Advancing Plug Load Efficiency with Behavioral- Focused Usage Evaluation

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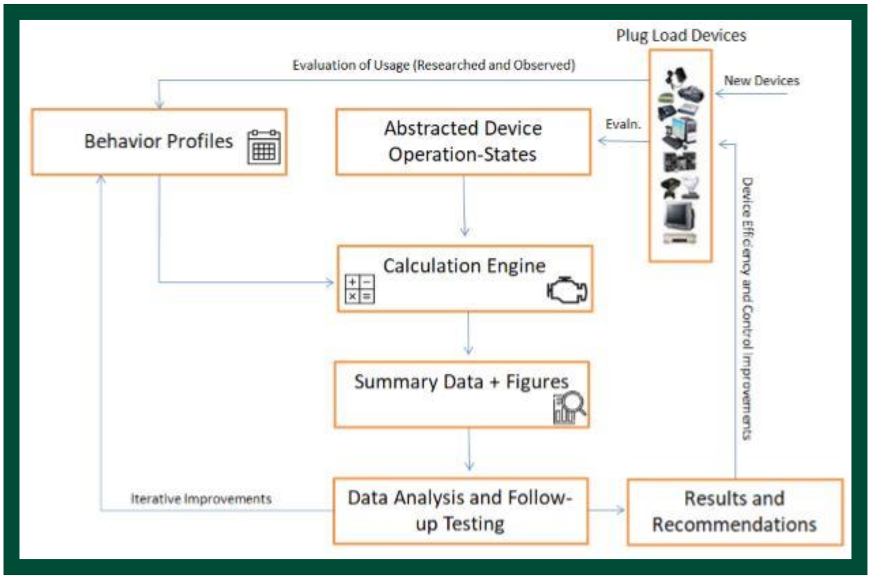

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EXECUTIVE SUMMARY

PROJECT OVERVIEW

California's ongoing push to Zero Net Energy (ZNE) for residential and commercial buildings encourages reducing energy consumption at all levels, including miscellaneous electric loads and other plug load devices. Understanding this problem from both a top-down and bottom-up approach is required to produce deep, forward-facing and sustainable technological solutions.

In an earlier project for SCE, "Technology Roadmap towards 2030 and Beyond" (Klopfer, Rapier, Luo, Pixley, & Li, 2017), CalPlug presented a top-down view of plug loads and the impact of these on ZNE efforts. In another related project for SCE, CalPlug presented a bottom-up view of plug load energy use in the first SIM Home (Simulation, Integration, and Management Home) report (Xia, Pixley, & Gago-Masague, 2017).

The current project is an extension of the analyses and methodologies outlined in the original SIM Home project, assessing the role of behavior and device configuration on energy use. To this end, CalPlug developed new open-source tools – the Plug Load Simulator Suite 1.2 (PLSim)[1] and the Marginal Intervention Savings of Energy Reporter (MISER)[2] – as well as a database for device state-wise energy usage. With these tools, CalPlug calculated energy usage across a defined range of usage conditions for household consumer electronics and other plug load devices, then analyzed each set of outcomes to determine points of substantial energy use related to usage behavior.

In the first SIM Home report, CalPlug proposed testing a range of device use profiles to supplement insights gained through standard energy testing. Standardized test protocols such as ENERGY STAR® assess and compare the energy consumption of all devices of a certain type using a single (presumably average) set of parameters. In most cases, this is based on a controlled and repeatable testing scenario rather than field observations of actual usage.

The device use profile method supplements this approach by asking how much consumption could vary depending on how devices are used across a wide range of households. CalPlug discussed three important aspects of use that could affect energy consumption. The first aspect is the amount of active use, such as the number of hours the users watch TV, or how many cups of coffee they make each day. The second aspect is the pattern of use over time, which may have an impact, particularly if gaps between periods of active use require additional warm-up stages or more periods of idle prior to automatically transitioning to standby or sleep mode. The third aspect is the extent to which Power Management (PM) options are used, such as disabling default sleep or auto-off settings (on-board, or automatic PM), or turning off the device when finished (manual PM).

In the original SIM Home project, CalPlug presented an automated testing and display system to evaluate the energy impact of these behavioral aspects of usage on a set of common household plug load devices. The scope of the work limited the original tests to three profiles for each device: high, low, and moderate usage. The results from these simulations indicated that even if households contained the same plug load devices, actual

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

[2] See: https://github.com/CalPlug/MISER

household energy consumption could be substantially higher or lower than standard estimates, depending on how devices are used.

The current project expands on the original project, and describes how profile-based evaluation can be expanded as a core component to assessing plug load device energy consumption. Compared to the previous study, a larger set of profiles was constructed for each device to fully address the roles of the three aspects of behavior (active use, pattern of use, and PM).

Eleven example devices were selected and tested: two TVs (HD and 4K), a sound bar, a satellite set-top box, a streaming device, a video game console, desktop and laptop computers, two pod coffee maker models, and a rice cooker. For each device, a minimum of three levels (low, moderate, and high) was defined for each aspect (active use, pattern, and PM). Each device's profile set included all logical combinations of levels of the three aspects. The levels of each aspect were based on ENERGY STAR protocols (for "moderate" active usage) and, whenever possible, on prior research, self-report survey data, and the devices' PM options and factory default settings. For any devices that did not have sufficient field data, educated assumptions were required to create the profiles.

The plug load devices were tested using high-resolution equipment to capture the states of operation and the power consumption at each state. CalPlug then created schedules that were entered into the energy modeling software as parameters to calculate energy consumption over time, given the usage pattern described by the device use profile. Lastly, the energy modeling software was used to output the annual energy consumption of the plug load devices. This investigation evaluated two primary points: the use of the specific methodology and tools developed here, based on granular usage evaluation across multiple residential devices, and the demonstration of a generalized approach for incorporating behavior into device energy use evaluation.

This report details the estimated effects of active use, pattern of use, and PM on energy usage for selected devices. This analysis first identifies which devices exhibit large variations in energy use across profiles. It then quantitatively assesses whether the variation for each device is more strongly driven by the amount of active use, pattern of use, or PM behaviors, each suggesting different remediation strategies.

FINDINGS

The impact of device use behavior on energy consumption showed major differences across the selected devices. The first set of findings focused on the range of energy consumption results for the device use profiles relative to that of the standard profile, which reflected the standard testing protocols. Some variation in energy consumption around the standard is expected and desirable; for instance, devices should use less energy if they are used for fewer hours, or if they employ more stringent PM strategies.

However, one device – the satellite set-top box – showed almost no variation across profiles; its energy consumption was not responsive to either the amount of active use or to PM settings. Device state-level tests revealed the low-power standby mode for the set-top box used almost as much energy as the fully-active operational mode, rendering it ineffective for saving energy. As there was no variation in energy consumption to account for the set-top box, this device's assessment stopped at this stage.

Other devices revealed much higher ranges between the lowest and highest energy-using profiles. The two TVs, and the streaming device, video console, and rice cooker all showed ranges of over 200% around their standard profiles, while the desktop and laptop computer showed ranges of over 300%. Ideally, this variation would be roughly equal above and below the standard, allowing the assumption that the standard profile results would represent the overall average. However, for all the devices just mentioned, the spread above the standard profile (that is, using more energy than expected) was much larger than that below the standard profile. The only exceptions were the two pod coffee makers, for which most device use profiles used less energy than the standard profile.

The Marginal Intervention Savings of Energy Reporter (MISER) tool was used to explore how delay times in PM settings can affect the range of outcomes. Data from a prior study of desktop computers was used as a test case in which MISER simulated applying alternate sleep settings to observed periods of active use and idle time in a field test. The results quantified the extent to which enabling sleep settings saves energy compared to disabled settings (given an assumed average consumption rate) and how shorter delay times save even more. This demonstrates the potential utility of the MISER tool in expanded assessment of other devices with varied PM setting options, but would require detailed observational data on how those devices are used.

Multivariate regression models were used to identify the proportion of variance in energy consumption across profiles that was explained by each of the three aspects: active use, pattern of use, and PM (a significant factor in predicting energy consumption for all ten remaining devices, which varied in effects of active use and pattern of use aspects).

Four patterns are exhibited: (1) strong impacts of both active use and PM aspects, with active almost as high as PM (4K and HDTVs); (2) significant impact of the active use aspect, but much lower than the impact for PM (streaming device, video game console, desktop computer, and laptop computer); (3) significant impact for PM alone (sound bar and both pod coffee makers); and (4) significant impact of pattern of use, exceeding that of PM (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.

The strong effect of active use for TVs, especially the larger impact for the more advanced 4K model, supports renewed efforts for reducing energy consumption during the active operation state. The same holds true for desktop and laptop computers, the video game console, and the streaming device, all of which showed substantial impact of the amount of active use.

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 PM fails (that is, automatic low-power settings are disabled and the user neglects to manually turn off the device). Thus, the increased power draw of the active state contributes to the energy waste attributed to the PM aspect in these results. Therefore, more aggressive improvements to energy efficiency during the active state would 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.

Pattern of use could affect energy consumption by increasing the number of warming or boot-up cycles during the day, or the number of times the device was left idle and stayed on until the PM delay time elapsed. Although some differences can be seen across profiles that confirm this expectation, the differences are small compared to the effects of different PM 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 minor distinctions between a small versus large amount of provided product or service. Specifically, the rice cooker requires relatively little additional time, and therefore additional energy, to cook three cups of rice as it does to cook one cup of rice. This means that cooking three cups of rice at one time takes substantially less energy than cooking one cup of rice at a time over three instances (say, at each meal). 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. This lesson should also apply to other types of kitchen appliances that cook food or heat water.

The device use profile PM definitions combined two factors: settings that automatically transitioned the devices into a sleep or soft-off state after a specified delay inactive period, and whether or not the users turned the devices off immediately after using them. For every device, a moderate level of PM is defined with the factory default automatic setting (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 PM 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 an automatic PM setting. The devices studied in the current project revealed three main failure points for PM: 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 idle periods. These problems are not unknown, but the approach used in the current project helps to identify and prioritize which problems to focus on for any specific device.

The most pressing problem is how to get more devices to automatically transition to 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 PM 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 – sometimes all day, 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 PM and leaving devices in the active state all day long is so large that even if only a small proportion of households did this, it would take a much larger proportion of households consistently enacting stringent PM behaviors to counteract all the wasted energy.

The simplest solution for the first failure point is to ensure devices enable PM by default. The lack of default PM in the pod coffee makers explained why most of the device use profiles saved more energy than the standard profile. A more complicated issue is how to design the PM settings and the associated user interface to best encourage users to keep them enabled. However, as shown with the set-top box, if the standby mode does not save a substantial amount of energy, the PM settings will be ineffective even if enabled.

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 devices ready to quickly resume full activity when the users return.

This approach might fruitfully be applied to other devices, such as the video game console tested here. When the device is not actively running a game, it switches to a main-menu state that uses almost as much energy as active gameplay, and remains in that high-power state until it transitions to sleep or is turned off. If it instead transitioned to a lower-power idle state, substantial energy could be saved.

A potential 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 the sound bar, and could be effective in others.

A major limitation of the method used here is that the device use profile definitions – like any testing or estimation standards – are only as accurate as the data underlying the assumptions. The shortage of available data on how these devices are actually used in real-life households means any savings claims are subject to unknown error margins. The findings shown here help underline the need for more systematic research into user behavior and how it affects energy consumption.

Multiple factors come into play when evaluating energy usage. The approach and tools developed here can provide a methodology for future research efforts, to systematically evaluate priorities for efficiency efforts beyond the devices tested in this project. Device use profiles can be used to identify modes of waste in a wide range of plug load devices, with further investigation clarifying and refining the techniques and assumptions. By providing a consistent set of profiles, devices in categories can be cross compared to assess savings potential in variable usage, beyond conventional benchmarking.

Data from this project, for all devices discussed as well as others in process, is provided in an open-source format to aid further research. This dataset and the tools developed during this project are available at: https://github.com/CalPlug/PlugLoadSimulator**.**

UTILITY RECOMMENDATIONS

The findings of this investigation highlight several device-category specific targeted points for energy efficiency programs. Testing and evaluating devices by factoring in a variety of uses on a per-state basis provides a systematic means of targeting components contributing to total energy use, as well as highlighting inroads to device efficiency improvement. This can allow the rapid evaluation of various types of plug loads, to highlight opportunities for incentive programs, voluntary agreements, and codes and standards.

This is similar to the manner in which other common energy modeling methods and corresponding software utilities are used to evaluate building envelopes for HVAC design and area layouts for lighting. A device use profile model with standardized profiles can be used independently, or can outline operational evaluations that may be performed to provide relevant bounds for energy usage, thereby saving time and streamlining testing. In addition to method takeaways, based on the specific tests conducted on the devices within this report, we provide recommendations focused on the following categories.

TARGETS FOR ENERGY EFFICIENCY PROGRAMS

Device evaluations provide insight on settings and configurations related to promoting energy savings without a reduction in overall utility (efficiency). All devices provide an opportunity for passive efficiency targeting. Categorizing device Unit Energy Consumption (UEC) based on usage models and a confidence band provides a more realistic way to track energy usage for direct device and device category evaluation. Considering this approach in program development can provide more realistic models for program returns considering dynamic action.

Field trial results for one device can yield a set of state-time-power values that can be used to improve profiles of usage and advance future evaluation acuity to better model upcoming devices. In this manner, the preliminary evaluation before CPUC workpaper development can be conducted quickly to screen new emerging technologies and approaches in dynamic usage. This method allows simplifying the operation model for coordinated, multi-device integrated energy management, especially in Internet of Things (IoT) device configurations.

LOAD SHIFTING PROGRAM CONSIDERATIONS

Plug load devices, including those evaluated here, are challenging to target for Demand Response (DR) programs. The problem is that, unlike HVAC, there is no lower-power active state to which a DR command can shift devices, and cutting device power while in active use creates unacceptable user disruption. Major issues still need to be addressed before demand management is affectively applied to many classes of plug load.

The current project cannot address the inherent challenges of remotely controlling these plug load devices during DR events. However, the device use profile approach combined with PLSim tool estimates could be used to predict and understand the effects of *voluntary* load-shifting behaviors, either in response to DR requests or Time-of-Use (TOU) pricing incentives. Analyzing various DR strategies could predict the savings potential of different implementation cases. Models could be developed using elements of the approach outlined here with PLSim, to evaluate the level of user compliance required to target a specific savings level for a device, device class, or multiple devices within a home.

INCENTIVES

By providing a method for improved evaluation, preliminary assessment leading to utility field trials can be streamlined, leading to faster appraisal and program development. This can help develop and confirm reasonable bounds to predict savings. Field trial data can be rapidly simulated across devices with operational differences, to assess the impact of feature changes prior to specific field trials for these updated devices. The feature changes can then be assessed to determine the extent of their impact on energy usage.

These factors lead to improved program development. Beyond technical-focused incentives, behavioral incentives – by rewarding behavior based on tangible metrics such as reduced energy use (commonly called "pay for performance") – have shown both short and long-term benefits, but can exhibit problems related to long-term performance and rebound effects when programs are terminated. Elements of this work show how behavior and energy usage are linked and may be addressed, and can be used to model the range of program effectiveness. Better understanding of user behavior in a variety of situations can guide device operation to limit energy usage. These features can be incentivized directly or indirectly, where the inclusion of behavior considerations may lead to reduced energy consumption for a class of devices in a category using such operational features.

