standby mode to enable significant standby energy savings.

The second implementation reduces standby power by keeping a device completely disconnected from power when it is not in use. This successfully reduces standby power, but can lead to long startup times once a user does want to use the device. To alleviate this, we predict the future usage times, and turn on the device in advance of the user needing it to balance energy saving with user satisfaction. To demonstrate the importance of understanding device relationships, we design and develop a load forecasting algorithm that only uses each device's usage history, and then augment that approach with usage data of the associated devices. Compared with traditional load forecasting approaches that do not consider device correlations [38], [46], our proposed method discovers device association rules from smart meter data. For example, users tend to perform routine activities such as "prepare food using the microwave, then clean dishes using the dishwasher", and thus devices like microwave and dishwasher are usually used together. This association can be learned through power readings. Detecting these association rules can achieve a better accuracy on load forecasting for home appliances, and thus can achieve a higher energy saving without sacrificing user comfort.

A. Smart Shutdown

In our first experiment, we use the Sony PlayStation 4 (PS4) [4] as our testbed as it has a power saving method to automatically switch to rest mode or turn off after 20 minutes. Figure 10 shows our prototype setup. To monitor and interact with PS4, we use a smart plug to measure power draw for status monitoring, and attach a development board to stimulate exterior control button press. We use a unified resource description architecture [56] between the gateway, smart plug, and the board to enable end-to-end control.

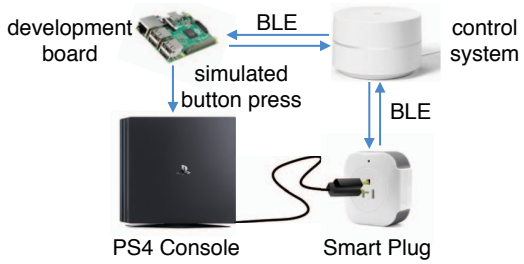


Fig. 10: Overview of the system. The control system interfaces with both the device and smart plug to optimize standby energy savings.

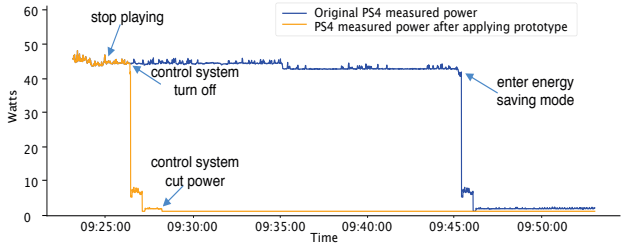


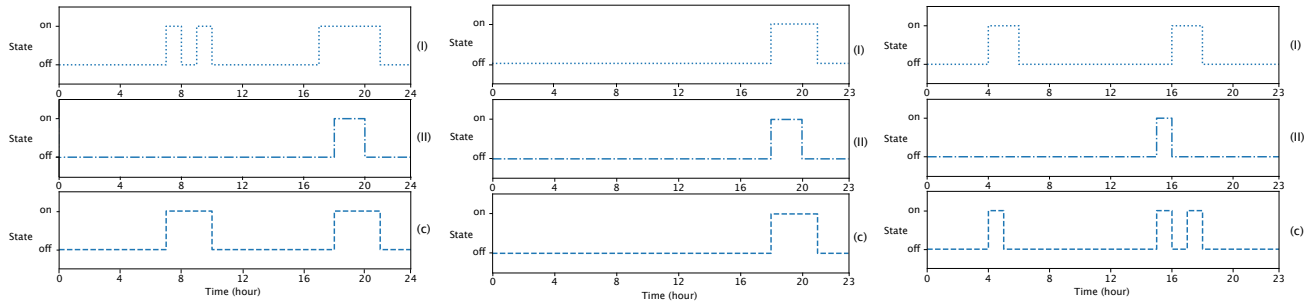
Fig. 11: Comparison of energy consumption of PlayStation 4 with and without external control. The energy consumed after a user finished playing is reduced by 14 Wh.

The system controls the device based on device status recognition. When a user finishes playing and the home screen appears, the profiling algorithm recognizes the state change and waits for 60 s before instructing the development board to simulate a long button press to turn off the PS4. After the system recognizes that the PS4 is in the off state, it sends a command to the smart plug to cut off the power supply. This ensures the PS4 is safely switched off.

