State Based Approximation of Behavior Contribution to Energy Usage

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Abstract Understanding how behavior affects consumer plug load device energy usage provides improved guidance on the development of testing standards, voluntary agreements, and incentive programs. In this study the authors demonstrated an approach for developing and analyzing device use profiles for common residential devices, to determine the range of energy usage bounds in plausible real-world usage scenarios and the relative impact of usage types. Three aspects of how devices are used were taken into consideration: the total amount of active use per day, the pattern of that use over the course of the day (e.g., how many periods of use), and power management settings and behaviors. For each aspect, at least three levels were specified (low, moderate, high). The bounds of each category were justified based on observed or reported device usage and the features of the specific device. Device use profiles were constructed using all possible combinations of the levels of the three aspects such that the impact of each aspect was evaluated while the other aspects were held constant in simulated operation. For each device, power consumption measurements were taken for each steady-state and transitional state observed in normal usage, and operational state chains were determined. A simulation tool, the Plug Load Simulator Suite 1.2 (PLSim), was developed for inputting device-state test results and modeling energy consumption across device use profiles. Multivariate regression models were used to identify the proportion of variance in energy consumption across profiles that was explained by each of the three behavior aspects. One device—the satellite set-top box—showed almost no variation across profiles: energy consumption was not responsive to either the amount of active use or to power management settings. Power management was a significant factor predicting energy consumption for all ten remaining devices. Devices varied in the effects of the active use and pattern of use aspects. Four patterns are exhibited:

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P. Bertoldi (ed.), *Energy Efficiency in Domestic Appliances and Lighting*, Springer Proceedings in Energy, https://doi.org/10.1007/978-3-030-79124-7_22

(1) strong impacts of both active use and power management aspects, with active almost as high as power management (4K and HD televisions); (2) significant impact of the active use aspect but much lower than the impact for power management (streaming device, video game console, desktop computer, and laptop computer); (3) significant impact for power management only (sound bar and both pod coffee makers); and (4) significant impact of pattern of use that exceeds that of power management (rice cooker). Assessments of the implications for each device class, and extensions for other similar devices, are discussed at length in the report; overall conclusions are summarized here. This approach provides an objective means to classify the impact of aspects of device usage between users and across devices within a specific category and shows promise for future evaluations.

1 Introduction

Utility companies have become increasingly more interested in understanding the real-world energy usage of devices in homes in their efforts toward a more sustainable grid. A particularly difficult area of this investigation is varying behavioral energy usages of miscellaneous electric loads (MEL) and plug/process loads (henceforth collectively referred to as plug loads). While many households contain the same plug load devices, there is a large range of usages from the standard usage estimates of how these devices are being used in the home which leads to the question of how to prepare the grid for these highly variable loads. With the total number of consumer electronics devices expected to rise in each household [1, 2], finding strategies to manage energy consumption from plug loads in current and new categories of devices has become very important.

Standard energy testing, reporting, and modeling protocols provide manufacturers, regulatory authorities, and consumers a way to evaluate energy use and to compare energy efficiency options. However, the single point evaluation tests on individual devices are not able to capture how these devices are used in real-life situations, when they are often connected to other related devices as a part of a network, and subject to various users' behavior. These issues lead to a significant roadblock when trying to assess the true saving potential of emerging technologies or to effectively communicate results to utilities and consumers [3].

Plug loads in general continue to be a growing source of residential and commercial total building loads in part also due to efficiency gains for space heating, water heating and lighting and due to new categories of devices and increased numbers of current device categories in use (see Fig. 1) [1, 4]. Considering macro changes, both the average living space and total numbers of devices have increased over time. Cisco estimates 13 devices per person by 2021 [5]. The average home boasts now more than 7 screens and 60% of a nationally representative sample of survey respondents use devices more than 3 h per day [6]. The 2016 EIA energy outlook to 2040 predicts miscellaneous loads (in which plug loads are included) will increase by with an adjusted average growth rate of 1.4% per year to 2040 with

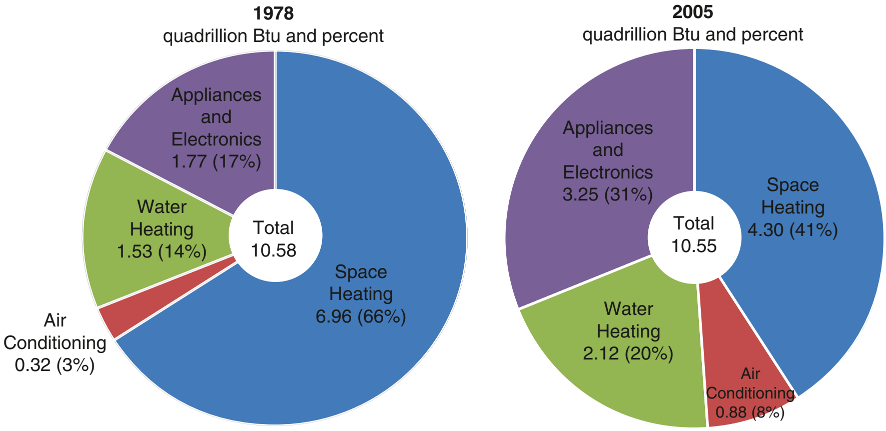

Fig. 1 The changing nature of residential energy consumption in the U.S. (Source: 1978 and 2005 Residential Energy Consumption Survey [1])

a commercial growth of 11.5% [7]. Audio systems and game consoles are major annual consumers [8], with electric grills, coffee machines acting as major active load devices [9, 10]. Considering both commercial and residential applications, plug-in devices are responsible for approximately two-third of California's residential electricity consumption, including 20% for TVs and office equipment and another 11% for miscellaneous devices [11]. It is estimated that plug-in equipment and miscellaneous loads will be responsible for 70% of electricity demand growth from 2015 to 2024 [12]. Therefore, while household plug load devices are individually low in energy demand, they collectively pose major challenges to future sustainability plans, such as California's Zero Net Energy (ZNE) initiative for all new homes set for 2020.

Assessing potential intervention strategies for both utility energy efficiency and demand response programs within multiple sub-classes of plug loads requires understanding the root cause source of waste. For analysis, by comparing variations in usage against controlled parameters, changes in energy use can be localized to specific, energy efficiency efforts can be applied in two main modes, passive and active. The next point is the boosting of the capability of power management features, this includes expanding the capability of features present or adding additional features.

2 Methods

In this study, we demonstrate a new modeling approach for estimating how energy usage can be impacted by behavior, across multiple devices and categories. This is essentially the inverse of standardized testing, in which one test protocol is applied to multiple models of the same type of device. Instead, we examine one model of each type of device, holding the device parameters constant, and vary the test parameters to reflect the range of ways it could be used in real-world conditions.