TESTING AND EVALUATION PROGRAMS, CODES AND STANDARDS UPDATES

The current project demonstrates an expanded approach to modeling plug loads compared to conventional methods. Plug loads as a load category are often poorly classified in building load models. When performing building analyses, the impact of plug loads on total building energy usage is often modeled as an energy usage value per square foot or a provided constant based on room usage and expected occupancy. This propagates the level of error to other calculations of building energy usage related to load and ZNE implementations.

Elements of this state-based approach provides improved granularity on a per-device level for modeling, along with an uncertainty value that can be propagated through calculations. This method also allows improved energy usage calculations for efficiency programs and efforts to target modes of device waste to improve future model design. Better knowledge of the role of behavior on energy usage can help improve testing programs used as discriminating factors for incentive programs. This information can directly improve testing programs or indirectly provide information when extending current programs across multiple consumer electronics categories.

ABBREVIATIONS AND ACRONYMS

4K TV	Ultra-High-Definition TV
A	Amp
AI	Artificial Intelligence
AC	Alternating Current
AEC	Annual Energy Consumption
AHCI	Advanced Host Controller Interface
APS	Advanced Power Strip
AV	Audiovisual
CalPlug	California Plug Load Research Center
CEC	Consumer Electronics Control (a feature of HDMI)
CLASS	California Lighting and Appliance Saturation Survey
CPUC	California Public Utilities Commission
DOE	Department of Energy
DVD	Digital Video Disc
DVR	Digital Video Recorder
EIA	Energy Information Administration
EPA	Environmental Protection Agency
EPIC	Electric Program Investment Charge
HDMI	High-Definition Multimedia Interface
HDTV	High-Definition TV
HVAC	Heating, Ventilation, and Air Conditioning
IoT	Internet of Things
IOU	Investor-Owned Utility
kW	Kilowatt
kWh	Kilowatt-hour
LCD	Liquid Crystal Display
LinearSVM	Linear Supervised Machine Learning (an AI method)

LSTM	Long Short Term Memory
MCMC	Monte Carlo Markov Chain
MELs	Miscellaneous Electrical Loads
MISER	Marginal Intervention Savings of Energy Reporter
Mod	Moderate
PC	Personal Computer
PF	Power Factor
PLSim	Plug Load Simulator, a software application developed for this project to model energy usage in devices based on usage states.
PM	Power Management
POU	Publicly Owned/Municipal/Co-Op Utility
RASS	Residential Appliance Saturation Study
RECS	Residential Energy Consumption Survey
SCE	Southern California Edison
SIM Home	Simulation, Integration, and Management Home
SNE	Small Network Equipment
SFF	Small Form Factor
THDi	Total Harmonic Distortion of Current
TV	Television
UEC	Unit Energy Consumption
USB	Universal Serial Bus
V	Volt
W	Watt
Wh	Watt-hour
ZNE	Zero Net Energy

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INTRODUCTION

BACKGROUND

Utility companies, in an effort to increase grid sustainability, have expressed greater interest in understanding real-world home device energy usage. A particularly difficult area of this investigation is the varying behavioral energy usage of Miscellaneous Electric Loads (MELs) and plug/process loads (hereafter collectively referred to as plug loads). While many households contain the same plug load devices, there is a large range of standard estimates on 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 electronic devices expected to rise in each household (U.S. Energy Information Administration, 2011, 2019), it has become very important to find strategies for managing the energy consumed by plug loads in current and new device categories.

State legislative goals combined with utility rate decoupling, or the separation between utility profits and energy sold, is a main driver of energy efficiency efforts. This rate-decoupling practice has been long entrenched in California’s Investor-Owned Utilities (IOUs) and Publicly-Owned/municipal/co-op Utilities (POUs), and is becoming common practice across the United States. When considerations, due to emissions at the state and national level, are factored in with green energy sourcing options (and availability of such resources), total energy reduction (as well as the time when demand is reduced to match supply) is increasingly significant.

As energy efficiency and supply and demand are aligned to match future energy balance with fewer fossil-fueled sources, less nuclear-sourced energy, and an overall reduction in spinning reserves, energy conservation becomes a greater challenge – on a daily, yearly, and multi-year basis. Continued efforts from state and regional legislative bodies and organizations, as well specific programs sponsored by the federal government (namely the Department of Energy [DOE], Environmental Protection Agency [EPA], and Department of Commerce) have continued to allow consistent energy reduction in California and across the US in general, but key areas of concentrated energy usage still exist. With plug load device usage increasing and electrification becoming a major effort, continued maintenance of California’s largely flat per-capita energy usage requires continued efficiency efforts across many device classes, including plug loads.

Evaluating and characterizing device-level energy usage plays a major role in determining focus points for efforts and evaluation of proposed solution effectiveness. Standard energy testing, reporting, and modeling protocols provide manufacturers, regulatory authorities, and consumers a way to evaluate energy use and compare energy efficiency options. Energy test procedures exist for a wide range of devices; however, there are three issues that complicate using current approaches.

First, energy efficiency test methodologies and procedures vary significantly across products, in part because they are often designed by proponents of a particular product. These test variations make it impossible to compare results across products. Second, even if the same test methodologies are used, conflict of interest becomes a concern when manufacturers or other proponents conduct the tests. Third, individual device single-point evaluation tests cannot capture how the devices are used in real-life situations, when they are often network connected to other related devices and subjected to a variety of user behavior. These issues lead to a significant roadblock when trying to assess the true savings potential of emerging technologies, or to effectively communicate results to utilities and consumers (Xia et al., 2017).

Because many devices within this class are consumer electronics or have strong behavioral components, to understand energy use and address opportunities for improvement, the role of behavior in testing and usage must be considered. When estimating the impact of device usage, one of two approaches is typically used:

1. A representative, reproducible test methodology is determined whereby a par-evaluation can be made between products. Elements from real-world valuations can be integrated where they fit into a revision process, to update the methodology and protocol for testing. In the end, a single number (or a feature-based numerical range) is produced. This approach is relatively low cost compared to alternative approaches, but is based on assumptions, which if judiciously held, can provide par-comparison between devices. The nature of this type of evaluation provides a methodology for comparing device energy usage based on testing assumptions.

2. A device class (or representative devices) is tested across a population of individuals in normal (or simulated-normal) usage. Logging and understanding this usage helps assess it across a period of time. While this method produces a more realistic representation of energy usage in the field, reproducibility is often a concern. If the device is changed or improved, the impact of the improvement may be hard to estimate without exceedingly granular test data – and even with it, only rough estimations are possible. This approach is often expensive, and small model changes require reevaluation, unless sufficient controls are in place to discount the modification as non-effective to measured outcomes.

ENERGY USAGE IN PLUG LOADS

In general, plug loads continue to be a growing source of residential and commercial total building loads, in part due to efficiency gains for space heating, water heating, and lighting, as well as new device categories and more categories being used (see Figure 1) (Nordman & Sanchez, 2006; U.S. Energy Information Administration, 2011). Plug loads included wall-plugged devices, in addition to MELs (included in this catch-all category are building wired-in loads for controls, environmental, and safety, as well as other uncategorized systems).

Plug loads specifically have grown across multiple categories contributing to individual device UEC or population Average Energy Consumption (AEC). In residential environments, this may include alarm and surveillance systems, thermostats, and integrated controls (but often not the controlled loads themselves). To maintain device population AEC, the UEC must be offset by dividing the expected device population growth by the total number of households with the device. Assuming constant proportionality, an increasing population leads to a larger number of devices in use. Similarly, for devices commonly used in multiples per residence, the per-household growth should be considered.

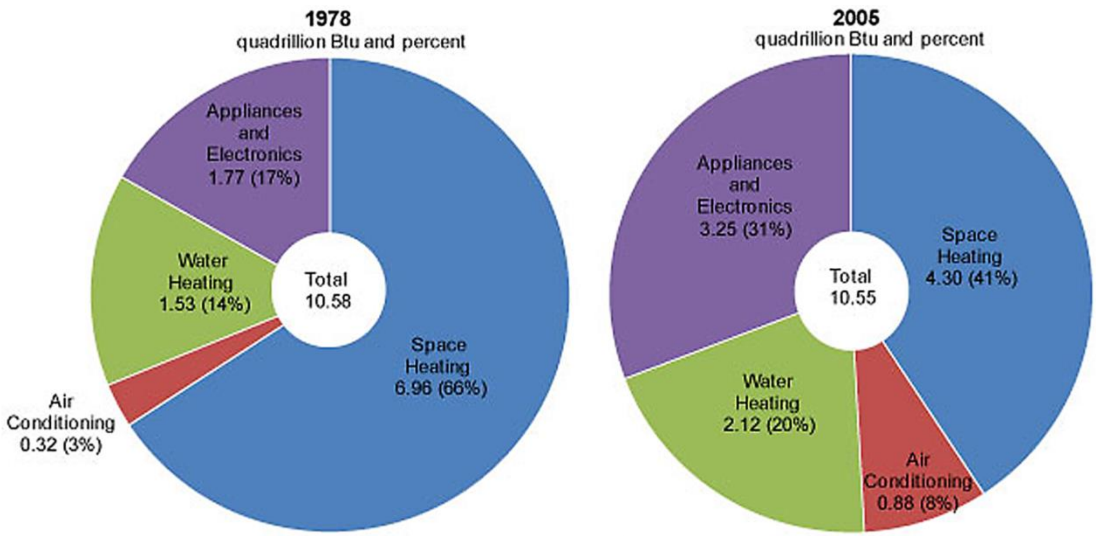

FIGURE 1. THE CHANGING NATURE OF RESIDENTIAL ENERGY CONSUMPTION IN THE US

Figure Source: 1978 and 2005 Residential Energy Consumption Survey (U.S. Energy Information Administration, 2011)

Considering macro changes, both the average living space and total numbers of devices have increased over time (Figure 2). Cisco estimates 13 devices per person by 2021 (Cisco, 2016). The average home now boasts more than seven screens, and 60% of a nationally-representative sample of survey respondents use devices more than three hours per day (ReportLinker, 2017).

The 2016 EIA energy outlook to 2040 predicts miscellaneous loads (plug loads included) will increase by an adjusted average growth rate of 1.4% per year to 2040, with a commercial growth of 11.5% (U.S. Energy Information Administration, 2016). Audio systems and game consoles are major annual consumers (Delforge & Horowitz, 2014), with electric grills and coffee machines acting as major active load devices (Gelber, 2017; Navigant Consulting & SAIC (now Leidos), 2017).

Targeting specific loads (including major appliances, HVAC, and lighting) in addition to setting efficiency standards for scale has provided major impacts in this effort. Technology and techniques have reached a point where continued scale and implementation are the major category growth directions. During this period, the disparate category of plug and process loads, which encompasses consumer electronics, increasing loads within categories of devices that provide health and safety as well as general connectivity are still major challenges.

As technology evolves, new categories continue to enter the marketplace, particularly as many plug load devices have connectivity that adds to (but also allows the potential for) coordinated and improved PM. Such devices could disrupt current progress without continued focused efforts. Because of the disparate nature of devices classified as plug loads, there is still a substantial effort to address current devices and prepare for new ones (Rubin, Nguyen, Hietpas, Young, & Tartaglia, 2016).

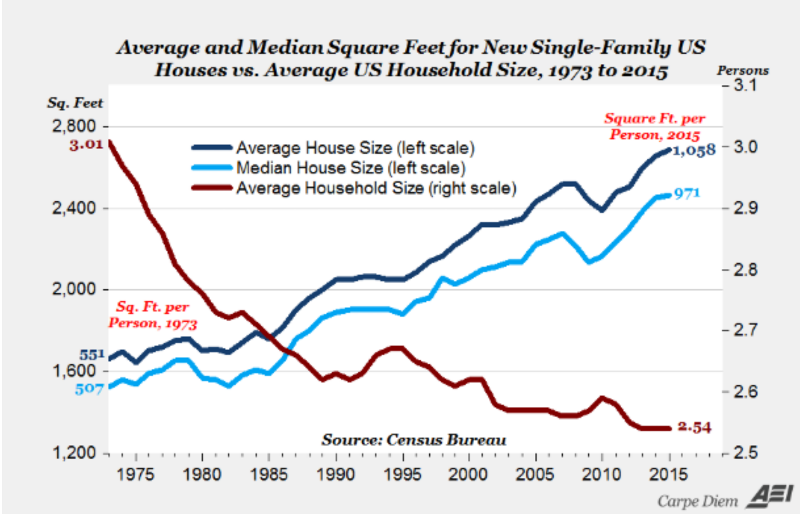

FIGURE 2. AVERAGE RESIDENTIAL SIZE AND OCCUPANCY OVER TIME

Figure Source: US Census, AEI (Perry, 2016)

Considering both commercial and residential applications, plug-in devices are responsible for approximately two-thirds of California's residential electricity consumption, including 20 percent for TVs and office equipment and another 11 percent for miscellaneous devices (Palmgren, Stevens, Goldberg, Barnes, & Rothkin, 2009). It is estimated that plug-in equipment and miscellaneous loads will be responsible for 70 percent of electricity demand growth from 2015 to 2024 (Delforge, 2015). 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 ZNE initiative for all new homes, targeted for 2020.

For a ZNE installation to be economically successful, reduced energy usage is a key first step (Table 1) to allow cost-effective offset generation sizing. Time-of-day usage is important when considering grid supply, but it is of very high importance for measuring the annual usage of strict ZNE installations that do not have net metering. Without net metering, usage must consider generation and storage to match demand (including miscellaneous electric, process, and plug loads), which play a role in reducing overall peak demand as well as in boosting efficiency to reduce total consumption. Although it is not a focus of the current report, the methods developed here could help model and assess device usage over time, as well as its contribution to peak load demand.

TABLE 1. THE 5 R'S OF SUCCESSFUL ZERO NET ENERGY INSTALLATIONS (GENERAL CASE)

Order	Action	Description
1	Reduce	Reduce structure on-peak demand followed by total demand.
2	Replace	Generate energy to offset building use, either as possible on an annual basis (net metering) or as much as economically possible on a momentary basis. Co-gen is viable in some commercial applications for energy offset.
3	Relocate (Commercial)	Campus or community generation can be shifted between localized over-generation and under-generation/overuse between structures or entities. Campus co-gen viable for energy offset in some cases.
4	Retain	Energy storage to offset campus-wide or individual building usage.
5	Reevaluate	Functional ZNE is dynamic equilibrium. Changes in devices, user behavior, equipment age, or control system disintegration may cause reduced performance. Inspections potentially followed with training, tuning, or control system adjustments may be needed to maintain continued performance.

Considering how devices are used, the impact of users and the ability of devices to use DR coordination to shed load varies. Better understanding these impacts can frame how smart technology can be incorporated into devices to better coordinate energy usage in an unobtrusive and commercially-sustainable manner, which is especially problematic for plug load devices. Onboard PM features and how users interact with devices frames the discussion for developing smart devices with better-integrated demand management.

With a continued focus on energy efficiency and DR as a dual goal across all categories, these efforts must not be at the substantial expense of user experience to be commercially effective. Evaluating the impact of savings modes with granular evaluations can help find and address sources of waste. In addition to post-development testing, such an approach can help manufacturers meet efficiency goals through streamlined testing during device development, and understanding how devices are intended to be used. Development of effective energy-saving features can be quickly evaluated by using behavioral data during development, allowing rapid design revisions.