To evaluate the performance of our hardware prototype, we measure the power draw of both a traditional HEMS and our proposed prototype, by having the same user play same game and simply leave the PS4 in home screen when finished. Figure 11 shows the power draw of the two comparison experiments. The PS4 draws 42 W while on the home screen, 6 W in rest mode, and 0.8 W when turned off. Since the system runs on existing gateways, the only hardware that is added is the smart socket which draws 0.4 W. The traditional method can only cut the power supply when PS4 is in rest mode or off. In our prototype, standby energy is reduced by 14 Wh just in turning off period, which is close to the energy savings by using the traditional system for an entire day. This result shows the potential in standby energy reduction by applying emerging technologies to smart devices.

B. Device Association and Load Forecasting

In our second experiment we explore the effect that usage relationships between devices can have on usage prediction and standby energy reduction. Our approach for identifying device associations uses the Apriori algorithm [24], a widely used algorithm in data mining for finding frequent itemsets and relevant association rules. To identify device relationships, we



(a) Prediction of oven on Wednesday (b) Prediction of oven on Sunday (c) Prediction of microwave on Wednesday

Fig. 12: Examples of the prediction result of an oven and microwave on different days. The top row shows the prediction with device associations, the middle row shows the prediction without, and the bottom row shows the actual usage. The results demonstrate the model using device associations can outperform the model without associations.

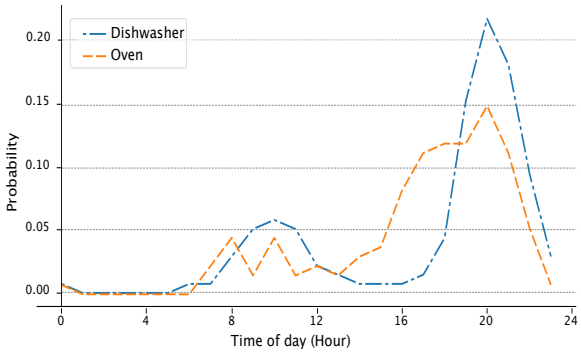


Fig. 13: Example of a daily usage distribution pattern of a dishwasher and oven on Saturday. The pattern indicates that dishwasher and oven tend to be used together.

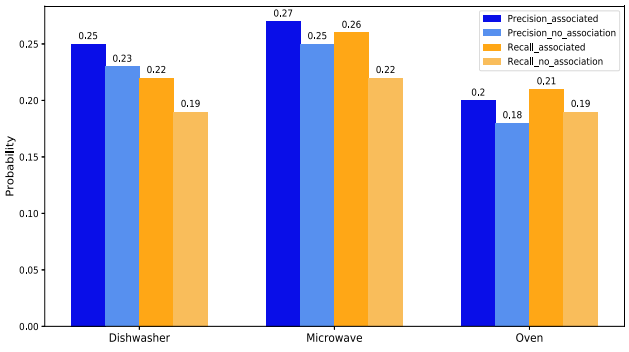


Fig. 14: Precision and recall for three associated devices. Although the basic LSTM model shows limited accuracy, it does demonstrates that adding device associations leads to better performance.

Antecedent		Consequent	Confidence
Dishwasher	→	Oven	0.438
Oven	→	Dishwasher	0.444
Dishwasher, Clothes Washer	→	Microwave	0.50
Dishwasher, Kitchen App	→	Oven	0.56
Clothes Washer, Kitchen App	→	Microwave	0.524

TABLE IV: Device association rules extracted from individual power traces. The result indicates that certain relationships exist between home appliances. These relationships create new opportunities for home energy management.

select 184 days of power data from six devices in the Dataport dataset house 1464 [5], including light plugs, dishwasher, oven, microwave, clothes washer, and a kitchen socket, and convert their power trace to on/off states with timestamps. The Apriori algorithm uses the generated states to generate frequent itemsets. Two key values are required to calculate the associations: support and confidence. Due to the fact that devices being considered are sparsely used, the support is set to be 0.002 and the confidence threshold is set to 0.4. The association rules we discovered using this approach are shown in Table IV. From the result, we identified that the dishwasher and oven are highly likely to be used together and the usage pattern is shown in Figure 13. Additionally, a user who uses the dishwasher and the small kitchen appliance is likely to use the oven as well, and a user who uses the dishwasher and the clothes washer tends to also use the microwave.