2.1 Device Selection and Testing

First, a set of residential plug loads was identified, prioritizing those where usage logically affects energy consumptions; for instance, devices that must always stay on were omitted. The 10 device types selected include: 4K (UHD) television, HD television, game console, satellite set-top box, audio sound bar, streaming device, desktop computer, laptop computer, pod coffee maker (two models), and rice cooker.

Second, each device was tested to determine all the states observed during use (including warming up, idle, and powering down periods) and the power consumption during each state. This step required a comprehensive examination of the operating conditions and mechanisms of each device, particularly as they affected the timing and stages of shifting from off or idle into active use, and from various active modalities into low-power and soft-off states. At this stage, all the power management functions were also examined and assessed for their implications for energy use. For details on the extensive testing performed in the larger project, see [13].

2.2 Device Usage Profiles

Third, device use profiles were constructed that vary on three main aspects of how the device is used in real-life situations:

1. How much the device is used per day (Active)
2. The timing or pattern of that usage (Pattern)
3. What power management settings or user behaviors affect efficient use (PM)

This approach was developed in an earlier project conducted using the SIM Home testing lab [3]. For each aspect, at least three levels are defined: usually low, moderate, and high. Whenever available, ENERGY STAR testing estimates for amount of active use were used to establish the moderate or standard level. Survey data on how devices were used in homes was analyzed to determine the reasonable range: the median was used for “moderate” active use, while the 10th percentile was considered “low” usage and the 90th percentile was considered “high” usage. See the first SIM Home report for more detail [3]. In the absence of any quantitative data, assumptions were made about realistic use cases.

For a given duration of use, the number of periods throughout the day could potentially affect energy usage. Many devices incur transition costs, such as warm up or cool down times, or experience idle periods prior to entering a sleep or standby mode. The pattern aspect reflect this, with “low” indicating that all the usage occurred in a single period, “moderate” being two periods, and “high” being more periods. For instance, 4 h of computer use may occur all in one sitting or be divided into two periods of 2 h, or even more periods of shorter duration. For devices with automatic standby settings, additional pattern levels were created to reflect varied periods between usage periods: for instance, if a device idles for an hour before transitioning to a low-power mode, whether the next use is in 30 min versus 4 h affects the amount of time spent idling.

The power management aspect affects what state the device is in when it is not being used. This involves two factors: whether automatic power management settings are enabled (and if so, at what delay setting) and whether the user turns the device off when finished or not. Here, the “moderate” level is set where the user does not act but the device is set at the factory-set automatic settings for transitioning off or to sleep mode when not used. “High” PM is where the user turns off the device regularly when it is not used and/or engages any automatic PM settings at high levels. “Low” PM is when where any automatic PM features are disabled (if possible) and the user never turns the device off. Given the great variation possible with PM behaviors, many devices were given more than three levels of PM to better reflect real-life conditions.

A set of device use profiles was created for each device by combining all levels of all three aspects. The profiles are represented in the form “active-pattern-PM,” so low-high-mod means Active-low, Pattern-high, PM-mod. A device that has three levels for each aspect which are all compatible would thus have 27 device use profiles, ranging from low-low-low to high-high-high. A device with multiple levels of any aspect would have more profiles. Some levels of active and pattern cannot be logically combined, resulting in fewer profiles. For instance, 13 h of television watching (Active-high) could not be divided into four periods with 5 h between (Pattern-high1) and still be contained within the 24 h period. Other combinations were not plausible: for instance, a half hour of television watching (Active-low) would not reasonably be broken up into four periods over the course of the day (Pattern-high1 and high2).

For each device, a “standard profile” was determined which matched the ENERGY STAR or other standardized testing protocol or, in the absence of such, approximated a standardized protocol. The standard profile represented Active-mod (the median amount of active use), Pattern-low (usage all in one period), and PM-mod (factory PM settings, no user intervention).

A full description of the device usage profiles used for all devices can be found in the second SIM Home report [13].

2.3 Energy Use Modeling

The Plug Load Simulator Suite 1.2 (PLSim)[1] is an open-source simulation tool that was developed in support of this project. PLSim is used to rapidly tabulate energy usage based on device states as modeled through the profiles. Device testing was used to verify state and general usage along with total energy consumption. The state model was developed and verified against the actual device using a modeled usage plan to verify the developed state mode. This tool is universal for all modeled devices and was the primary tool used in this work for energy modeling. A per-device, state-wise energy usage XML database is generated by testing device operation per aforementioned testing approaches. This database provides a list of states. A developed time-based (temporal) profile maps the time the device spends in a given period for a given action to energy usage. Daily energy usage is calculated as a temporal combination of all event states during a 24 h period (see Eq. 1). In this relationship PS_l is used to model the lowest energy usage state (assumed to be the lowest power modeled state) while Nx, Px, Tx, are used to model the average power consumption and number of periods a state exists during a 24 h period.

Calculation of daily energy usage based on generic event frequency and classification:

Shown explicitly with two terms:

$$EC = \frac{P_l\left(24-\left(\left(N_1T_1\right)+\left(N_2T_2\right)\right)\right)+\left(P_1\left(N_1T_1\right)+P_2\left(N_2T_2\right)\right)}{1000} \tag{1}$$

Where:

Variable	Value
EC	Daily energy consumption in kWh for the modeled system.
$N_{X(shown:\ 1,2)}$	Average number of events of a particular event of a given duration that occurs in a 24 h period: the value for x increments for each event.
$T_{X(shown:\ 1,2)}$	Average duration (in hours) for a particular event which occurs in the 24 h period: the value for x increments for each event.
$P_{X(shown:\ 1,2)}$	Average power consumption (in watts) for a particular event which occurs in the 24 h period: the value for x increments for each event.
P_l	Average power consumption (in watts) for the lowest power operational mode, such as soft-off, sleep mode, or standby mode.

The set of device use profiles were then programmed into the PLSim tool that CalPlug developed. Adding power consumption data from in-house testing of the device in all possible states into PLSim produces the total simulated energy consumption for each profile. For comparison, lower and upper boundaries are also

[1] See: https://github.com/CalPlug/PlugLoadSimulator

modeled, showing the energy consumption if the device remained in the lowest usage state possible or the highest usage state possible for 24 h.

2.4 Energy Use Analyses

The PLSim calculations produced estimates of total 24-h energy consumption for each device use profile for each device. These were assessed in three steps.

For each device, a graph showing the energy consumption across profiles was produced, ordered so that the overall patterns of different consumption results could be visually attributed to changes in active use, pattern, or PM. This descriptive step helped give insights into the data, and to verify and make sense of the summary results shown later. To illustrate, the graph of energy use estimates across device use profiles is shown below for the desktop computer that was tested (see Fig. 2). The first three profiles all have low active use (30 min) and low pattern (that is, all at one time), and differ only on PM. The pattern shows a very high energy consumption for profile #1, with PM-low (disabled sleep settings) and much lower for those with PM-mod or PM-high. That same pattern repeats through the rest of the graph. The energy consumption rises with the amount of active use, especially for profiles with moderate or high PM. However, the primary distinguishing pattern continues to be the much higher energy usage for profiles with PM-low versus all others. As these graphs are illustrative rather than analytical, they are presented illustratively at this point in the discussion (Sect. 3) here (see [13]).