It can be challenging to develop effective PM. A balance must be struck between sufficient savings to merit the effort and impact on the user experience. In some use cases, users have been willing to make reasonable changes to expectations. An example of this is having a computer monitor turn off when not used for a specified period of time, provided the computer returns to operation when required. Monitor sleep is enabled by default, and is observed to be engaged for most desktop computers (Klopfer, Pixley, Syed, & Li, 2019; Pixley & Ross, 2014).

When set as the initial default, computer sleep is not as universally maintained as monitor sleep, possibly in part because of a denial of some usage capabilities in practice, including delayed startup, interrupted downloads and processes, and a lack easy remote access. Similarly, mobile device users are somewhat more tolerant to energy-saving actions, since not using them leads to rapid battery depletion and denial of service. Even so, user compliance with energy-saving features is still a matter of the developer's judicious decisions. A phone or tablet computer sleeping during use sessions could often be interpreted by the user as a malfunction or pernicious activity.

Clearly, a balance of action is necessary for energy savings. Unlike other building loads, the direct contact nature of plug loads precludes using strategies such as delayed, period-reduced, or shifted use (common for HVAC and water heating), or reduced utility (for example, light source dimming). While it is difficult to apply a wide brush across many plug load sub categories, using consumer electronics as an example case, actions such as slowing down device computation speeds, response actions, or screen brightness parallel to classic DR actions are difficult without severely hampering the user experience and possibly confusing users about proper device operation. With consumer electronics, three specific waste categories are noted: standby load, inappropriate usage, and wasteful usage (see Figure 3). For each category, there are multiple energy management methods. The modes of waste are outlined here:

1. Standby Load: Clearly, it is wasteful for non-operating load to draw excessive energy. The rise of the soft-off modes and transformer-driven linear AC/DC power in many devices led to a relatively-steady increase in standby power requirements from the 1980s through the early 2000s.

   In the early 2000s, improved efforts to limit standby load, along with the addition of efficient switching (and later, “burst” mode) power supplies and more thoughtful design, continued to reduce standby energy load. In many household devices, this represents less than 1.0 watts (W). Continued work by the European Union (European Commission, 2014), Energy Commission for the State of California (California Energy Commission, 2018; Singh & Rider, 2008), the Consumer Technology Association (Urban, Roth, Singh, & Howes, 2017), the Lawrence Berkeley National Laboratory (Lawrence Berkeley National Laboratory, 2019), and other groups has continued to reduce device standby load for existing, mature categories.

   As effectiveness eventually leads to efficiency, new categories (for example, High-Definition [HD] flat-panel TVs) may still require evolution through this process. New technical energy consumption challenges are present with 4K TVs, which have substantially-higher energy consumption compared to current-generation HDTVs. Increases occur with new device categories, and are mitigated with continued focused research and development efforts.

2. Inappropriate Usage: This mode of waste happens when less-efficient devices are used in place of more efficient alternatives. This may include actions such as using a toaster oven in place of a regular toaster for cooking a slice of bread, or using a range oven instead of a toaster oven for reheating a slice of pizza. All devices discussed operate as intended, but waste can be avoided through more careful user choice.

3. Wasteful Usage: Using devices that consume energy beyond what is needed to satisfy the desired outcome or service is covered within this mode. This is most problematic when the device uses a relatively high amount of energy (see the catch-all solution #0 in Figure 3) in multiple usage modes. This is a major category of multiple sub-modes of targeted waste. The effect can be based on four specific directions:

   a. The user behaves in ways that are inherently wasteful – for example, a TV that is commonly left on with nobody watching it, or a space heater used in a drafty room.

   b. The user (knowingly or unknowingly) does not take advantage of the device's energy-efficient operational modes. They may not be aware of the impact of these features, or even of their existence. Examples may include a user who falls asleep in front of a TV without using the sleep timer, or a user who disables a computer's PM features.

c. The device either does not have effective energy management capabilities, or it is designed in a manner that does not allow easy or sustained usage by typical end users. Examples may include a rice cooker that does not have auto-shutoff, or a set-top box that provides energy-saving modes, but actually delivers limited savings in these modes.

d. Compared to best-known practices, the device uses a larger amount of energy compared to alternative solutions. This may be due to inherent wasteful operation, such as low boiler insulation in a hot water dispenser requiring substantial energy to reach and hold a temperature set point.

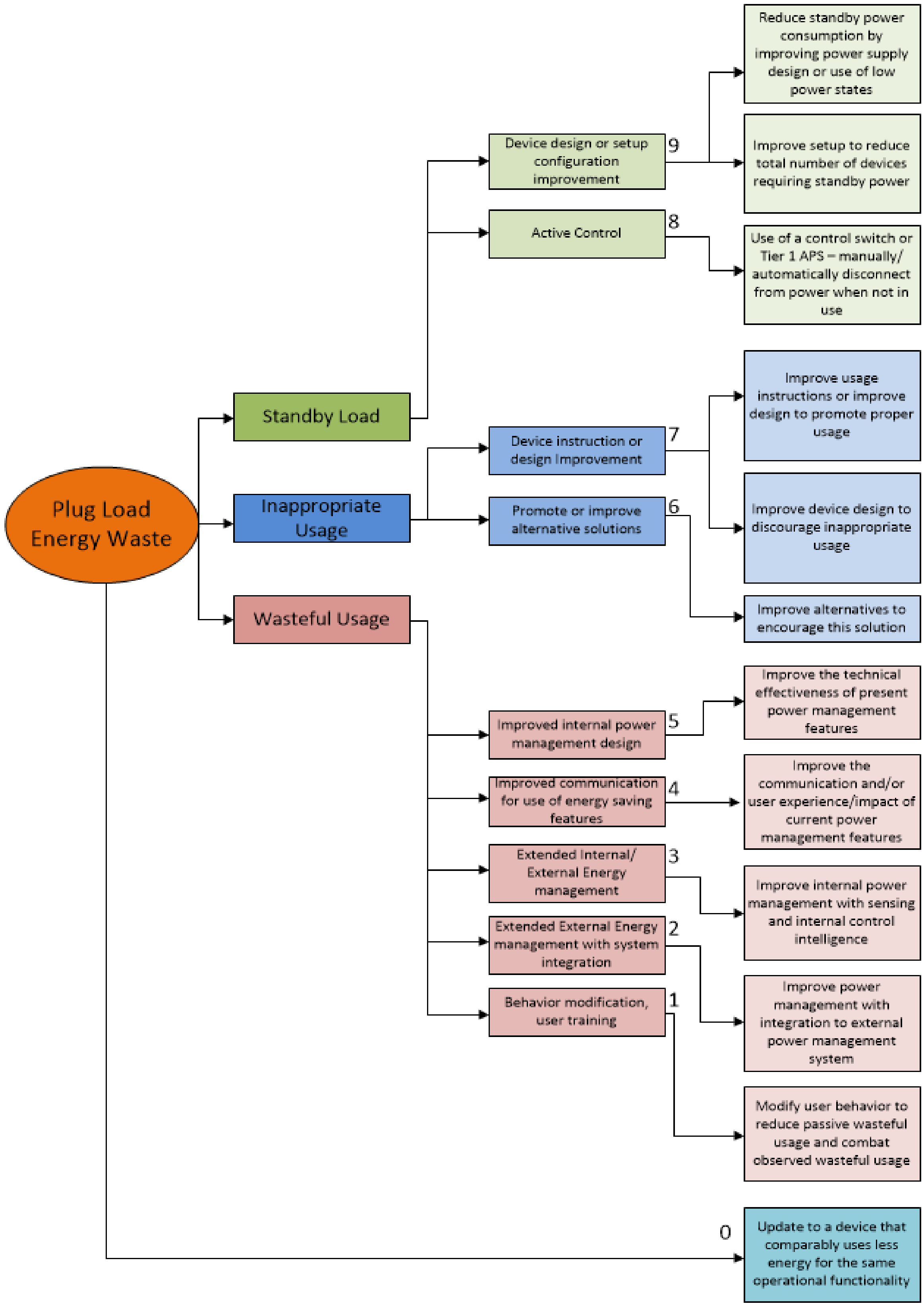

FIGURE 3. FLOW DIAGRAM OF PLUG LOAD WASTE MODES AND INTERVENTION STRATEGIES.

Assessing potential intervention strategies for both utility energy efficiency and DR programs, within multiple sub-classes of plug loads, requires understanding the root-cause waste source. Proposed solutions must consider scalability and impact, as well as the difficulty of intervention strategies. Some devices are more energy- intensive than others (for example, portable heaters compared to coffee makers) and obviously, devices with higher energy consumption produce higher device-level savings when wasteful use is reduced.

However, the impact of devices that have lower energy use but more waste (for example, set-top boxes) can be even greater. Although the vast majority of these devices consume between 10 to 35 W, they are among the highest home energy users (Lawrence Berkeley National Laboratory, 2019). Clearly, each device category has unique requirements for specific interventions to be shared across plug load groups due to device commonalities.

For analysis, by comparing variations in usage against controlled parameters, changes in energy use localized to specific energy-efficiency efforts can be applied in two main modes: passive and active. In passive efficiency efforts, each state is targeted to reduce energy usage by device design and operation, to reduce total energy usage at an operational state level. The “always on” state is the first target, along with other states in which the device is run for extended periods. Granularly, each state is investigated to see if running a given device can shorten its operation in a higher-power state and transition sooner to a lower state, or reduce power consumption in a particular state.

Active efficiency includes using PM and improving interfaces to promote user efficiency, either by making PM features more intuitive to use, or by boosting the marketed benefits or seamlessness of these features in general device operation. The next point is boosting PM feature capability (by expanding existing capability or adding more features). The third approach is active PM through features such as presence sensing, timed actions, or coordinated PM across devices. All of these approaches can be modeled using the methods outlined in this work.

INVESTIGATION OVERVIEW AND STUDY FOCUS

In this study, we demonstrate a modeling approach for estimating energy usage and the impact of behavior-related effects on energy use across multiple devices and categories. Using modeled user device actions, energy states related to action pathways are broken down to a granular degree required to sequence typical device actions. Accordingly, a variety of behaviors can be applied to the model to generate a spread of energy usage across known actions. By using alternative approaches based on behavior chains, device-based actions can be quickly simulated to produce energy usage outcomes.

To accomplish this, we constructed profiles describing device use over a 24-hour period based on three main aspects of how the device is used in real-life situations: total amount of active use, pattern of active use, and PM settings and behaviors. This approach was developed in an earlier project, referred to in this paper as the original SIM Home report (Xia et al., 2017), which was conducted using the SIM Home testing lab. The current project extends the idea and performs the tests that were outside the scope of the initial report.

For the simplest devices, variation in active use should explain all (or almost all) energy use variations. For instance, a basic hot air popcorn machine has only two states of operation: (1) on; and (2) blowing hot air when plugged in, and off when unplugged. Because it only uses energy when plugged in, the total amount of active use time is adequate to summarize its usage.

However, many plug load devices are more complex than this simple example. For devices with heat-up or cool-down periods, the pattern of use may be important; that is, whether all of the use happens in one period, or is spread out over the course of the day. Finally, an increasing number of entertainment, office, and kitchen appliances use “vampire” load energy, even when they are turned off, or have standby modes that they may or may not transition to when not being used. Therefore, energy usage estimates may be substantially affected depending on available PM options and whether users enable or disable settings, and turn devices off when finished. Estimations based on nameplate maximum power consumption values produce exceptionally-high usage estimates.

A range of device use profiles was developed to supplement the standard testing procedure and establish a range of energy usage per device. Standardized testing methods provide a consistency for each device being tested against an average usage profile, which when comparing across many devices of a certain type (i.e. different brands of 4K TVs) it is imperative that each device be tested using the same procedure, to obtain an accurate device comparison.

However, there is a huge variation in how people actually use these devices in their homes, and investigating these differences helps us understand them. Therefore, SIM Home seeks to supplement standard testing procedures by looking at multiple behavioral profiles across one device to get a wide view of real-life plug load energy usage.

Simulated behavior processes based on tested devices with known actions of use are applied to abstracted device models. By carrying forward energy use probabilities based on device-state energy usage, ranges can be estimated. By comparing differences in actions and the impact on energy, a distribution of uses and conclusions can be drawn about device operation to improve user-device interaction and reduce energy consumption in future device models. As with assessing the role of solutions, this report discusses each of the three mentioned modes.

In this study, the possible states of each device are observed during testing, and modeled based on any state order dependency. Ideally, each device has one steady state that is used in active operation, and other states that take the device to the steady state, then through operation and back to this state. The only exception is when multiple sequential states are required to reach a steady state. An example of this is “soft off,” or active operation in a “hold” mode. For instance, a device may require bootup, then user actions take the device through a state (or state sequence) by device action, and once finished, return the device back to a steady state.

Energy usage values are shown, in addition to simulation where knowledge of device actions and multiple pre-determined, sequenced actions and events are considered. Usage profiles were constructed based on encapsulating usage within categories of usage, PM, and daily usage cycles. For each category, a minimum of three specified variance categories is specified – typically light, moderate, and heavy. Accordingly, through multivariate regression against energy usage, each category’s impact can be estimated.

Specifically for this analysis, the moderate or standard usage profile was set at the median amount of time the device was used according to survey data, with default PM settings (if any) employed. By comparison, if the household actually exhibited low use – defined as in the 10th percentile of duration and frequency of use and high-PM settings – the moderate estimate would overestimate consumption by 236% (Xia et al., 2017).

Per the initial SIM Home study, if the household actually exhibited heavy use – defined as in the 90th percentile of duration and frequency of use and disabled PM settings – the moderate estimate would underestimate consumption by 61%. Comparing the heavy-use household to the low-use household indicates that some households may consume over 700% more than others.

Yet this is certainly an underestimate of the extent of the problem, as SIM Home simulates a one-bedroom household that contains eleven modeled plug load devices. Most one-bedroom households would have many more devices, and of course larger homes would have even more; with every device added to the estimate, the range between the lowest-use household and the highest-use household can be expected to grow. That is, the extent to which any "average" estimate of energy usage is wrong would get larger and larger. The discussed devices are ones deemed both popular and relevant for potential energy-saving measures due to past discussion and ongoing future-facing discussion.

Evaluating device-specific energy usage profiles provides a range of values in different operating conditions. Taking the energy usage results for each profile and performing a multivariate analysis considering profile parameters can provide insight on factors of influence, and therefore which technical and behavioral factors have the greatest impact on energy usage for a given device.

EVALUATION METHODS

CONSTRUCTING DEVICE USAGE PROFILES

Developing usage profiles for devices tested in this project required several steps: selecting which devices would be included in the scope, determining the possible states each device experienced during normal use, testing device power consumption during those states, testing to confirm the state-energy relationship, and constructing usage profiles incorporating the possible states, possible PM options, and likely range of user behavior.

Devices can be modeled as abstracted or real, to provide energy usage examples. An abstracted device is one for which a real or composite set of devices provides the feature set, and potentially the time-state-power information, used to match operational logic with energy usage. Devices can be built heavily on a real-world device or be a balanced mix of carefully-chosen aspects of similar devices in a class. This type of representation can be used to model a general device with a given class-representative feature set. A real device model is based on a contemporary device that has profiles built directly from operational logic, feature set, and time-state power information. Profiles are built directly from device operation in common device tasks. Both approaches have merits, but in this study, real devices are evaluated.