We also prototype a control system to show how the device associations can be leveraged. The control system attempts to use an appliance's previous power trace to predict when it will be used in the future so that it can be switched off in unused times yet switched back on before a user needs it. This prediction is challenging for appliances which are used infrequently because of the sparsity of activations in the data. Device association, then, can assist with load forecasting by providing additional contextual information. To demonstrate this, we design a load forecasting method based on LSTM algorithm. Instead of forecasting load usage from a single power trace, we use power traces from associated devices and the testing device itself. Based on the assumption that each device's hourly usage is associated with the day of the week, we build appliance hourly usage profiles π, where $\pi_{d,h}^{a_n}$

($\sum_h \pi_{d,h}^{a_n} = 1$) denotes the probability that device a_n is used during the hth hour of day d. Thus, appliance usage state $z_{d,h}^{a_n}$ follows the multinomial distribution $M(z_{d,h}^{a_n}|\pi)$. The LSTM predicts the number of times a device is used on the eighth day given seven day power traces of the device and its associated devices. Once we know the usage times of a device t, we can predict its hourly on/off states by sampling t times from the multinomial distribution.

For some situations, when a device is not used for more than 7 days, the system would predict no hour of operation for the following future day if the associated devices are not in operation as well. However, because the prediction system is based on the device and its associated devices, we recognize that there is a limitation that may result in loss of performance on predicting usage of the device if associated devices behave abnormally or fail entirely.

An example of the result of our proposed model is shown in Figure 12, where we forecast the usage of the dishwasher on Wednesday and Sunday, and the microwave on Wednesday. On Wednesday, the non-associated model predicts the oven will be used once between hours 18-20. The associated model predicts the oven will be used three times, during hours 7-8, 9-10, and 17-21. The actual usage is from hours 7-10 and 18-21. The associated model mispredicts at hour 8-9 while non-associated model mispredicts at hour 7-10. Prediction of the oven on Sunday and microwave on Wednesday also shows more accurate prediction with the associated model on both usage times and operation hours. Figure 14 shows the comparison of overall performance of the LSTM model under two conditions. These results demonstrate that the model using device associations outperform the model without using associations.

VI. Conclusions

The progress towards IoT has dramatically expanded the capabilities of common and ubiquitous devices and appliances. This is creating a new standby energy problem, however, as smart devices draw a certain amount of standby power even when they are off. Through a data-driven study, we analyze today's smart devices to understand the scope of the issue, and diagnose several causes of why smart devices are exhibiting worse phantom power over time. We find that commercial smart devices are lagging behind best practices from the low power wireless system research community, and that home-level energy management systems need to fully consider smart devices and not just traditional loads. Building on these observations we present several avenues for future improvement, with links to promising technologies across the system stack. To make this more concrete, we also demonstrates two preliminary approaches that are tuned for today's smart devices.

This study and analysis highlights the emerging challenge that new Internet of Things devices present when trying to manage energy consumption in buildings. We hope the related research community embraces this challenge, and works towards an energy-efficient IoT future.

VII. Acknowledgement

We wish to thank our shepherd, Rajesh Balan, and the anonymous reviewers for their detailed comments and feedback. This work was supported by the Department of Energy (DOE) under grant DE-EE0008225.

Appendix

A. Power measurement of all tested devices

Table V shows the complete set of our measured devices.

Device Name	Off Mode (W)	Standby Mode (W)
Google Home Max	4.72	4.72
Amazon Echo Show	0.17	7.36
SmartThings Hub	1.35	1.52
Philips Hue Hub	1.63	1.63
Sengled Hub	1.12	1.12
Lutron Hub	1.13	1.13
Amazon Fire TV 4K	2.62	2.62
Google Chromecast	1.69	1.69
Sony PlayStation 4	0.17	6.31
Xbox One S 1 TB	0.28	24.50
Geeni Smart Socket	0.25	0.25
Edimax Smart Socket	1.43	1.43
Geenie Smart Socket	0.25	0.25
Witenergy Smart Socket	0.16	0.16
Wit Smart Socket	0.16	0.16
Apple 60W Laptop Charger	0.01	0.92
Mophie 7.5W Wireless Charger	0.12	0.12
Samsung 9W Wireless Charger	0.24	0.24
Belkin 10W Wireless Charger	0.52	0.52
Philips Hue Bulb	0.40	0.40
Lifx Bulb	0.48	0.48
Sengled Bulb	0.43	0.43
Keurig K40 Coffee Maker	3.26	4.12
Gourmia GCMW4750 Coffee Maker	0.95	0.95
Sony X800E Smart TV	0.42	23.80
Bose Wave SoundTouch Speaker	3.48	6.92
Amazon Cloud Camera	1.84	1.84
Nest Hello Wireless Doorbell	1.88	1.88
Awair 2nd Edition Air Quality Sensor	1.17	1.17
Dell E2216H Monitor	0.11	17.8
Epson Pro G7400U Projector	1.24	1.24
Google AC1200 Wifi Router	3.32	3.32
Frigidaire 8000BTU Portable AC	0.58	0.58

TABLE V: Power measurements of all tested devices

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