Next, for each device, simulated energy consumption for the standard device use profile was compared those with the median, highest, and lowest energy consumption estimates, and the range. These provide quantitative assessment of how much

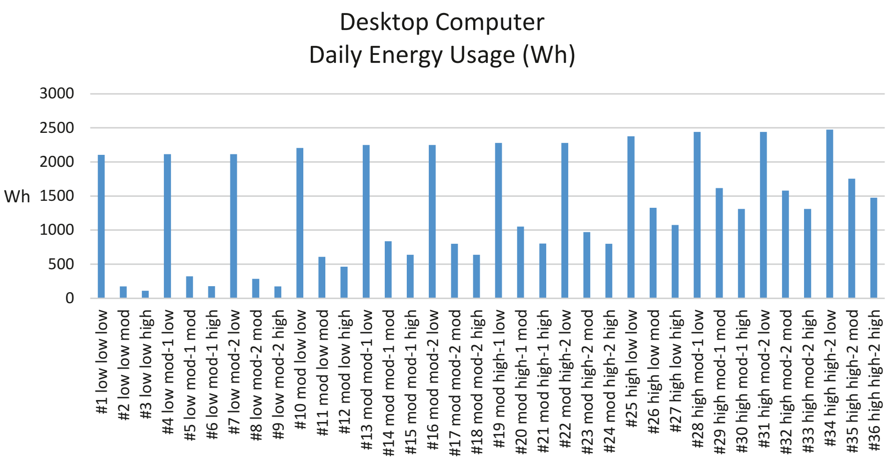

Fig. 2 Desktop computer energy usage profiles

higher or lower energy consumption could be for a particular device in at least some homes, compared to estimates based on the standard testing protocol. Although the simulated results do not allow for comparisons across real households, they do help identify potential problem areas that deserve additional scrutiny.

Finally, multivariate regression analyses were run. For each device, the number of device use profiles was the sample, the estimated energy consumption for each profile was the dependent variable, and the predictor (independent) variables were the levels of active, pattern, and PM. The standard device use profile is the default in all models. This means Active-mod is the omitted variable and the regression tests the effect of Active-low versus Active-mod, and the effect of Active-high versus Active-mod. Likewise, Pattern-low and PM-mod are the omitted variables, with the effects of the other levels of each aspect compared against them. This allows the model to show which levels of which aspect significantly differ from each other. The regression analyses also indicate how much of the variance in energy consumption is explained by the three different aspects (e.g., whether variation in power management matters more for energy consumption than amount of active use).

3 Results

3.1 Range of Energy Consumption Across Profiles, by Device

Given a reasonable range of usage behaviors, what energy consumption results would we observe in these tests? That is, if we assumed that all devices in all households were operated according to the standard device use profile, how inaccurate would our estimates be about the highest- and lowest-usage households? If the range for a device is relatively small, this suggests that standard tests would give good estimates across a range of households. However, if the device's energy consumption is high across all usage patterns, perhaps additional development of low-power states could help lower consumption during non-active periods. Alternately, if the range of energy consumption across profiles is very large, especially in terms of values much higher than the standard testing profile, this points to possible intervention points either in reducing active use consumption or in promoting more effective power management.

The ranges of energy consumption for the highest and lowest profile, compared to that of the standard profile, are presented in Fig. 3. Three general patterns are observed: devices with very small ranges; devices with low or moderate ranges, either mostly higher or mostly lower than the standard profile; and devices with large ranges that span in both directions from the standard profile but err more on the side of higher values than lower.

For instance, the standard profiles for pod coffee makers exhibit almost as high of energy consumption as for the 4K television, and higher than the HD television. However, almost all the variations in how pod coffee makers are used result in lower

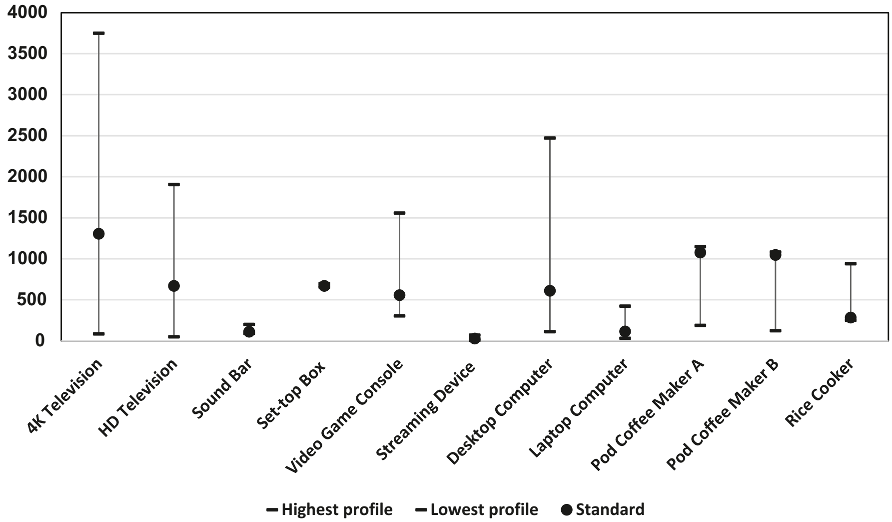

Fig. 3 Range of daily energy consumption of profiles, by device

consumption, whereas the top range for televisions is substantially higher. The rice cooker shows the opposite pattern, with other ways of using the device resulting in higher energy consumption than the standard profile. The same is true for the desktop computer, game console and set-top box: the standard profiles for these devices show similar energy consumption. For both the desktop computer and game console, variation in usage can lead to higher consumption, whereas there is almost no variation by usage for the set-top box.

The range between the minimum and maximum should be considered in the context of the median energy consumption for that device. For instance, a range of 50 Wh would be small if the device's median energy consumption was 1000 Wh but substantial if it was 100 Wh. Logically, it is possible for the maximum profile to be more than 100% higher than the standard profile (that is, use more than twice as much energy) but the difference between the standard and minimum profiles must be less than 100% than the standard profile, probably much less (as 100% lower would mean zero energy consumption for the minimum profile).

Among the entertainment devices, the two televisions show the largest energy consumption ranges, but the range for the video game console is also high, especially compared to the small ranges for the sound bar and set-top box. The streaming device shows a large range, but the energy consumption of the standard profile is so low that this is not substantively important. The television profiles' energy consumption estimates range by almost 300% of the standard device use profile: most of that represents how much higher the maximum profile is, but the minimum profiles save an impressive 93–94% energy compared to the standard profile. By contrast, the satellite set-top box shows the lowest ranges for all the device shown here. For most of these devices, the maximum estimates are more impactful on variation in energy consumption than the minimum estimates.