SELECTING DEVICES

As in the first SIM Home project, the first phase of the current project involved selecting, obtaining, and installing plug load devices to populate the SIM Home environment, and planning the tests that were conducted later. In the earlier project, secondary analyses were conducted on several household studies to determine which devices were most prevalent. For detailed results, please consult this work (Xia et al., 2017).

Briefly, the studies included CLASS 2012 (California Lighting and Appliance Saturation Survey), RECS 2009 (Residential Energy Consumption Survey), RASS 2009 (California Residential Appliance Saturation Survey), SKA 2015 (Small Kitchen Appliance survey, conducted by Mintel), and). In cases where raw datasets were not available, results from published reports were used instead, including reports from PASUS 2009 (Portable Appliance Saturation and Usage Survey, conducted by the Association of Home Appliance Manufacturers), the Bureau of Labor Statistics' American Time Use Survey, device field trials, and Nielson. In a later addendum to the original SIM Home report, results were updated when RECS 2015 data became available. This information is not available in all published versions, and accordingly, the relevant updated and extended tables are included in Appendix A of this report. The RECS 2015 data did not indicate any substantial change in prevalence of the tested devices.

For the current project, one priority was to focus on the same device types that were included before (although some of the specific models of SIM Home devices have changed). The criteria used were that devices should still be considered prevalent, or trending upward in prevalence, in U.S. households and that their energy consumption could potentially vary by the aspects assessed. That is, devices that must stay on at all times cannot vary by length of usage time, pattern of usage, or PM, so would not be relevant for these tests.

The final list of tested devices is shown in Table 2. This includes all devices evaluated through this project, although a number of devices CalPlug legacy tested were imported into this record format and included in the PLSim XML database, in addition to placeholder device categories based on lists of common plug load devices for which no representative had yet been evaluated.

All devices shown here were run through basic power testing, and those results are included in the PLSim energy usage database. Devices marked with an asterisk went through additional testing and analyses necessary for the device use profile testing presented in this report. This database includes all listed devices, and is provided with usage information in Table 2, including those devices that were not evaluated with profile-based energy use simulation.

TABLE 2. INVESTIGATED DEVICES AND CORRESPONDING CATEGORIES

Device Category	Tested Devices
Audiovisual/Entertainment Devices	4K (UHD) TV * HDTV * Game Console * Satellite (HD) Set-top Box * Audio Sound Bar * Streaming Device* DVD Player Blu-ray Player 5.1 Audio System Small Audio System
Computers	Desktop Computer * Laptop Computer * Monitor Computer Speakers Printer (inkjet-MFC and laser types) Media Server/Network Attached Storage DSL Modem
Cooking and Kitchen	Pod Coffee Maker (2 models) * Drip Coffee Maker Induction Hot Plate Rice Cooker * Electric Kettle Hot Pot (hot water dispenser) Stand Mixer
Illumination	LED Smart Bulb LED Luminary
IT and Connectivity	Mesh Network Router Network Router
Health and Security	IoT Hub System IoT Plug Meter/Switch Adjustable Bed White Noise Generator Electric Fan, Heater Electric Blanket Portable Heat Pump/ Dehumidifier Smart Speaker
Transportation	Electric Vehicle Charger (EVSE) Automotive Battery Maintainer

* Items underwent device use profile testing.

DEVICE STATES

From the device list and categorization, each device was tested to establish every state it entered in response to various actions (for example, being activated, being used in certain ways, or being left idle for a certain period) and the power draw during each state. Some of these states were static in terms of power draw, while other states varied (for example, warm-up cycles). Determination of operational logic made for the most commonly-used functions was evaluated and mapped with respect to state order and time. The possible PM options were also assessed at this point, such as auto-shutoff timers, sleep mode timers, and auto stops, as well as their effect on transitioning to other states and power draw.

On the device side, inspecting each device allowed us to divide common operation into a sequence of possible action states (determination of the operational logic). Power, rather than specific user actions, was used to define a specific state in the time-state-power mapping. For example, on many DVD players, a state of playing versus paused has no effective energy usage difference; but in a paused state, after an elapsed period of time, power-saving features may be activated. In this case, a single state for "play" and "paused" would be noted, with a caveat for activating PM functions.

Each "static" state should be defined as a logical user action – for example, "play a DVD," "hold at DVD menu," etc. However, there are specific actions the DVD player must do for each logical action (for example, "play the disc") including spinning it up, seeking the laser head, and then buffering and playing. This combination of actions is considered a composite static state. Each of the listed states are identified as static or transient. A "static" state occurs during a process with any action averaged in that period. A "transient" state is a short-term device action that transitions devices between states – for instance, heating water to a desired temperature, or a series of transitions required to shut down a machine.

For ease of use, these transient states are combined with other transient or static states into a single, reproducible action, with energy measures that reflect the total energy used during the process. These device actions compose transient states to a logical user action. When determining device states, an independently-linked chain of states is used, whereby each state should form a divergence from a steady or null state (holding condition) and not be linked to another state or series of states, when at all possible. This approach shares some aspects to Markov chains (used to decisively describe a process) as states in that each linked state (when possible) is an independently defined entity independent of other entities prior to the previously-active state.

One exception may be a sequence, such as a boot-up or pre-heating required to bring a system to a steady state, at which the other device states may be acted on logically. The independent-state condition is typically maintained, but may be unenforceable on individual, singular states in specific scenarios where logical, linked states are required to describe a user action (for example, a coffee maker's "clean" mode may only be active during warmup, as an extension of the warmup process). In this case, the defined state should encompass the linked actions as a group, as opposed to the individual state. The noted exception is any state required to enter the steady state, or a null state (holding condition). In practice, few exceptions to the Markov approach applied on a per-state basis are typically necessary, and cases where this is required are usually rare when judiciously considered.

Typically, transient states should be as granular as possible. At times, measurement may require divergence from protocols, or short samples averaged over multiple periods. Transient states with particularly-divergent measurement requirements should have this information noted. Some transient states are composed of actions that are not apparent to the user. For example, in a heater, the act of driving a heating element may also incorporate artifacts of other processes currently active, such as the operation of a fan. In other cases, multiple actions may happen together in temporally tight sequences, or have a low apparent power signature compared to background processes. For example, the various states that a DVD player must go through to play a disc are potentially each transient states, but characterization of each may be too difficult and provide too little modeling benefit to be worth the exercise.

Testing should be conducted under different conditions, to build device operation intuition for separating states as best as possible, and to denote any observed concurrent actions in the descriptions of transient states. Specific transient states were recorded, but not used in the evaluation. Only static states, classified in name by a state designator combined with a specific descriptor, were used in constructing profiles. The state designator was used to identify if the device was in a major state, such as "soft off," "active," or "standby," while the sub designator specifies the current action or status under this state. Further state details are found in each state description.

In some devices, initial conditions have a profound impact on energy use or action sequencing. For example, a hot pot water heater filled only halfway to capacity will take longer and require more energy to heat up to a common set point by simple thermodynamics. Similarly, a hot pot water heater filled with water above ambient temperature will heat up to the set point faster compared to water at ambient temperature, while changes in ambient temperature may have an impact on the energy required to raise and maintain the water temperature (Klopfer, Xia, Pixley, Rapier, & Li, 2017). The recommendation is to use the most common representative parameters as possible as a starting point, and measure device energy use to model any set of specific initial conditions desired. In the current evaluation, 22°C (ambient temperature) was used as a common cycling water temperature, as a starting point for heating.

Delineation of static states may be more of an art than an adherence to hard-and-fast rules, but considering guidelines, the result energy calculation result will ultimately be the same. Typically, one would examine whether a substantial energy usage difference exists between unconnected user actions. In a composite state, if multiple pathways exist, consider breaking it down into multiple states. If different states have indistinguishable energy consumption but the states are logically connected (for example, "play" and "pause" on a DVD player) they can be combined to a common state. The use of a student's two-tailed t-test with a $p<0.01$ can be used as a distinguishing energy consumption factor. If the null hypothesis is not disproven, the two readings are considered non-indistinguishable, and the states are combined in the action model.

These guidelines are applied in an illustrative example of a state-mapping narrative for a 4K TV. Table 3 provides an example of the fields of the database XML file showing various states that a high-definition TV may cycle through, and how each state varies by power, power factor, and Total Harmonic Distortion of Current (THDi).

TABLE 3. EXAMPLE 4K TV STATE LIST DATA

State #	State Name	State Description	State Type	Power (W) Mean	Power (W) Std Dev	Power (W) Median	Power Factor Mean	Power Factor Std Dev	Power Factor Median	THDi Mean	THDi Std Dev	THDi Median
1	Active-BlankScreen	TV in active with blank black screen.	Static	160.56	1.12	161.25	0.979	0.01	0.979	33.57	1.10	33.26
2	Active-Bootup	TV in 30 second bootup	Static	63.1	2.14	63.20	0.793	0.02	0.790	25.14	2.10	25.20
3	Active-DynamicImageSettingVideo	TV with default settings showing active video	Static	173.53	2.89	173.22	0.972	0.02	0.972	33.57	1.10	33.26
4	Active-SMPTEBarsStaticImage	TV showing static SMPTE HD bars from generator in default settings	Static	153.53	2.99	153.21	0.972	0.02	0.972	33.57	1.10	33.26
5	Active-StandardPictureExtraBrightSettingWithVideo	TV showing images with brightness up	Static	156.21	3.79	157.21	0.972	0.02	0.972	33.57	1.10	33.26
6	Active-StandardPictureModeBlueScreen	TV displaying static blue screen, no input	Static	164.27	3.15	162.32	0.972	0.02	0.972	33.57	1.10	33.26
7	Active-StandardPictureStaticImage	TV displaying static image content	Static	135.25	2.99	135.20	0.972	0.02	0.972	33.57	1.10	33.26
8	SoftOff	TV immediately past boot-up in On state, black screen, no content	Static	0.115	0.002	0.115	0.028	0.002	0.0025	33.57	1.10	33.26

Extending beyond the current project scope, the application of Markov chain theory in future versions of PLSim can provide clustered states based on the probability of transitioning states, with respect to duration, to provide a Monte Carlo-style simulation (Monte Carlo Markov Chain Simulation) of event chains. This creates a statistically-determined profile set that can be used for further analysis. Currently, defined static state chains with set durations are used in analysis.

DEVICE USAGE

When developing the simulated behavioral profiles, CalPlug investigated three aspects of device usage that would affect energy consumption:

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

For each aspect, at least three levels are defined: usually low, moderate, and high. Each device is assessed separately for how each aspect applies to it. For example, amount of use was approached differently depending on whether devices are more productively seen as used on a duration basis (number of hours) or as a frequency (number of times).

The majority of plug load devices included in the SIM Home are used on a duration basis. For instance, TVs are watched for some number of hours per day. For these devices, we examine not only average use but also distribution of use. In the results presented below, we cover the full range of use reported in these studies.

Testing focused on very low and very heavy use, defined as the 10th and 90th percentiles, compared to moderate use, defined as the median. In some studies, survey questions about use employ response categories rather than a continuous measure; in these cases, the midpoint of the category is used to calculate the distribution of use. For instance, a category of "one to three hours" is recorded as two hours for all survey respondents who chose that category. This necessarily results in less precision than continuous measures, and may explain some of the variation across surveys. However, the point of the current analyses is not to ascertain hourly usage of devices to an exact degree, but to better understand the real-life range of behaviors. As such, even these approximate measures offer a sufficient basis for estimating likely device use profiles.

Other devices are used on a frequency basis. For example, a pod coffee maker is used some number of times per day. Here, testing focused on the behavioral variations that are logically reasonable for that device, utilizing study data whenever possible. To complicate matters, some frequently-used devices also incorporate an element of duration – for instance, making two cups of coffee rather than ten, using a warming plate for ten minutes versus an hour, or printing a longer versus shorter document. The testing profiles for these devices were modified to fit, but were kept as close as possible to the testing plan followed for most devices.

Whenever available, ENERGY STAR testing estimates for amount of active use established the moderate or standard level. In the previous SIM Home report, survey data on how devices were used in homes was analyzed to determine the reasonable range of use amount. Specifically, the median was used for "moderate" active use, while the 10th percentile was considered "low" usage and the 90th percentile was considered "high" usage.

The same data sources were used here as were discussed earlier for the frequency of device ownership – please see the first SIM Home report for more detail (Xia et al., 2017). As before, updated information from the RECS 2015 study was sought, and again, the results did not change (see Appendix A). Unfortunately, RECS 2015 did not provide the same data on computer usage that was available for RECS 2009, due to changes in data collection methodology. Additional updated data sources were sought for all devices on frequency and pattern of use, but no new results could be located, so the same figures were applied.

Use spacing may also vary over time. For instance, four hours of computer use may occur all in one sitting, or may be divided into shorter periods. Many devices incur transition costs, such as warm-up or cool-down times, or may idle prior to entering sleep or standby mode. For a given duration of use, the number of periods throughout the day can also affect energy usage. Testing also incorporated the same duration split into two or more periods, to examine where energy inefficiencies may occur.

A similar approach was taken for frequency devices, testing how energy costs differ when use happens in a short period versus being spread throughout the day. The number of periods were set at low, moderate, and high, which typically corresponded to one, two, or many periods over the course of the day (the exact number for "many" will vary by what a reasonable single use of each device might be). The definition also specified the amount of time between usage periods, and took into consideration the possible PM settings. For instance, if the lowest delay for a device's sleep setting is one hour, testing two patterns that both leave the device idle less than one hour will not result in exposing much variation.

The PM aspect involves what state the device is in when it is not being used. This includes a combination of two factors: (1) whether automatic PM settings are enabled and if so, at what delay setting; and (2) whether the user turns the device off when finished or not. Some devices may stay on and idle if they are not turned off, while others automatically transition to a low-power mode, or off.

User behavior can vary both in terms of whether they manually turn the devices off and whether they enable, disable, or otherwise change any automatic low-power settings. Conceptually, high PM is where the user turns the device off regularly when it is not used and/or engages any automatic PM settings at high levels; moderate PM is where the user does not act, but the device is set at the automatic factory settings for transitioning off or to sleep mode when not used; and low PM is where any automatic PM features are disabled (if possible) and the user never turns the device off. Some devices had multiple PM options and were given more than one level of moderate or high PM. These levels are not intended to exhaustively cover all possibilities, but to represent realistically high and low levels of PM behavior, to contrast with a standard or moderate level.

Some usage profiles, especially in combinations of long active use and multiple periods throughout the day, may seem unrealistic to the average person. However, these profiles represent device usage under less-common but still valid circumstances. For instance, people who are retired, unemployed, or disabled may reasonably watch substantially more TV than the average working adult. It is also important to remember that these are profiles for the devices, not the individual users. Households with multiple adults working different shifts may reasonably take turns using coffee makers, computers, or game consoles both day and night. Likewise, children may use entertainment devices early in the day while adults use them later in the evening.

Although the levels of each of aspect were based on empirical research as much as possible, there is little data available on the range of active usage of most of these devices, and even less is available on how people time their usage or what PM features they employ. In the absence of survey or observational data on real-life active usage amounts, estimates were made based on similar devices or on assumptions. It should be emphasized that the reliability of the results depends entirely on the extent to which these assumptions are realistically reflective of user behavior toward these devices. To that end, the defined aspect levels are given in sufficient detail for the reader to examine and assess.

The three aspect choices were not intended to cover every possible behavior, but represent a reasonable range of scenarios in terms of energy savings compared to an average.

DEVICE USAGE PROFILES

The device usage profile set includes all possible combinations of the levels of the three aspects that are logically possible, as defined for that specific device. If there are three levels of each aspect, and all of them can be combined, the result is 27 profiles for that device. If additional levels of pattern or PM have been defined to more adequately address functionality for that device, more than 27 profiles will be produced. A generic device use profile is shown in Table 4. As a practical matter, some of these combinations were skipped for certain devices. For example, for especially low active use durations, multiple periods (moderate or high for pattern) may not be reasonable.

TABLE 4. POSSIBLE COMBINATIONS OF DEVICE USE ASPECTS

		Aspects	
Profile Number	Active Use	Pattern/ Times	PM
1	Low	Low	Low
2	Low	Low	Moderate
3	Low	Low	High
4	Low	Moderate	Low
5	Low	Moderate	Moderate
6	Low	Moderate	High
7	Low	High	Low
8	Low	High	Moderate
9	Low	High	High
10	Moderate	Low	Low
11	Moderate	Low	Moderate
12	Moderate	Low	High
13	Moderate	Moderate	Low
14	Moderate	Moderate	Moderate
15	Moderate	Moderate	High
16	Moderate	High	Low
17	Moderate	High	Moderate
18	Moderate	High	High
19	High	Low	Low
20	High	Low	Moderate
21	High	Low	High
22	High	Moderate	Low
23	High	Moderate	Moderate
24	High	Moderate	High
25	High	High	Low
26	High	High	Moderate
27	High	High	High

In the next section of this document, each device's use profiles are detailed in their respective settings. Since devices may have more than three levels of each aspect (for example, a moderate-1 and moderate-2 pattern level) and also vary in their possible combinations, numbers assigned to each profile differ across devices. To facilitate discussing profiles, a shorthand is used to list each level in the order shown above: for instance, "Mod-Low-High" would be the profile that is moderate for active use, low for pattern or number of times, and high for PM. In analysis, comparing the variation of each of the states of these three categories, a multivariate analysis can provide information about the "impact" of that particular effect on device total energy usage. In addition to linear multivariate regression, a DBSCAN graphical analysis in Mathworks Matlab was used to compare clustering in preliminary visualization for results screening during the reporting process.

CALCULATING ENERGY CONSUMPTION

PLSIM 1.2

Two open-source simulation tools were developed in support of this project: MISER and PLSim. MISER 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 energy modeling tool used in this work.

A per-device, state-wise energy usage XML database (seen in Figure 4) is generated by testing device operation per the aforementioned testing approaches. This database provides a list of states. A developed time-based (temporal) profile maps the time the device spends during a particular period for a given action to energy usage. This is either entered directly or as a CSV file as a simplified input method. A diagram of PLSim is shown in Figure 5.

```xml
<data>
    <!--Calit2/CalPlug generated Tested Device State Database, format compatible with CalPlug PLSIM 1.2 Utility -->
    <!--California Plug Load Research Center(CalPlug) -  Project Administrators - Michael Klopfer, Ph.D., Saniya Syed, Prof. G.P. Li and Joy Pixley, Ph.D. -->
    <!--Project sponsored by Southern California Edison (SCE) - 2019-->
    <!--Version XXXX (DISCUSSION EXAMPLE), May 20, 2019-->

    <!--NOTE: Invalid fields or fields with no data are omitted or marked with a numeric value of "-1"-->
    <!--NOTE: Validate XML formating using a consistancy checker if modifications are made, an online tool is: https://www.w3schools.com/xml/xml_validator.asp -->
    <device-class name="Entertainment Electronics"> <!--General Device Type Category-->
        <device-type name="Televisions(4K)">  <!--General Type-->
            <device-brand name="Samsung">  <!--Brand-->
                <device-model name="Model UN 50JU6500F" comments="4K Smart TV, 37 inch">  <!--Model with basic typical specifications as a comment-->
            </device-brand>
            <device-brand name="Visio">
                <device-model name="Model PQ65-F" comments="4K HDR LED LCD Smart TV, 65 inch">
            </device-brand>
        </device-type>
        <device-type name="Televisions(HD)">
        <device-type name="Set Top Boxes">
            <device-brand name="DirecTV/AT&amp;T"> <!--Note format for ampersand character-->
        </device-type>
    </device-class>

    <device-class name="Kitchen Appliance">
        <device-type name="Pod Coffee Maker">
            <device-brand name="Keurig">
                <device-model name="B60" comments="Button controlled, no screen">
                <device-model name="K40" comments="Button controlled, with screen">
            </device-brand>
        </device-type>
        <device-type name="Drip Coffee Maker">
            <device-brand name="Cuisinart">
        </device-type>
    </device-class>
</data>
```

```xml
    </device-class>
    <device-class name="Climate Control">
        <device-type name="Portable HVAC System">
            <device-brand name="Delonghi">
                <device-model name="Penguino Model#AN140HPEWS" comments="Plug in portable HVAC unit with exhaust fan ducting and heat pump heating">
                    <state name="SoftOff" type= "static" power="0.434" power_factor="0.3467" thd="145.3" comments="Plugged in only, not turned on" />
                    <state name="Standby" type= "static" power="4.61" power_factor="0.628" thd="126.2" comments="Turned on, no fans or motors operating, active standby state" />
                    <state name="Active-FanatLowLevel" type= "static" power="53.605" power_factor="0.8702" thd="3.81" comments="Fan in low mode, no heating or cooling activated" />
                    <state name="Active-FanatMedLevel" type= "static" power="59.193" power_factor="0.9122" thd="3.66" comments="Fan in med mode, no heating or cooling activated" />
                    <state name="Active-FanatHighLevel" type= "static" power="69.027" power_factor="0.992" thd="3.68" comments="Fan in high mode, no heating or cooling activated" />
                    <state name="Active-FanatHighLevelInletBlocked" type= "static" power="52.975" power_factor="0.8650" thd="3.83" comments="Fan in high mode, no heating or cooling activated, inlet to recirculation fan is blocked" />
                    <state name="Active-ACOnFanHighLevel" type= "static" power="52.975" power_factor="0.8650" thd="3.83" comments="Fan in high mode, cooling activated" />
                    <state name="Active-HeatOnFanHighLevel" type= "static" power="1178.3" power_factor="0.989" thd="3.82" comments="Fan in high mode, heating activated" />
                    <state name="Active-DehumidifyOnFanHighLevel" type= "static" power="1172" power_factor="0.989" thd="3.82" comments="Fan in high mode, dehumidify activated" />
                    <state name="Active-DehumidifyOnFanMedLevel" type= "static" power="1138" power_factor="0.984" thd="3.81" comments="Fan in mid mode, dehumidify" />
                </device-model>
            </device-brand>
        </device-class>
```


FIGURE 4. GENERAL STRUCTURE OF THE DEVICE-STATE XML-BASED DATABASE USED FOR PLSIM

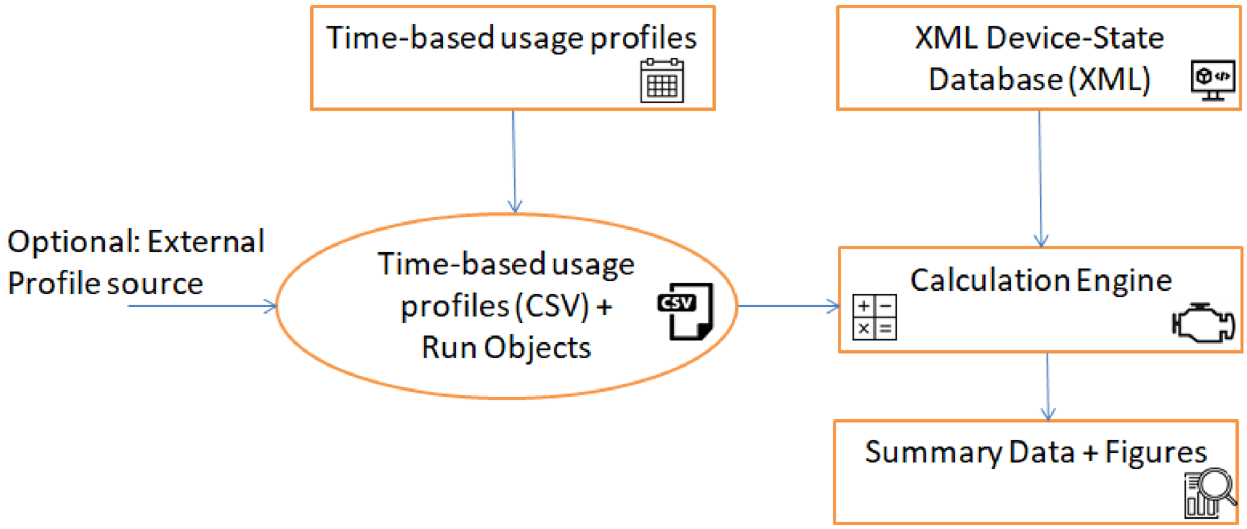

FIGURE 5. FLOW DIAGRAM FOR THE OPERATION OF PLSIM

Source: CalPlug, FlatIcon

PLSim is developed in Python 3.6 and can be run from Eclipse Java IDE (tested in Photon/2018 version) using Miniconda3 as an Eclipse Python interpreter. Configuration and operation details can be found in the project GitHub repository. Energy data is calculated on a state-wise basis for time over the period of one 24-hour analysis period. Energy usage can be interpreted universally, or with respect to the lowest state. In a universal sense, total energy usage is compared to either first principles of device operation or equivalent devices as a context for interpretation. This approach is often used when the fundamental device design is to be discussed, including the power supply or standby load.

Universal framework is commonly used when interpreting pre-post study results referencing baselines. Alternatively, the lowest-state reference uses the device in its lowest possible state to show a reference case, and a totally-unused device in its lowest power state. Comparative savings can be due to usage changes (changes in utility) or energy consumption changes without total utility reduction (changes in efficiency). The lowest-state reference is often used as a contextual framework to interpret the behavioral aspects of usage due to changes in device energy usage (either due to utility or efficiency changes). Daily energy usage is calculated as a temporal combination of all event states during a 24-hour period (see Equation 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-hour period.

EQUATION 1. CALCULATION OF DAILY ENERGY USAGE BASED ON GENERIC EVENT FREQUENCY AND CLASSIFICATION

Shown explicitely with two terms:

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

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-hour 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-hour 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-hour 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.

In this formula presentation, the inactive mode is the default case, and activities interrupt a 24-hour period of sleep to modify energy consumption during specific event periods.

An example of the PLSim XML database for devices and corresponding states is shown in Figure 4. A hierarchical tree structure is used to describe devices under a categorical classification. Within each device, a set of states is defined. In PLSim 1.2, only "static" states are used for modeling energy states. Where available, median and standard deviation values are provided for power, power factor, and measured THDi quantities.

PLSim 1.2 provides the ability to calculate bands of energy usage corresponding to +/- 1 standard deviation, with respect to the average term for each measured quantity. This provides a quickly-defined band for potential energy usage. Confidence intervals and other statistical discrimination factors could be used given the evaluation period sample length, but this adds to complications related to data interpretation (especially between changing states) without providing substantial added benefit to merit the effort in current usage. In the current study, Power Factor and THDi are not interpreted from PLSim results. Both measurements can be used to assess power quality related to devices. In future developments, such information may help model areas of concern for simultaneously-operating devices related to power quality.

The current dataset analyzed in this report is available as a sample for PLSim as a work product and is publicly available from the project Github repository.

MISER

MISER is another open-source tool developed by CalPlug. Similar to PLSim, MISER was also developed in Python 3.6 and can be run from Eclipse Java IDE (tested in the Photon/2018 version) using Miniconda3 as an Eclipse Python interpreter. MISER is used to calculate changes in marginal energy usage for personal computers as an effect of changing PM settings. In this evaluation, MISER is only applicable to timed PM schemes, and was only used for modeling desktop computer automatic sleep settings.

This tool specifically uses field test data for time spent in states of operation, and can be used to calculate energy savings potential by adjusting settings for power-saving states. A classic use of this tool is for desktop computers (Klopfer et al., 2019). Using known settings and energy usage for field trials, adjusted PM settings can be modeled to provide a difference in energy usage due to setting changes. Sleep-blocking events (failures to enter sleep), either legitimate (for example, through a program purposely preventing initiation of sleep) or unintentional can be estimated.

MISER modeled computer energy usage due to changes in PM settings using the 115 person CalPlug desktop Monitoring Study as a reference data set, but with the operational states modeled from testing (Pixley & Ross, 2014). An important caveat is that the original Monitoring Study state data was reported in 15-minute blocks – in each block, the software indicated how many minutes the computer spent off, in sleep mode, on but actively being used, or idle (on but not being used). As such, it was not possible to definitively assess the length of short idle periods.

A pattern-matching approach was used to mitigate the impact of periods carrying between multiple blocks from being interpreted as multiple shorter periods. Some specific patterns are easy to identify – for example, when a block includes idle and sleep time, the idle time precedes the sleep time, and the sleep time carries over to the next block. Various strategies were used to estimate likely patterns of states within blocks; this is explained in more detail in Klopfer et al. (2019). The power of this tool is limited by the working dataset and any shortcomings in its fidelity or representation.

The utility allows the selective summarization of state data from the study (passive analysis). It also uses daily state-time data to simulate alterative usage scenarios based on changed settings (active analysis). The Monitoring Study’s state-time information can be used to provide a snapshot of general office desktop computer usage. Based on the state periods for all 115 study machines presented in Table 5, and the PM settings presented in Figure 6, the average computer is in an idle state more than 50% of the time. Monitor sleep (screen blanking) is common; true computer sleep is less common. These findings were confirmed with the 2017 follow up to the Monitoring Study. These summarized results are presented in Figure 7.

TABLE 5. THE TIME SPENT IN EACH STATE FOR THE 115 OBSERVED OFFICE DESKTOPS IN THE MONITORING STUDY WITH SUB STATES SHOWN

	Weekday Average		Weekend Average		Overall Average	
Computer State	**Percent**	**s.d.**	**Percent**	**s.d.**	**Percent**	**s.d.**
On	77.7%	31.0%	68.7%	41.7%	75.1%	34.6%
User active	*13.2%*	*7.4%*	*1.0%*	*3.3%*	*9.7%*	*8.5%*
User Idle	*64.0%*	*31.3%*	*66.3%*	*42.4%*	*64.6%*	*34.9%*
User Unknown	*0.5%*	*3.6%*	*1.5%*	*2.3%*	*0.8%*	*1.8%*
Sleep	8.2%	20.0%	6.9%	21.8%	7.8%	20.6%
Off	11.8%	22.3%	21.0%	36.1%	14.4%	27.3%
Unknown	2.2%	10.1%	3.4%	14.0%	2.64	11.4%

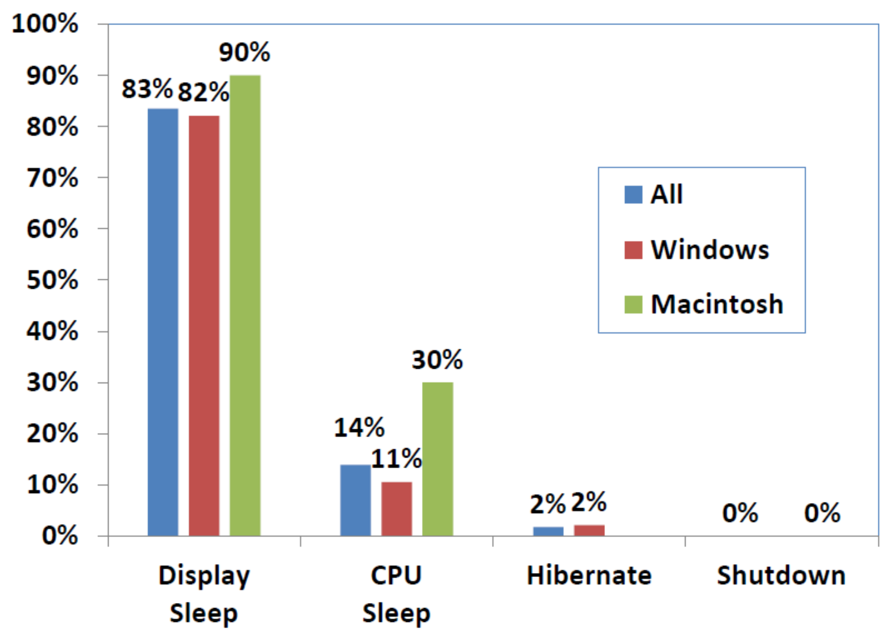

FIGURE 6. PREVALENCE OF ENABLED SETTINGS FOR MACINTOSH (OSX) AND WINDOWS COMPUTERS IN THE MONITORING STUDY.