The desktop computer tested here uses substantially more energy in the standard device use profile than the laptop computer. However, their relative ranges are similar. The minimum profiles for both computers save a similar proportion of energy relative to the standard profiles, but the desktop's maximum profile uses proportionally more than that of the laptop.

The two pod coffee makers have very similar results. For both, the range is about 90% of the standard profile's energy consumption, and almost all of that is due to the minimum usage profile being substantially lower than the standard profile. Note that pod coffee makers have power management features available but are shipped with those settings disabled, so the moderate PM level has no low-power mode, and all PM levels are more energy saving than the standard profile.

By contrast, the rice cooker shows a very large range of energy consumption, with the maximum being much higher than the standard profile.

3.2 Effects of Usage Aspects

The team used regression models to evaluate what proportion of the variation in modeled energy consumption across device use profiles can be attributed to the three aspects tested here, given the specific definitions of each aspect used. Particularly for devices with a large range of estimated values, is the deviation from the standard default device use profile largely due to differences in the amount of active use, in the timing or pattern of that use, or in the power management settings or behaviors?

For each device, four models were run: one for each aspect alone and one full model including predictor variables for all three aspects. The sample for each model is the set of device use profiles for that device, and the dependent variable is the energy consumption calculated for each profile. Each regression model produces an R^2 statistic indicating the proportion of the variance in the dependent variable explained by the parameters in that specific model. For example, if the R^2 statistic for the Active Model were 0.50, that would indicate that 50% of the variance in energy consumption across the device use profiles was due to whether they had high, moderate, or low active use.

The results of the regression models are summarized in Fig. 4. The asterisks indicate which models were statistically significant. These results reveal major differences in the relative importance of active use, pattern, and power management for energy consumption across these devices.

These effects should also be considered within the context of how much energy consumption varied across profiles for that device. For example, for the set-top box, power management explains 72% of the variance in energy consumption. However, compared to the standard profile for the set-top box, energy consumption only ranges from 2% lower to 4% higher across other profiles (see Table 1), so there is

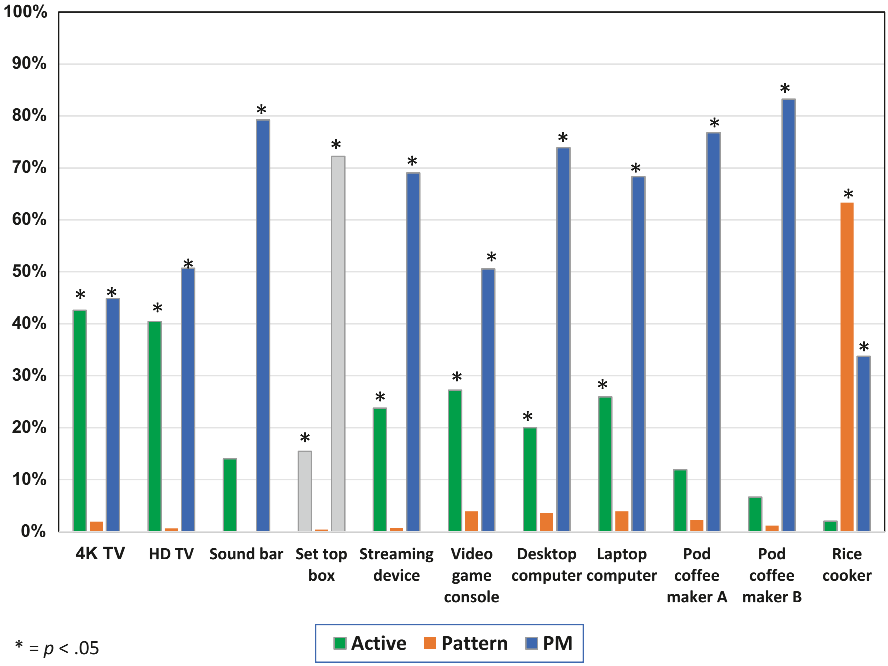

Fig. 4 Proportion of variance in energy consumption explained by each aspect

essentially no variance to explain. For that reason, the set-top box is not discussed here. For the sound bar and the streaming device, the variation is higher as a percentage of the fairly low standard energy consumption although the range still represents a small increase or decrease in energy consumption.

4 Discussion

The impact of behavior on energy use is a major consideration to produce accurate evaluation of device energy consumption for both modeling and mitigation efforts. In this project, the authors evaluated the effects on energy consumption of three aspects of user behavior toward devices: the amount of active use, the pattern of that use, and power management. This method was applied to common residential plug load devices. Using carefully defined device use profiles, comparisons across profiles were used to identify the impact of each aspect, to prioritize and focus efforts to address improving energy usage in specific devices. Future testing and evaluation methods could expand upon this method to continue to refine procedures to match devices as they evolve, considering behavior and usage. The analyses in this report address two main questions. The first question is how large a range of energy consumption outcomes the device use profiles generate for each device, based on

Table 1 Summary of ranges and differences from standard profile

	Std (Wh)	Median (Wh)	Min (Wh)	Min % from Std	Max (Wh)	Max % from Std	Range (Wh)	Range % of Std
4K Television	1305.1	1981.5	82.4	94	3746.7	187	3664.3	281
HD Television	667.4	743.3	48.5	93	1903.2	185	1854.7	278
Sound Bar	111.7	148.1	90.4	19	198.0	77	107.6	96
Set-top Box	669.9	684.6	654.1	2	699.7	4	45.7	7
Streaming Device	28.1	35.4	6.9	76	68.9	145	62.0	220
Video Game Console	556.9	644.2	303.5	46	1557.8	180	1254.3	225
Desktop Computer	609.5	1310.3	110.0	82	2472.5	306	2362.5	388
Laptop Computer	112.3	243.1	28.9	74	423.3	277	394.4	351
Pod Coffee Maker A	1076.9	639.9	189.0	82	1147.6	7	958.6	89
Pod Coffee Maker B	1046.4	535.7	123.3	88	1081.4	3	958.1	92
Rice Cooker	282.2	529.4	249.0	12	937.9	232	688.9	244

reasonable assumptions about the range of real-life usage. A follow-up to this question is whether the range is primarily higher or lower than the standard profile produced by standardized testing protocols. If the range is fairly small or if it is evenly distributed, standardized tests are more likely to produce accurate estimates of real-life outcomes if averaged over a large number of households. However, if the range is very small, this raises a new concern: that the energy use of the device is not responding to the amount of time the device is actively being used and that any power management features are ineffective at saving energy.

The second question is how much of the variation in that range of energy consumption outcomes across profiles is explained by differences in active use, versus by differences in pattern of use or differences in power management behaviors. Energy consumption is expected to vary by active use: if that is the main driver of energy use, then energy-saving strategies would logically focus on reducing the operational costs of active use for that device. If engaging power management options fails to save energy, that suggests those options are ineffective. However, if much of the variation attributable to power management behaviors results in higher energy usage, that suggests that power management options may not be effectively engaged by users, which prompts additional research and development into modes and user interfaces that will work in everyday usage. Although the device usage profiles are based on observed or self-reported behaviors as much as possible, several assumptions had to be made when defining the levels of each aspect. Thus, any conclusions are limited by the extent to which the assumptions about average and also extreme behaviors (that is, behaviors at the 10th and 90th percentile) are accepted as reasonable.