Delay setting distributions for computer sleep and display sleep are shown in graphical form in Figure 7, emphasizing the prevalence of settings at 30 minutes and, for display only, 10 minutes. Display sleep settings are substantially more likely to be enabled than computer sleep settings. This is an important point of consideration for Tier 1 Advanced Power Strip (APS) usage linked to display-state triggering.

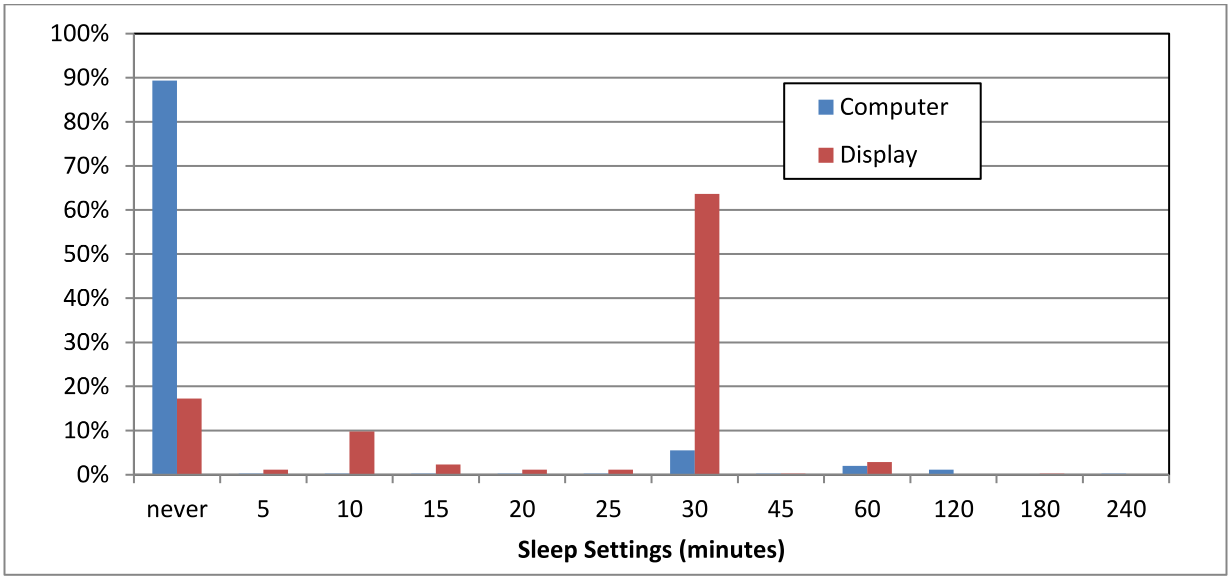

FIGURE 7. OBSERVED SLEEP SETTINGS FOR UNIVERSITY OFFICE DESKTOPS FROM CALPLUG PMUI STUDY

Source: Pixley, Gago-Masague, and Fallman (2018)

MISER enables actively evaluating computers and using different PM settings to model potential savings. Effectively, the results are presented as active time that could be converted to sleep. This delta value is considered savings, and can be applied to a baseline usage figure.

While MISER helps model energy usage for workstation computers, there are several substantial concerns. The Monitoring Study dataset observed office desktop computers, so the results are not necessarily applicable to residential desktop computers or laptops.

Additionally, MISER uses perfectly-simulated PM activation. In their Power Management User Interface (PMUI) Study, CalPlug further investigated the impact of "sleep blocking" events and determined they could have a substantial impact on how computers transition to sleep states. For example, a browser tab containing an active video could prevent the computer from entering the sleep state at its normal idle period. Because this event is very situationally specific, added logic and a better field understanding of the prevalence of this type of event is necessary to incorporate this modeling capability into MISER. Residential laptops also create a complicated energy usage scenario. Unlike in offices, where laptops are often docked or plugged in during daily use, home laptops are used in various locations and are charged at non-corresponding times.

While MISER sheds some light on the impact of the energy used by desktops, as well as laptops that are used in a similar manner to desktops (continually plugged in, never charging), substantial aspects are modeled in a way that may not be directly representative of residential computer use scenarios. Accordingly, the authors present MISER data alongside the conventional methods used through the other evaluated device categories to provide an additional category energy usage reference.

MULTIVARIATE REGRESSION ANALYSIS

Regression is a statistical method for modeling the relationship between a dependent variable (outcome) and one or more independent variables (predictors). In the current analyses, we focus on two results made possible by regression analyses. First, we examine the estimated effect on energy consumption for a given device of each aspect level relative to other levels of that aspect (for example, high active use versus moderate active use). Second, we compare the amount of variance in energy consumption explained by the three different aspects (for example, whether different levels of PM matter more for energy consumption than for total amount of active use).

The basic linear regression equation is shown in Equation 2:

EQUATION 2. ORDINARY LEAST SQUARES REGRESSION

$$Y_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots \beta_N X_{Ni} + \varepsilon_i$$

Where:

Variable	Value
Y_i	Dependent variable
α	Intercept term
β_x	Coefficient representing the estimated independent effect of its associated independent variable, net of the other variables in the model
X_{xi}	Independent variable predicting Y
ε_i	Error term

In the current analyses, the dependent variable is the calculated amount of daily energy consumption (in Wh) used for each usage profile *i*. The independent variables represent the level for each of the three aspects (active use, pattern of use, and PM) in each behavior profile. For each aspect, the possible levels were coded as a set of dummy variables (0 or 1). Each usage profile for each device would have a value of 1 for the level of aspect it represents, and a value of 0 for all other options. For instance, Device A (a laptop computer) has three possible levels for active (low, moderate, and high). Usage profile A-22 is "high" for active, so the variable "active-high" would equal 1, while the variables "active-low" and "active-moderate" would equal 0.

The regression equations were run as a series of nested models, first predicting energy consumption using each usage profile aspect by itself, then incorporating all the aspects into the final, full model. When a single concept (for example, active aspect) is represented by a set of two or more dummy variables (such that every case has a value of 1 for only one dummy variable) one of these variables must be omitted as the referent (or comparison case) in a regression equation. For instance, the model regressing energy consumption for Device A on the active aspect is shown in Equation 3.

The variable for active-moderate is omitted, and the coefficients for active-low and active-high are interpreted as the direction and size of the effect of "low versus moderate" and "high versus moderate," assuming the coefficients are statistically significant. Using the moderate level of each aspect is a conservative choice, forcing the differences across profiles to vary from the average or medium; differences between the highest and lowest extremes would have to be tested separately.

EQUATION 3. EXAMPLE OF REGRESSION OF ENERGY CONSUMPTION ON ACTIVE ASPECT VARIABLES

$$EC_i = \alpha + \beta_1 * Active\text{-}low_i + \beta_2 * Active\text{-}high_i + \varepsilon_i$$

The equations differ by device because usage profiles differ on the number and types of levels within each aspect. For instance, Device A has five levels of the pattern aspect (low, moderate-1, moderate-2, high-1 and high-2) whereas Device C has only three (low, moderate, and high). When there is more than one moderate level of an aspect, moderate-1 is chosen as the omitted category.

A regression model produces a statistic called R-squared (R^2), which is the proportion of the variance in the dependent variable that is explained by the model.

Accordingly, the impact of a particular category of modeled behavior (time of use, PM setting, or cycles of operation) can be analyzed to identify if it is statistically significant (set at α=0.05). Accordingly, based on how a category is formed for a given device, the impact of these corresponding actions can be assessed for their effect on energy usage. Multivariate analyses were performed using the SAS 9.4 statistical suite.

RESULTS

The device evaluation results are presented in two parts. The first section provides simulation results for the energy consumed by each plug load device and how it differs by profile. The second section presents the multivariate analyses that tested the relative impact of each of the three aspects – active use amount, pattern of use, and PM – on the profiles' energy consumption.

PLUG LOAD DEVICE ENERGY EVALUATIONS

Devices are grouped into three categories: entertainment devices, computers, and kitchen equipment. Details of the device categories and corresponding devices are presented within each subsection.

First, for each device, definitions of the three usage aspects are identified. As explained earlier, whenever possible, the number of hours or times given for the active use aspect is based on existing data and/or ENERGY STAR protocols. Moderate usage is defined as the real-life testing standard or median of reported usage, and low and high usage is defined as the 10^{th} and 90^{th} percentile of reported usage.

Likewise, the moderate PM option describes the default state of the device's power-saving features, along with an estimation of likely average user behavior. The research team developed the other category definitions based on what were considered reasonable user behavior assumptions. It should be noted that the energy usage results rely heavily on accepting these assumptions; alternate definitions would produce at least slightly-different projections.

A set of device use profiles was then constructed by starting with all possible combinations of the three aspect levels, then eliminating those that were not possible or logical. There are two reasons why aspect combinations would be eliminated. First, some combinations of active use and pattern would add up to more than 24 hours, due to the number and lengths of idle periods between active use periods. Second, some active use times are short enough that they become unreasonably small when divided into the number of periods in a pattern. This is device-specific – for instance, while someone might wake their computer to check email for only a few minutes, it is unlikely that users would watch TV for less than 30 minutes at a stretch.

If a feature or setting is not mentioned in the aspect descriptions, it is set at the factory standard and held constant for all tests (e.g., brightness setting).

The resulting set of device use profiles was then programmed into CalPlug's PLSim tool. Entering power consumption data from in-house device testing (in all possible states) into PLSim produced the total simulated energy consumption for each profile. These results are presented and discussed in this section to show how energy consumption varies across all the device use profiles included here. For comparison, lower and upper boundaries are also modeled, showing energy consumption if the device remained in the lowest or highest usage state possible for 24 hours.

ENTERTAINMENT DEVICES

The entertainment devices modeled here include TVs, set-top boxes, video game consoles, streaming devices, and sound systems. Despite belonging to a common category, these devices have substantial operational differences.

4K TV

The tested device is a 4K TV with a 50-inch screen. This Ultra-High Definition (UHD) model is called 4K because it is capable of 3840 x 2160 pixels, which is four times the pixel resolution and two times the line resolution of a 1080 HDTV at a 120 Hz screen refresh rate. The tested device provides two types of onboard automatic PM.

"No signal power off" turns the TV off (soft-off) after no signal has been received from the connected source for a set period of time. The default setting is a 15-minute delay; this can be disabled by the user, or changed to 30 or 60 minutes. "Auto power off" turns the TV off (soft-off) after receiving no input from the user (via the remote control) for a set period of time. By default, this function is set to never; the user can choose a delay period of four, six, or eight hours.

This model also includes a sleep timer option that allows the user to fall asleep with the TV on without leaving it on all night; it turns the TV off after a set delay time, from 30 minutes to up to three hours (with 30-minute increments). The sleep timer resets to "off" after each use and should not be confused with the two automatic settings, which remain in effect unless disabled. There are also several settings related to brightness control. Tests for this device were conducted with the auto-brightness (ECO Sensor) control turned off, consistent with ENERGY STAR protocol.

In comparison to HDTVs, on average, energy consumption is substantially higher for 4K TVs, due to increased pixel counts and higher brightness of individual pixels to produce substantial total screen brightness with tighter-pitched pixel arrays.

Device Usage Behavior Model

The definitions of the three aspects constructed for 4K TVs are shown in Table 6. Survey data shows a large range of usage for TVs, and those results constructed the active use categories in the original SIM Home analyses. Since that report, the results were updated with the 2015 RECS study. Because the results were identical (see Table A8), the same active-use definitions (based on median, 10th percentile, and 90th percentile) were used in the current study.

The moderate PM definition uses the default settings, with the "no signal power off" feature enabled and set at 15 minutes, and the auto-off setting disabled. The lowest (most energy-wasting) PM behavior reflects those households where the TV is left on in the other room even when nobody is watching it, so it stays on for most of the day. This may seem like extreme usage, but anecdotally, such households clearly exist, and the PM setting is similar to those for other devices included in this report, which users leave on when they are not being used.

An interim (Low-2) PM definition has the auto-off feature set at its most energy-efficient delay (four hours) with the TV left on. In this version, the "no signal power off" feature is disabled, but the same outcomes would be observed if that feature were enabled but no external input were used. Note that for the high-PM definition, enabled settings do not matter for the current calculations (although they would have some effect in the long run, as even conscientious users can occasionally forget to turn off the TV).

Table 6. 4K TV Profile Aspects

Aspect and Level		Description
Active Use		
	Low	0.5 hour
	Moderate	5 hours
	High	13 hours
Pattern		
	Low	1 period
	Moderate-1	2 periods, 5 hours between
	Moderate-2	2 periods, 1 hour between
	High-1	4 periods, 5 hours between
	High-2	4 periods, 1 hours between
PM		
	Low-1	No signal power off and auto-off disabled; user leaves on after use, leaves on when they go to sleep but without sleep timer (add 8 hours at end)
	Low-2	No signal power off disabled; auto-off set for 4 hours; user leaves on after use (either leaves input on or not using external input)
	Moderate	No signal power off set to 15 minutes (default), auto-power off disabled (default); user shuts off input after use but leaves TV on
	High	Default settings; user turns off after each use

The set of device use profiles is comprised of the combinations of these aspects that are logically and practically possible. An example of this first device is shown in Table 7. As described above, there are two reasons for why a particular aspect combination might not be an appropriate device use profile, and both are true for this device. First, some combinations of active use and pattern would add up to more than 24 hours. This is the case with high active use combined with the high-1 pattern, which would result in four periods of three hours each, with three interim periods of five hours each, adding up to 24 hours or more with no break (that is, non-active use) between the last active period of one day and the first active period of the next.

Second, some use periods are too short to be realistic. Because this decision is subjective, the research team erred on the side of inclusion rather than exclusion. For TVs, the combination of low active use with either of the high patterns resulted in four active periods of 7.5 minutes each. Although this would admittedly be unusual viewing behavior, the research team determined that it was no more extreme than 13 hours of continuous active use, so these profiles were retained.

For every device, one profile is designated to represent or approximate the standard testing protocol. For many, this combines active-moderate (the median level of active use), pattern-low (all the usage in a single period), and PM-high or moderate. In the case of TVs, the PM level used for the standard profile is high, reflecting the fact that standardized energy consumption testing does not assume leaving the device on and waiting for it to automatically transition to sleep mode.

Table 7. Profile Combinations of Device Use Aspects for 4K TV

		Aspects	
Profile Number	Active Use	Pattern/Times	PM
1	Low	Low	Low-1
2	Low	Low	Low-2
3	Low	Low	Mod
4	Low	Low	High
5	Low	Mod-1	Low-1
6	Low	Mod-1	Low-2
7	Low	Mod-1	Mod
8	Low	Mod-1	High
9	Low	Mod-2	Low-1
10	Low	Mod-2	Low-2
11	Low	Mod-2	Mod
12	Low	Mod-2	High
13	Low	High-1	Low-1
14	Low	High-1	Low-2
15	Low	High-1	Mod
16	Low	High-1	High
17	Low	High-2	Low-1
18	Low	High-2	Low-2
19	Low	High-2	Mod
20	Low	High-2	High
21	Mod	Low	Low-1
22	Mod	Low	Low-2
23	Mod	Low	Mod
24	Mod	Low	High
25	Mod	Mod-1	Low-1
26	Mod	Mod-1	Low-2
27	Mod	Mod-1	Mod
28	Mod	Mod-1	High
29	Mod	Mod-2	Low-1
30	Mod	Mod-2	Low-2
31	Mod	Mod-2	Mod
32	Mod	Mod-2	High
33	Mod	High-1	Mod
34	Mod	High-1	High
35	Mod	High-2	Low-1
36	Mod	High-2	Low-2
37	Mod	High-2	Mod
38	Mod	High-2	High
39	High	Low	Low-1
40	High	Low	Low-2
41	High	Low	Mod
42	High	Low	High
43	High	Mod-1	Low-2
44	High	Mod-1	Mod
45	High	Mod-1	High
46	High	Mod-2	Low-1
47	High	Mod-2	Low-2
48	High	Mod-2	Mod
49	High	Mod-2	High
50	High	High-2	Low-2
51	High	High-2	Mod
52	High	High-2	High

Device Results

A summary of PLSim results for 4K TVs is shown in Table 8. The standard device usage profile (#24, mod-low-high) produces a usage of 1305.13 Wh. The median energy usage falls between the values of profiles #22 (mod-low-low2) and #44 (high-low-high). The profile with the minimum usage was #4 (low-low-high) and maximum usage was a tie between profiles #33 (mod-high1-low1), #45 (high-mod1-low1) and #53 (high-high2-low1), producing a large range of modeled outcomes that vary by usage.

For comparison, the minimum boundary level (at soft-off power for 24 hours) is estimated as 2.76 Wh, while the maximum boundary level (active power on for 24 hours) is estimated at 3746.71 Wh, providing reference boundaries for excessively-wasteful/longest-possible use (maximum usage) and non-usage.

TABLE 8. 4K TV SUMMARY RESULTS

	Standard (Wh)	Median (Wh)	Min (Wh)	Max (Wh)	Range (Wh)
4K TV	1305.13	1981.54	82.38	3746.71	3664.33

Daily energy usage for each individual profile is shown in Figure 8. Profiles are shown in the same order as described in Table 7. This means that the first group of profiles has low active usage, the middle groups have moderate usage, and the last groups have higher usage. Within each of these groups, the low-1 PM profile comes first and the high-PM profile comes last (remember that “low” PM means less use of energy-saving features, which should result in higher energy usage than high PM).

Analyzing the results in order of increasing energy impact visually reveals three main patterns. First, the low-1 PM profiles repeatedly show higher energy consumption than the low-2, while the moderate and high-PM profiles are much lower and do not differ much. Second, the differences between the moderate and high active usage profiles are not as great as those between them and the low active usage profiles. Finally, that pattern does not seem to have a strong effect for this device. For instance, profiles 41, 42, 43, and 44 show the effect of PM when active usage is high and pattern is low: highest for low-1 PM, a little lower for low-2 PM, and much lower for mod and high PM. Almost identical results are seen for the next three sets of profiles, despite changing the pattern aspect.

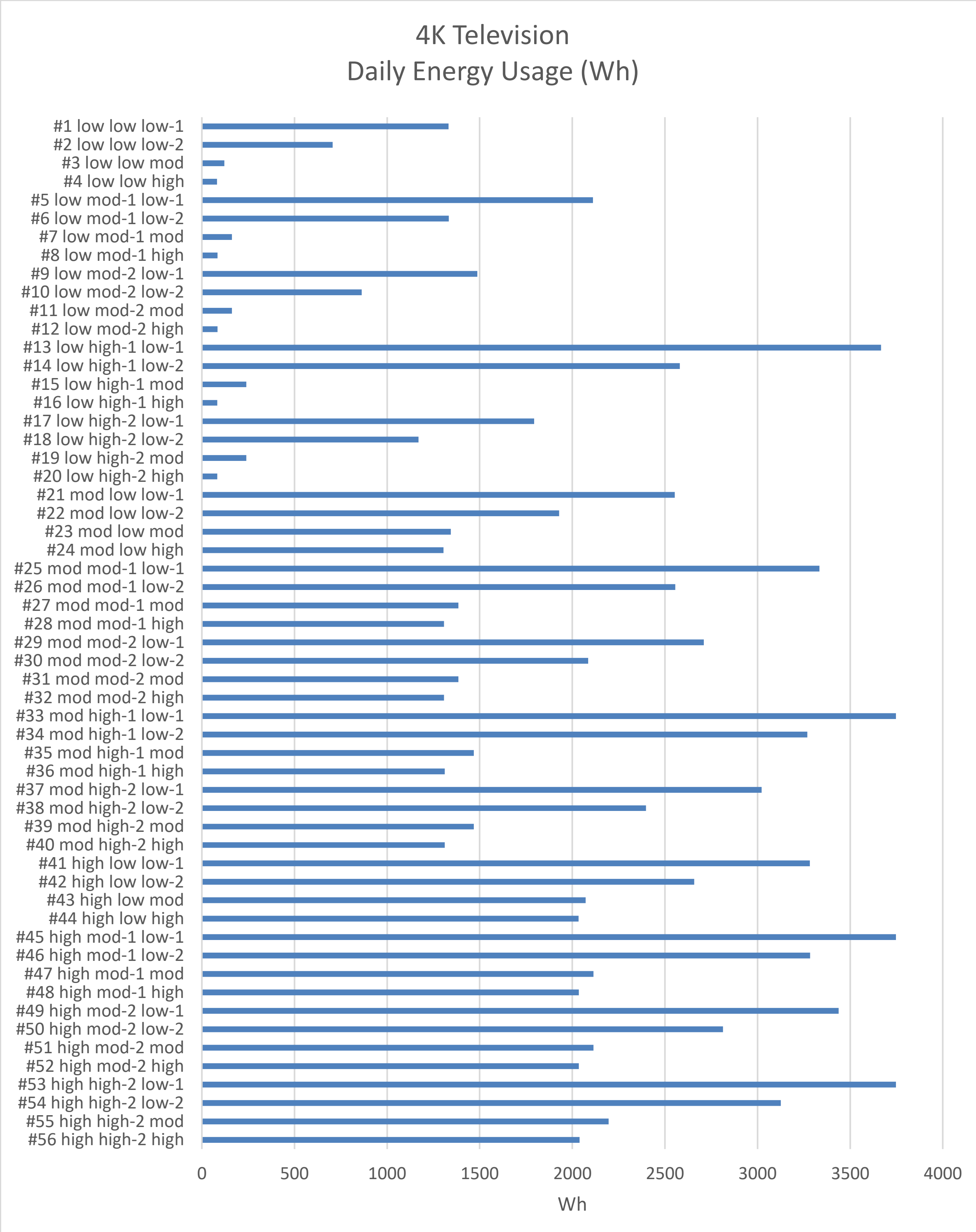

FIGURE 8. 4K TV DAILY ENERGY USAGE PROFILES

HDTV

The evaluated, modeled HDTV is a name-brand, 50-inch device with onboard “smart” capabilities to display internally sourced content. In the evaluation, all content is provided by an HDMI source. This TV has fewer low-power modes than the 4K model. It offers a feature called "auto-power-off" which functions the same as the "no signal power off" feature of the 4K TV; to reduce confusion, the same term is used here. This feature only has two options: enabled with a 10-minute delay (the default factory setting) or disabled. There is no feature that automatically turns the TV off in the absence of user input. A sleep timer is available, with possible settings of 30 minutes up to three hours. As with the 4K TV, this timer must be reset every time the user wishes to use it.

Device Usage Behavior Model

The device use profiles shown below are based on those developed for the 4K TV (see Table 6 and Table 7). Two exceptions for this device are that the PM Low-2 definition cannot be used for the HDTV because the auto-off feature is not present, and that the default for the "no signal power off" setting is 10 minutes rather than 15 minutes. As with the 4K TV, possible profiles combining high active use and the high-1 pattern were excluded, because they exceeded 24 hours.

Table 9. HDTV Profile Aspects

Aspect and Level		Description
Active Use		
	Low	0.5 hour
	Moderate	5 hours
	High	13 hours
Pattern		
	Low	1 period
	Moderate-1	2 periods, 5 hours between
	Moderate-2	2 periods, 1 hour between
	High-1	4 periods, 5 hours between
	High-2	4 periods, 1 hours between
PM		
	Low-1	No signal power off*disabled; user leaves on after use, leaves on when they go to sleep but without sleep timer (add 8 hours at end)
	Moderate	No signal power off* set to 10 minutes (default), user shuts off input after use but leaves TV on
	High	Default settings, user turns off after each use

* This feature is called "auto power off" for this model, but operates the same as "no signal power off" for the 4K TV.

Device Results

A summary of the HDTV's PLSim results is shown in Table 10. The standard profile (#17, mod-low-mod) produces usage of 687.11 Wh. Median usage falls between the values of profiles #7 (low-mod2-low) and #29 (mod-high2-mod). Minimum usage was #3 (low-low-high) and maximum was a tie between profiles #25 (mod-high1-low), #34 (high-mod1-low) and #40 (high-high2-low). Again, this produced a large range of modeled outcomes that vary by usage. For comparison, the minimum boundary level (at soft-off power for 24 hours) is estimated as 7.20 Wh, while the maximum boundary level (active power on for 24 hours) is estimated at 1903.15 Wh.

Table 10. HDTV Summary Results

	Standard (Wh)	Median (Wh)	Min (Wh)	Max (Wh)	Range (Wh)
HDTV	687.11	743.34	48.48	1903.15	1854.67

Figure 9 shows daily energy usage for each individual profile. With the exception of having only one low-PM level, similar patterns are seen as for the 4K TV. Specifically, moderate and high active usage are similar, while low active usage is much lower; low PM results in substantially-higher energy usage; and pattern does not have a demonstrable effect.

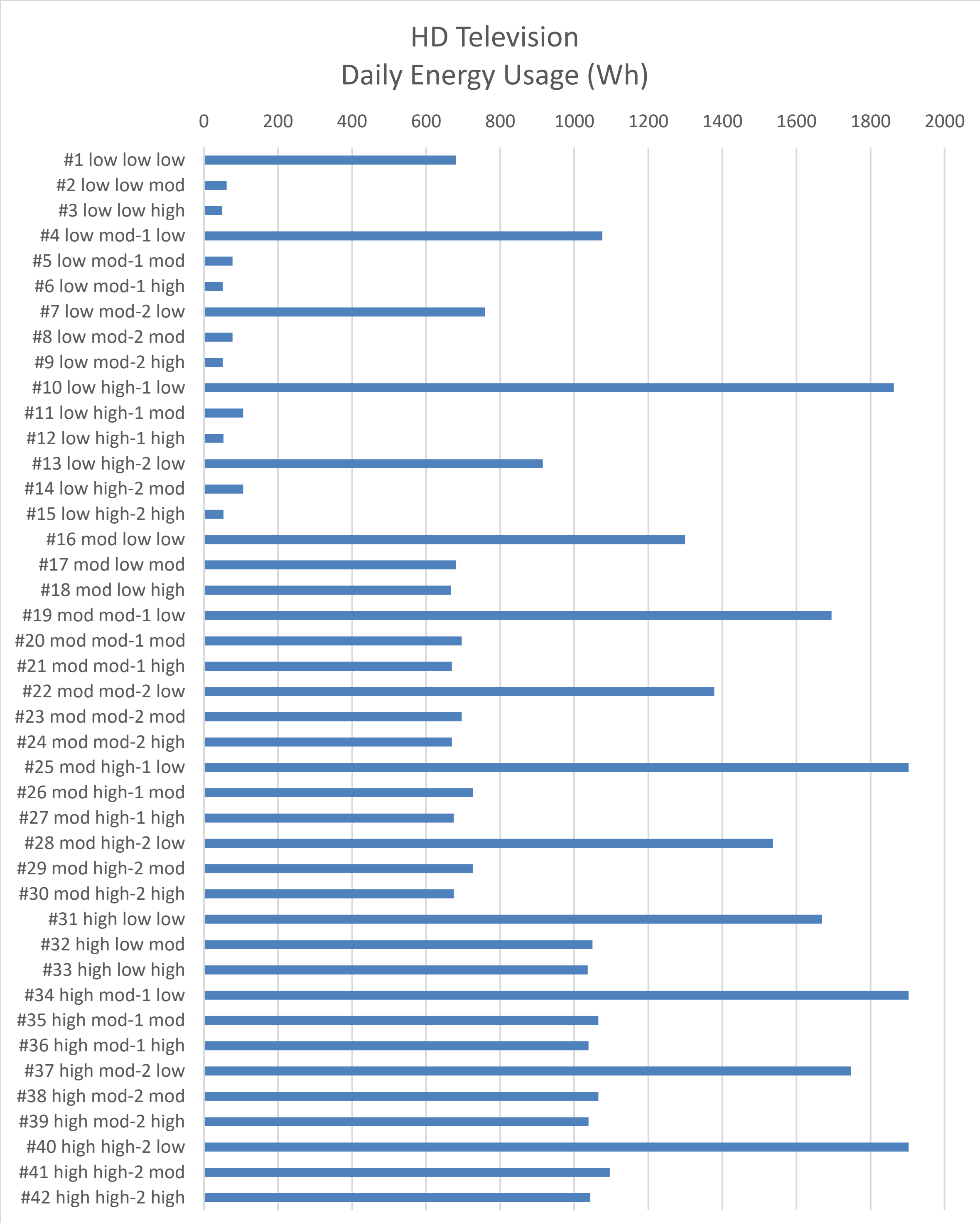

FIGURE 9. HDTV ENERGY USAGE PROFILES

Sound Bar

During testing, a major (matching) brand sound bar model was used in conjunction with the previously-discussed 4K TV. This device uses an optical audio link for primary audio content, which is sourced by the TV. An attached subwoofer is connected for low-frequency audio, and the power is supplied by an adapter. The device can receive audio content from various sources, including optical digital input, Bluetooth, TV SoundConnect, USB, or AUX input.

A remote control was used to trigger automatically-synchronized “on” and “off” actions and demonstrate control coordination between input activity and the TV. The device has an auto power-down feature enabled by default, and operates differently depending on the input type. If the input is through AUX mode, the unit automatically switches to soft-off after five minutes if the AUX cable is disconnected, or turns off after eight hours if there is no key input and the AUX cable remains connected. For any other type of audio input, the auto power-down mode switches to soft-off if there is no audio signal for five minutes. The user can disable the auto-off feature, but there are no other delay options. The current tests were conducted with the TV as the audio input. All tests were run with the volume set at 20%, or an average of about 35 decibels with audio input provided.