The answers to both of these questions differed greatly across the plug load devices tested here. For that reason the discussion below focuses on specific devices, with the ordering adjusted to help compare similar device results.

5 Specific Devices

5.1 Televisions

The 4K television tested here uses almost twice as much energy in its standard profile than the HD television (1305 Wh versus 667 Wh). However, the pattern of results for the two devices are otherwise similar. Both televisions produce a large range of energy consumption estimates across the profiles (3664 Wh or 281% of standard for 4K and 1855 Wh or 278% of standard for HD). In both cases, the upper range is twice as large as the lower range. For instance, for the 4K television, the lowest-use profile is only 82 Wh (lower by 94% of the standard profile) while the highest-use profile is 3747 Wh (higher by 187% of the standard use profile). This suggests that, to the extent that these device use profiles reflect real-life behavior patterns, estimates based on standard usage would underestimate total usage across households.

The high energy consumption for the standard profiles for these devices, especially for the 4K television, and the very high range in energy consumptions shown by the profiles (especially, higher than the standard profile), motivates a close look at the relative impact of the three device use aspects. The two televisions show a pattern not seen in other devices, in which the active use aspect is almost as strong of a predictor of variation in energy consumption as the power management aspect.

The pattern aspect does not significantly impact energy consumption for televisions, which makes sense, given the lack of a substantial boot-up period.

As active use and power management are both important contributors to energy use for televisions, they provide avenues for potential energy savings. Reducing energy consumption during active use is already a main consideration in energy efficiency regulations aimed toward manufacturers. These results could encourage stricter regulations for devices such as televisions. Options that adjust the screen brightness can potentially save energy during active use, although not enough is known about how these features are used (or misused) in real households, and whether this behavior negates any possible savings.

On the other hand, improving power management options and their use could potentially save as much energy with less extensive modifications to the devices themselves. Both of these televisions have very low-power standby modes; the challenge is to transition the device into standby mode whenever feasible. Both televisions have a feature that transitions the device to sleep after a delay period with no signal from the connected source. The feature for the 4K television has three delay settings from 15 min (default) to 60 min, while the HD television has only one delay setting, 10 min. This feature can potentially save substantial energy, but only in specific circumstances: when the television is receiving content from an external device (rather than through apps in a smart TV), and when the user either turns that device off when done or has that device set to sleep after a short period of inactivity. Otherwise, the sleep transition due to lack of signal will not activate.

The 4K television also has an auto-off feature that transitions to sleep mode in the absence of user input (i.e., through the remote control), but the lowest possible delay period is 4 h, which is the default setting. The HD television has no such auto-off feature. One relatively simple improvement would be providing such a feature in all televisions, and offering shorter delay period options, as short as 1 h, and making a 2-h delay the default setting. Informative user interfaces are essential for encouraging users to enable (or not disable) PM settings and to understand how to use them effectively, such as motivating explanations on the PM setting screen, and a signal that warns users of an impending sleep transition, so that they can easily avoid it by pressing a key on their remote control.

5.2 *Video Game Console*

The video game console tested here showed results closest to that of the HD television in terms of its standard profile energy consumption (557 Wh) and its range of consumption across profiles (225%). However, the total range was not as large as for the HD television (1254 Wh versus 1855 Wh). Compared to televisions, the lower range for the video game console is smaller (lower by 46% of the standard profile) while the upper range is almost as large (higher by 180% of the standard profile). In other words, the video game console uses less energy than the HD television (and much less than the 4K television), but a larger proportion of its estimated use is higher than the standard profile compared to lower than it.

Like several of the other devices, the video game console showed a large impact of power management on variation in energy consumption across devices, and a smaller but significant impact of active use. The difference between the two is less pronounced compared to most other devices (that is, a relatively larger impact of active), making the video game console more similar to the televisions in this respect. As such, the results support a similar approach to that described above for televisions, focusing on reducing consumption during active use and improving power management.

The video game console tested here has a standby state (called "rest") which uses 10.7 W compared to active game play at 69.5 W and a main system menu page which uses almost as much energy, at 63.7 W. When the user stops playing, the system automatically switches to the main system menu page and stays there until the user turns off the device or the automatic standby delay is activated. The standby delay period can be set from a minimum of 20 min to a maximum of 5 h. As with any other device, effective user interface instructions may help motivate users to enable the standby option and use a shorter delay setting. Users may be especially reluctant to turn off gaming devices or let them sleep because of fears that their game progress will be lost, even if this concern is unfounded; added security and reassuring communication may be helpful here. Another point to raise is that the main system menu page, if not interacted with, is functioning similarly to a standby mode, and yet consumes almost the same power as actively gaming and continues to do so no matter how long the device goes unused. This suggests that exploring a "deep idle" mode, similar to that for computers, could save additional energy by pausing certain processes after some shorter period of inactivity.

5.3 Set-Top Box

The set-top box provided a unique pattern of all the devices tested here, in that the energy usage of the standard profile (678 Wh) was higher than many others, while the range of energy use estimates across profiles was negligible. The total range across profiles is only 45.7 Wh, or 4% above standard and 2% below standard. In fact, this mirrors the maximum boundary conditions range for this device, which consumes 699.7 Wh at the highest possible use state (active video) for 24 h versus 654.0 Wh at the lowest possible use state (standby). This quantifies the extent to which the energy use for this device is not responsive to any variation in behavior: the device uses essentially the same energy while idle as while active. Indeed, the minimum and maximum device use profile results were the same as the minimum and maximum boundary conditions—that is, the least the device could possibly use (if on standby all day) and the most it could use (if actively used all day). This reflects the fact that set-top boxes must maintain continuous connections for program and encryption services; thus, even in its lowest-power standby mode, it uses substantial power. As a result, users are limited in how much they can affect energy savings on this device.

Given the lack of variation in energy consumption across profiles, the multivariate analyses explaining which use aspect caused that variation is moot. A closer examination of the operations of this device shows that the power management features of this device are completely ineffective, due to the high power usage of the idle and standby states relative to the active state. The device uses 27.25 W while in standby mode compared to 29.16 W while being actively used. The only power management option is a delay time of 4 h; this leaves the device in idle mode, which uses the same power as the active use. Ideally, shorter delay times would also be available and used as the default, but without an effective lower-power mode to transition into, this is of secondary concern.

If it is not possible to reduce relative power consumption during standby because too many of the same functions must operate even when the device is not in use, then the only avenue for saving energy with this device is to reduce consumption during the active use mode.

5.4 Streaming Device

The streaming device uses the lowest energy for its standard profile of all the devices tested here, and shows one of the narrowest absolute range of energy consumption estimates, at 62.04 Wh between the lowest and highest device use profiles. This is only somewhat larger than the range for the set-top box (at 45.7 Wh). Because the streaming device has such low standard energy consumption, the proportional range is moderate compared to the other devices (76% lower and 145% higher than the standard profile). That said, relative to other devices tested here, there is not a substantial absolute amount of energy variation to explain, or to save.

The streaming device benefits from having an aggressive power management as a default setting, with an elaborate and engaging screensaver. The applications that run on this streaming device do not appear to contribute substantially to sleep blocking for idle states (device sitting at a paused video or menu). However the device will continue to play active video wastefully even if not being viewed, which suggests one possible avenue of saving energy.

5.5 Sound Bar

When presented in comparison to other devices, the sound bar most closely resembles the streaming device, in that the standard profile energy use is low compared to most others tested here (112 Wh), and the range between the lowest and highest device use profiles is relatively narrow (108 Wh, or 96% around the standard profile). However, the absolute range of energy consumption is over twice as large as that for the streaming device, indicating more potential room for substantive energy savings.

The sound bar is one of the three devices where the majority of variation in energy consumption across profiles is explained by power management, and neither active use nor pattern are significant factors. Indeed, if all profiles using PM-low were removed, the maximum profile usage would drop by 48 Wh, cutting the range by almost half. This illustrates the importance of doing more research on how these devices are used in actual households, to help establish which assumptions are reasonable for high and low behavioral usage.

5.6 Desktop and Laptop Computers

Desktop and laptop computers show a similar range of energy consumption estimates (388% around the standard profile for the desktop and 351% for the laptop) and the pattern is similar as well, in that the upper range is much larger than the lower range. However, as the desktop computer uses so much more energy in its standard profile than the laptop computer (609.5 Wh versus 112.3 Wh), the absolute range for the desktop is much larger, and the substantive effects of the higher-use profiles are even greater. Put another way, the highest-use profile for the desktop uses 1862.9 Wh more than the standard profile (306% more) whereas the highest-use profile for the laptop uses 311.0 Wh more than the standard profile (277% more). In terms of how much the standard profile potentially underestimates real-life usage, the desktop is second only to the 4K television. Depending on how many households exhibit higher-use profile behaviors compared to those who exhibit lower-use profile behaviors, average estimates assuming the standard use profile could be off by enough to negate variation in any other household plug load device.

Like the video game console, streaming device, and set-top box, active use and power management aspects are significant contributors for desktops, but power management has a much greater impact. Pattern of use shows more impact for computers than for other devices covered so far, but not enough to achieve significance. In theory, pattern should make a difference for computers in that they automatically transition to a "long idle" state after being in a "short idle" state for 10 min, although the difference in power consumption is not large and may be overshadowed by other factors. Pattern may also interact with sleep settings in ways that are not represented by the average state use estimates utilized here, and which are beyond the scope of this report to explore.

Power management options and low-power states are well-developed in both desktops and laptops. As the PLSim results confirm, enabling sleep settings is a highly effective way to reduce energy consumption in computers, especially during long periods of user inactivity (such as overnight or during work hours for residential computers). The challenge not currently addressed by regulations or voluntary agreements is how to get more users to enable (or not disable) their computer sleep settings. As there are valid reasons why some users would need to prevent their computers from entering a low-power mode, either permanently or occasionally, it would be infeasible to remove the option of disabling sleep settings and make them involuntary. Instead, efforts to reduce energy in computers would be more fruitfully turned toward research into how users behave toward computer power management. Specific tasks include designing more effective and convincing user interfaces, and understanding and addressing the barriers that lead to users disabling or otherwise underutilizing computer power management options.

5.7 *Pod Coffee Makers*

The two pod coffee makers showed very similar standard profile energy usage estimates (1076.9 and 1046.4 Wh), which are higher than any device other than the 4K television, and similar ranges (89% of the standard profile versus 92%). Both pod coffee makers showed a unique pattern in this set of devices, in that most of the range was lower-energy compared to the standard profile: the highest-use profile was only 7% above the standard profile for Model A and 3% above the standard profile for Model B. In other words, most of the variation in usage predicted by the current model results in lower energy consumption than the standard profile.

The pod coffee makers are also unique among this set of devices in that the active aspect is not a significant factor explaining variation in energy use across profiles. Although the heating and brewing cycle during the active period is quite energy-intensive, it requires only 2 min to heat the water cache from cold state, and 1 min to dispense each cup. Instead, power management accounts for the majority of the energy consumption variation across profiles. Energy consumption is very similar across profiles using PM high-1 and high-2 (in which auto-off is enabled and set at 2 h and the user turns the device off after use, respectively) but much higher for profiles using PM-mod, in which auto-off is disabled. There is no low level of power management, as the standard PM aspect—the factory default—is already as inefficient as possible.

The first solution to saving energy with pod coffee makers thus seems straightforward: change the factory default so that auto-off is enabled. This assumes that users are less likely to disable the setting if it is enabled by default than they are to enable the setting if it is disabled. This would not change the potential range of the device use profiles, but it would shift the standard profile down considerably, and make the higher-use profiles less likely to occur in actual households. Offering shorter delay periods—such is already done for the more advanced Model A device—would also save energy, and may be considered as a default setting. This could work well for households where only a few cups of coffee (or tea) are brewed within a short time frame every morning.

Unlike many other devices discussed (especially in the entertainment category) these devices are not intended to run for extended duration, as their utility comes from producing a product (a cup of coffee) quickly rather than providing screen time. Accordingly, leaving the device on for extended periods beyond producing coffee is wasteful. At the same time, users may become frustrated if the pod coffee maker takes what they perceive as "too long" to warm up from a standby state when they want a cup of coffee, especially as one expected benefit of pod coffee makers is their speed and convenience. One possible reason why users disable sleep settings is that they get annoyed at waiting for the device to resume from sleep mode. Speeding up the warm-up period and providing a user interface showing the progress of the device in warming up may help prevent this annoyance, allowing a shorter sleep delay time to be effective without reducing user satisfaction.

5.8 Rice Cooker

Although the rice cooker, like the pod coffee makers, also involves heating and keep-warm states, the results here show a drastically different pattern of effects. The standard profile for the rice cooker produces a fairly low energy consumption estimate compared to other devices in this set (282.2 Wh), and although the range is somewhat smaller in absolute terms than that for the pod coffee makers, almost all the other profiles showed higher consumption than the standard profile. That is, the standard profile is almost as low as the lowest-use profile, and most of the other device use profiles result in higher energy consumption.

The rice cooker is unique among the devices tested here in that pattern of use explains a large and significant proportion of variance in energy consumption across device use profiles. The amount of active use—in this case, how much rice is cooked in total that day—has little effect in this analysis, but the number of times the rice cooker is used does. A closer look reveals that this is because the additional amount of energy used to cook, say, three cups of rice is incrementally small compared to the amount of energy used to cook one cup of rice. This comes down to timing: with the white rice used for testing here, it takes 32.5 min to cook one cup of rice, and only an additional 8 min to cook three cups of rice. However, changing the pattern and cooking that total of three cups of rice in two or three fresh batches over the course of the day (say, for lunch and dinner separately), requires a new baseline level of cooking time. In other words, with a pattern of use spread out over multiple periods per day, it takes more total time to provide the same amount of rice. This differentiates cooking appliances from experiential devices such as a television or computer, where the amount of time actively watched or used is synonymous with the amount of service received. As such, although the pattern aspect reveals the additional energy consumption, it is the consumption during active use that would need to be reduced in order to save energy. The rice cooker is similar to other category devices not tested here that involve heating water and/or keeping food or liquids warm, such as drip coffeemakers, under-sink or table-top water heaters, hot pots, and electric pressure cookers, and some conclusions can be cross applicable.

While power management is also significant, it is less impactful than the pattern of use over the course of the day. Other things being equal, profiles using low power management—where the user keeps the rice warm most of the day—use much more energy than others, whereas turning the rice cooker off as soon as it's done saves only a small amount of energy compared to leaving it on for another hour (say, until the meal is over). The rice cooker is unique among devices tested here, in that users deliberately leave the device on in the keep-warm state. An online search reveals many people who prefer to make a large pot of rice and keep it warm all day, despite warnings about food safety. According to the current results, it uses more energy to make a new, smaller pot of rice three times a day (and turn off the warmer after 1 h) than to make one large pot and keep it warm all day. So if a user perceives these as the competing options, the "worse" power management strategy would actually use less energy.

6 Overall

6.1 Range of Energy Consumption

The range of energy consumption across profiles for each device is shown to identify the highest and lowest energy usage that would be seen in real-life usage, given the assumptions in the profile definitions. The ranges are compared against the "standard" profile that represents or approximates the standard testing procedure. This indicates not only the percentage difference from the standard usage but also whether more of the range is above the standard or below it.

A device exhibiting a moderate range in energy consumption across profiles is not necessarily a bad sign, either for energy efficiency or for the accuracy of standard testing protocols. It is reasonable that devices would use more energy if actively used more hours, and that devices would save more energy if more aggressive power management features were used. Likewise, a very small range is not necessarily a good sign, as it indicates that the device does not effectively reduce energy use for shorter active periods or in response to power management.

Ideally, the range of device use behavior—and thus profile energy usage—would be normally distributed around the standard profile, in which case using standard testing methods would produce accurate and reliable estimates of the population. The current study cannot speak to whether this is the case, as it depends on how common the device use behaviors discussed here are in the population, which would require consumer behavior research that the field is sorely lacking.

The larger the range in possible energy consumption outcomes, the more likely it is that the real-life pattern of outcomes are skewed, which is especially concerning when results show energy consumption levels much higher than the standard profile. For most of devices tested here (both televisions, video game console, desktop and laptop computers, and rice cooker), the upper range was much larger than the lower range, indicating that deviations resulting in higher use would be more extreme than deviations resulting in lower use. Only the two pod coffee makers exhibited more profiles with energy consumption below the standard profile than above, which is due to the power management settings being disabled by default for those devices.

6.1.1 Active Use

The duration or frequency of active usage is a significant factor influencing energy consumption for many of the evaluated devices. Indeed, were power management not being tested, the effects of active use would be more pronounced for most devices.

Even considering the weight of power management, active use explained 40–43% of variation in energy consumption for the 4K and HD televisions, and 20–27% of variation for the desktop, laptop, video game console, and streaming device. Of these devices, the televisions, video game console, and desktop computer use a relatively large amount of energy in their standard profile compared to others. It is especially troubling how much more energy is used by the newer 4K television than the HD television. These results thus add weight to efforts to reduce power draw during the active state for these devices.

It is important to distinguish between active use (when the user directly benefits from the device being active) and the active state itself, which may continue long after active use has ended, if power management fails (that is, automatic low-power settings are disabled and the user neglects to manually turn off the device). Thus, the high power draw of the active state contributes to the energy waste attributed to the power management aspect in these results. More aggressive improvements to energy efficiency during the active state would thus also save energy during user-idle time, when the devices are left on and unused either prior to or in the absence of automatic transitions to a low-power state.

Reducing energy usage during operation typically requires comparable device utility: that is, to modify the device so that it uses less power without sacrificing functionality or features. For computers, this would be improving the way energy is used during idle periods. When not required, the device will self-regulate to passively save energy. After testing multiple generations of computers for this project, improvement in idle energy usage was easily observed. Promotion of alternate solutions when possible helps. For example a substantial energy penalty is paid to stream online content on a video game console versus a dedicated streaming player.

6.1.2 Pattern of Use

The pattern of use for this investigation was defined as the number of times or periods the device was used, and the amount of time between those uses, given a specific amount of total active use. One way pattern of use can affect overall energy consumption is if the device requires an energy-intensive warm-up or boot-up period at the beginning of each use or if it has a long or otherwise wasteful cool-down period after each use. Some devices tested here, such as the video game console, do have a separate boot-up and/or shutting down process with a relatively high power draw. However, as these processes are quite short in duration, the resulting contribution to overall energy consumption by restarting the device multiple times during the day is not substantial.

Another significant issue for pattern of use is the idle time due to automatic sleep or auto-off settings with long delay times, which accumulates every time the device is used and left idle again. In this case, pattern of use can be seen as an example of a power management problem, in which the solutions are to reduce the amount of energy used when the device is on but idle and reduce the amount of time the device spends idle. Some devices exhibited a small effect of pattern due to long delay times, such as the streaming device. All other things being equal, pattern does matter in such situations. However, this effect was overwhelmed by variation in active use and in power management behaviors.

The rice cooker provided a third way in which pattern of use matters for energy consumption: when the device requires a baseline amount of energy for a single use, with fairly small distinctions between a small versus large amount of product or service provided. Here, the effect of pattern can be interpreted as an effect of active use, in that the only solution would be to reduce the baseline energy consumption for the active cooking state. The lesson should also apply to other types of kitchen appliances that cook food or heat water. Although it would seem that pod coffee makers would suffer from this effect, the design has largely addressed the problem already: instead of heating the entire reservoir of water, the pod coffee makers only heat enough water for a single cup at a time, greatly reducing the impact of a long keep-warm period even when power management settings are disabled.

In sum, pattern of use can affect energy consumption of plug-load devices, but the effects for most plug-load devices are small compared to effects of power management and active use.

6.1.3 Power Management

The power management definitions used for the device use profiles combined two factors: settings that automatically transition the device into a sleep or soft-off state after a specified delay time of inactivity, and whether or not the user turns off the device immediately after using it. For every device, a moderate level of power management is defined with whatever automatic setting is the factory default (if any) along with the most likely user reaction at the end of use. Most devices have at least one low level, in which any power management setting is disabled and the user leaves the device on, and at least one high level, in which the user turns the device off after each use, negating any effect of automatic power management setting. Given this wide range of behaviors, it is not surprising that power management had a significant impact on energy consumption for all devices, and was the primary factor in variation across profiles for most devices. Still, while few would question the general idea that power management is important, this study helps show the importance of systematically examining when and how much specific power management behaviors (both settings and manual shut-downs) affect energy consumption.

The devices studied in the current project revealed three main failure points for power management: when automatic settings are disabled or otherwise ineffectively utilized, when low-power modes do not save much energy, and when devices remain in a fully functional active state during long periods of idle. A potentially missed opportunity for reducing energy consumption was also identified: automatic transitions to a low-power state based on the status of connected devices was shown to be very effective in one device, and could be effective in others.

The most pressing problem is how to get more devices to automatically transition into sleep or other low-power modes. Unlike those of earlier generations, all of these devices offered at least one low-power mode and an automatic power management setting for transitioning to it. However, if automatic sleep or auto-off settings are disabled, they do not save any energy. Worse, they result in devices remaining on for long periods, even all day long, every day. CalPlug's field study shows that many office desktop computers are left idle at all times, but little research is available to indicate how often users leave other devices on all the time. However, the effect of not using power management and leaving devices in the active state all day long is so large that even if only a small proportion of households do this, it would take a much larger proportion of households consistently enacting stringent power management behaviors to counteract all the wasted energy.

The simplest step to getting more devices into low-power states is to enable the energy-saving settings by default. To their credit, most devices already do this. The pod coffee makers are the one exception: for both models, the user would have to realize that the setting existed, realize that it was not enabled, and figure out how to enable it. For some devices, it may be possible to take away the users' ability to disable power management settings without reducing user satisfaction; this is already done with smart phones, and users have broadly accepted that limitation. However, this approach could be problematic for other devices where users are accustomed to having more control, especially for those where users may have valid reasons for leaving the device on and idle for long periods (for instance, computer users who cannot remotely access their work desktops if they are in sleep mode). More research into when and why users disable their sleep settings would be needed before the effects of enforcing settings could be estimated.

A more complicated issue is how to design the power management settings and the associated user interface to best encourage users to keep them enabled. Although little research has been done on this topic, anecdotal evidence—including countless tech forums answering users' questions about why their devices are mysteriously turning off—indicates two problems. First, users are confused about sleep settings. Second, the most common response to being annoyed by even a few undesired sleep and shutoff events is to disable all automatic PM settings. Once settings are disabled, users may forget they even exist. Most manuals and settings pages, including for the devices tested here, do little to explain the reasoning behind the settings, or encourage users to change the settings to a longer delay period rather than disable them, or to try to motivate users with energy-saving or "green" messages, which have worked in other applications. Furthermore, almost nothing is known about exactly what settings users would ideally want to use, what signals might work to help prevent unwanted shut-down events, or what their annoyance threshold is for how long they're willing to wait for a device to restart from sleep. For instance, if a television gave users a certain signal that it was going to switch off in 5 min, so that users could easily forestall a false auto-off, it could be possible to set the default auto-off delay time to 1 h instead of 4 h without any decrease in user satisfaction. Much more research and development is needed to fully address these issues.

The second main failure point was illustrated in the current research by the set-top box, for which the stand-by mode uses almost as much energy as the fully functional active state. As a result, the device showed almost no variation in energy consumption across device use profiles, even when the power management settings were enabled. The solution here is simple, at least in concept: reduce the energy consumption of the supposedly low-energy state. The overarching goal is to get devices to spend more time in the low-power state, and the more that goal is met, the more important it is to incrementally reduce power draw in the sleep or standby state.

The third failure point identified here is when devices spend considerable time at full power during periods of inactivity when they could conceivably enter a lower-power idle state. Computers lead by example here, by shifting into "short idle" and then into "long idle" states in the absence of user input; these states pause certain processes to save energy, yet leave the device ready to quickly resume full activity when the user returns. While worthwhile efforts to further reduce energy in idle state for computers continue, efforts to do the same for other devices are warranted. For example, when the video game console is not running a game, it switches to a main menu state that uses almost as much energy, where it remains indefinitely unless it transitions to sleep or is turned off. Reducing the consumption of the main menu state would be a substantial improvement.

Finally, use of linked devices for guiding power management was an effective approach for the sound bar. Specifically, an input-specific power management option switches the sound bar off when the device sending audio input to the sound bar, such as a television, sends no input for 5 min. This feature could function similarly in other connected devices that offered no such option, indicating a missed opportunity for savings. For example, any device that requires the television to display content could be set to transition to standby or soft-off if the television is turned off or transitions to sleep mode. A related alternate approach is to use a Tier-2 Advanced Power Strip (Tier-2 APS) to turn off devices, as well as reduce the burden of standby loads from these devices.

In sum, the evaluation of the effects of power management and potential improvements in its use and effectiveness, especially if combined with variation in active use and use patterns, is a rich area for continued investigation.

6.1.4 Evaluation Method Limitations

The current analysis shows the promise of the device use profile approach for assessing potential energy consumption across various users. However, the approach is inherently limited by the quality and reliability of the information used to define the model's parameters. In the current format, each aspect—active use, pattern of use, and power management—was defined with at least three levels of behavior: low, moderate, and high. Unfortunately, solid data on how devices are used in the field is sorely lacking. As such, most of the definitions used here were constructed by the research team based on assumptions and anecdotal observations, and for power management, by the options offered by the device. Self-reports of the amount of active use per day are available for a few of the devices here, but even for those, many survey questions use categories (e.g., a range of hours of TV use) rather than point estimates. No reliable data could be found on how people actually use power management in other devices, or on patterns of usage over the day. For this reason, no attempt was made to further differentiate weekday versus weekend use or to extrapolate to estimated annual energy consumption, which would require additional levels of assumptions that could not be warranted.

In short, as with any research of this sort, the results of the device use profile analysis are only as good as the assumptions that underlie its measures. Even assuming that the definitions are accepted as representing *some* users, the lack of data means no conclusions can be drawn about *how many* users fit each profile. The findings provide useful boundary conditions and a range of energy consumption results based on reasonable behaviors. If most of those behaviors produce much higher energy consumption estimates than the standard or "moderate" device use profile, this reduces the chance that natural variation in device use will average to the standard testing's mean and increases the chance that users with higher energy use profiles will outweigh those with lower-use profiles. This illustrates the importance of conducting more research on how devices are actually used in real-life situations, if accurate estimates of annual energy consumption for device types are desired.

The findings demonstrate the utility and potential of the PLSim tool that was developed and described here. In the present version, each parameter was input into a template usage file. This file was used to create a usage schedule in PLSim. This manual process serves as an effective demonstration, but can be tedious in usage and warrants additional development to add automation.

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