Device Usage Behavior Model

As with content-providing systems (such as streaming devices or satellite set-top boxes) the TV-connected sound bar can only operate when the TV is used. The sound bar is intended to provide audio output. While there may be some capability to provide audio play for smartphones or tablets, this is probably a secondary usage scenario. It is likely that the sound bar is always used with the TV, and aside from the previously-noted exceptions, other non-TV use would be considered wasteful. Accordingly, the TV/display profile for the 4K TV was used as an example profile, with the same active use and pattern definitions as for TVs. The definitions of PM aspects are shown in Table 11.

Given the same aspect definitions as for TVs, the same profiles were excluded, specifically those combining high active use and the high-1 pattern, due to exceeding the total number of hours in a day.

Table 11. Sound Bar Profile Aspects

Aspect and Level		Description
Active Use		
	Low	0.5 hour
	Moderate	5 hours
	High	13 hours
Pattern		
	Low	1 period
	Moderate	2 periods, 1 hour between
	High	4 periods, 1 hours between
PM		
	Low	User leaves on after use, device auto power down disabled, device stays in idle rest of day (active no sound)
	Moderate	User leaves on after use, device auto power down enabled, device turns off automatically after 5 mins of no input
	High	User turns off after each use

Device Results

Table 12 provides a summary of PLSim results for the TV sound bar. The standard profile (#11, mod-low-mod) produces a usage of 111.70 Wh. The median profile is #24 (high-mod-high). The minimum profile is #9 (low-high-high) and the maximum was a tie between all profiles with high active use and low PM. Again, this produced a large range of modeled outcomes that vary by usage. For comparison, the minimum boundary level (at soft-off power for 24 hours) is estimated as 88.30 Wh, while the maximum boundary level (active power on at 100% volume for 24 hours) is estimated at 333.54 Wh (note that the maximum boundary level at 20% volume for 24 hours would be 198.60 Wh).

TABLE 12. SOUND BAR SUMMARY RESULTS

	Standard (Wh)	Median (Wh)	Min (Wh)	Max (Wh)	Range (Wh)
Sound Bar	111.70	148.14	90.42	198.04	107.62

Daily energy usage for each individual profile is shown in Figure 10. Profiles with low PM are uniformly high due to being on all day long, whereas little difference is seen across moderate and high-PM levels. Moderate increases are shown for higher active usages, but there are no differences by pattern.

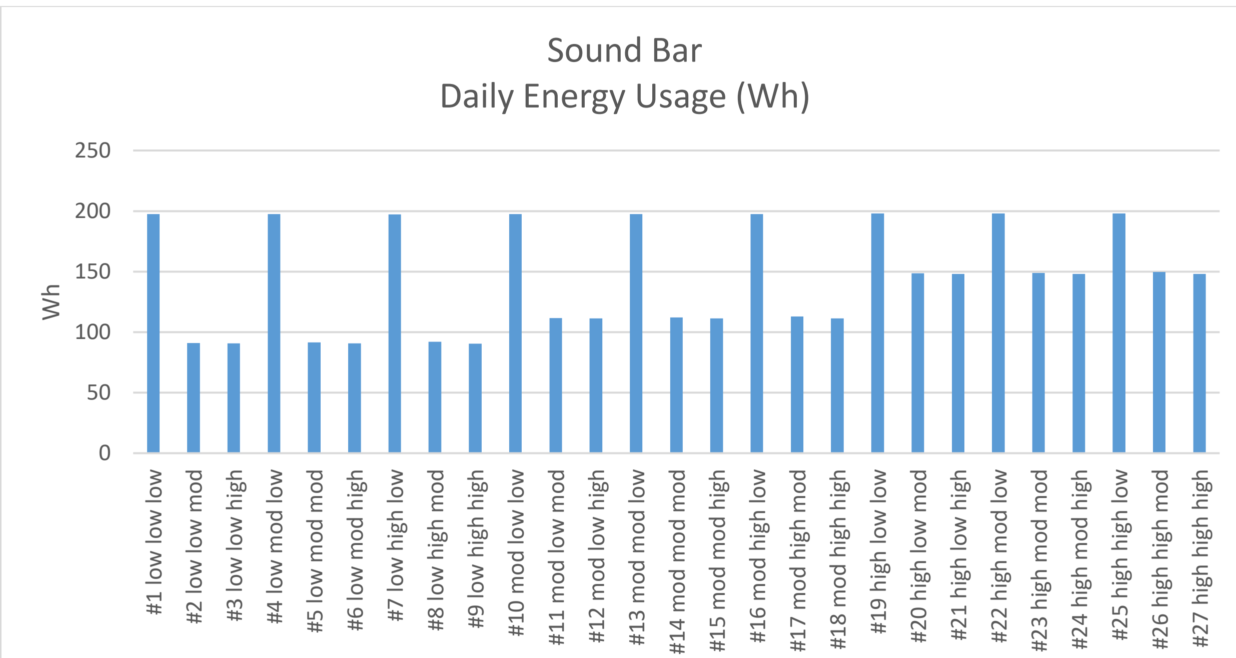

FIGURE 10. SOUND BAR ENERGY USAGE PROFILES

SATELLITE SERVICE SET-TOP BOX

A Digital Video Recorder (DVR) pay satellite TV service box from a major provider was used for evaluation. This device maintains a one-way connection from the head end, to keep security and content access information updated. In addition to having DVR functionality, the device can simultaneously record live TV and replay content by using multiple onboard tuners. The energy consumption of the recording features is relatively small, because the onboard hard disk drive is constantly active for buffering received content.

The device offers a standby state, during which content is not sent over device output and onboard LED indicators are extinguished; however, energy consumption is high in this state compared to other devices. This set-top box can still record content when in the standby state. Although it can serve content to thin client boxes, a single content source (like this type of box) is required for such a network to operate, which is why this particular device was chosen for evaluation. An auto-standby option is available where, by default, the box will go into power-saving standby mode after four hours of inactivity (the user can disable this option). In addition, there is no energy reduction when the set-top box is idle versus when it is showing live content, so leaving it on is the same as constant active use.

Device Usage Behavior Model

Table 13 provides definitions of three aspects constructed for satellite set-top boxes. Active usage and pattern aspects were based on those for TV usage. Although it is possible for someone to use their TV without a set-top box, the opposite is not true; therefore, for any given household, a set-top box may either match the TV profile or have lower active use.

Given the same aspect definitions as for TVs, the same profiles were excluded, specifically those combining high active use and the high-1 pattern, due to exceeding the total number of hours in a day.

Table 13. Set-Top Box Profile Aspects

Aspect and Level		Description
Active use		
	Low	0.5 hour
	Moderate	5 hours
	High	13 hours
Pattern		
	Low	1 period
	Moderate-1	2 periods, 5 hours between
	Moderate-2	2 periods, 1 hour between
	High-1	4 periods, 5 hours between
	High-2	4 periods, 1 hours between
PM		
	Low	User leaves on after use, auto standby disabled
	Moderate	User leaves on after use, auto standby after 4 hours (default) idle
	High	User turns off immediately after each use

Device Results

A summary of PLSim results for satellite set-top boxes is shown in Table 14. The standard profile (#18, mod-low-high) produces usage of 669.90 Wh. Median usage falls between the values of profiles #11 (low-high1-mod) and #29 (mod-high2-mod). Minimum usage was a tie between #12 (low-high1-high) and #15 (low-high2-high). All profiles with low PM and high active use are tied for (or within 1 Wh of) maximum usage.

The energy consumption range is relatively small across profiles, and is almost the same as the minimum and maximum boundary states. For comparison, the minimum boundary level (standby for 24 hours) is estimated as 654.00 Wh, while the maximum boundary level (active, showing live content for 24 hours) is estimated at 699.72 Wh. This high minimum boundary reflects the fact that set-top boxes must maintain continuous connections for program and encryption services, so even in their lowest-power standby mode, they use substantial power. As a result, users are limited in how much they can affect energy savings on this device. Also note that the profiles tied for using the most energy use the maximum for this device; this is because the energy consumption is the same for leaving the device on and idle as it is for actively using it for 24 hours.

TABLE 14. SET-TOP BOX SUMMARY RESULTS

	Standard (Wh)	Median (Wh)	Min (Wh)	Max (Wh)	Range (Wh)
Set-Top Box	669.90	684.57	654.07	699.72	45.65

Daily energy usage for each individual profile is shown in Figure 11. The pattern of results suggests PM is a key energy usage key factor for this device, and active usage provides only a slight variation. Note the figure is zoomed in for higher clarity, but the entire chart spans only 80 Wh. The differences shown here are small, and even the range between the most aggressive and least aggressive PM profiles is not large.

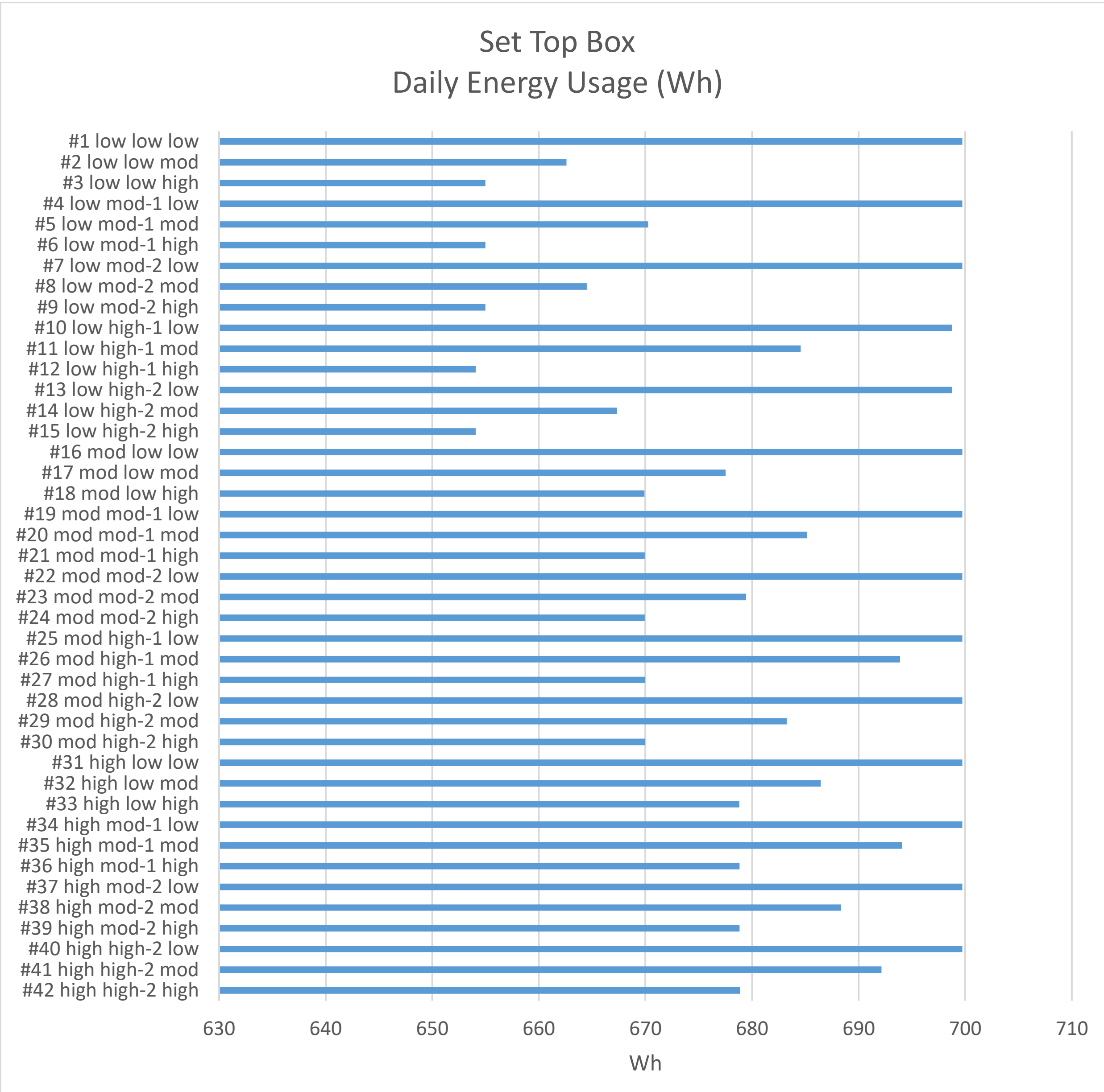

Figure 11. Set-Top Box Energy Usage Profiles

Streaming Device

This device is a single-box streaming system with 4K output, from a major manufacturer. It uses an onboard AC-to-DC converter to accept wall power directly, without the need for an external power supply. The device offers an automatic standby setting, which transitions the device into soft-off mode in the absence of video or user activity. The possible delay periods are: never, 15 minutes, 30 minutes, 1 hour, 5 hours, and 10 hours.

The factory default setting has the standby setting enabled at 15 minutes. A connection via HDMI, with Consumer Electronics Control (CEC) communication enabled, can provide a trigger to shut down the connected TV and in some cases, other attached accessories. Specific CEC-triggered linked device shutdown was not explicitly investigated as part of the evaluation for this device. When booted up or taken out of soft-off mode, the device will display a menu of apps that can be selected for operation.

This device’s soft-off power usage was very low at 0.22 W, although operational power usage was also low at 2.94 W. Through extensive testing, sleep blocking was not observed. All TVs tested with this streaming device could be triggered via the sent CEC commands, and changing inputs away from the device would cause it to power down if the standby setting was enabled. From our investigation, only a single standby mode (soft-off) exists for this device. When the front LED indicator is on, it means the device is active, and when the indicator is off, the device is in soft-off mode.

Device Usage Behavior Model

Active and pattern aspects were based on the same as those for TV usage. As with the satellite set-top box, the streaming device might not be used every time the TV is used. However, some users may only watch TV with this device; therefore, this is a maximum-usage case.

Given the same aspect definitions as for TVs, the same profiles were excluded, specifically those combining high active use and the high-1 pattern, due to exceeding the total number of hours in a day.

TABLE 15. STREAMING DEVICE PROFILE ASPECTS

Aspect and Level		Description
Active Use		
	Low	0.5 hour
	Moderate	5 hours
	High	13 hours
Pattern		
	Low	1 period
	Moderate-1	2 periods, 5 hour in between
	Moderate-2	2 periods, 1 hour in between
	High-1	4 periods, 5 hour in between
	High-2	4 periods, 1 hour in between
PM		
	Low-1	Sleep disabled, user leaves on
	Low-2	Sleep set at 1 hour, user leaves on
	Moderate	Sleep set at 15 minutes (default), user leaves on
	High	User manually puts to sleep after every use

Device Results

A summary of PLSim results for satellite set-top boxes is shown in Table 16. The standard profile (#24, mod-low-high) produces a usage of 28.13 Wh. Median falls between the values of profiles #26 (mod-mod1-low2) and #34 (mod-high1-low2). Minimum usage was #4 (low-low-high). All profiles with low PM and high active use tied for maximum usage. For comparison, the minimum boundary level (at soft-off power for 24 hours) is estimated as 5.41 Wh, while the maximum boundary level (active, application running for 24 hours) is estimated at 70.64 Wh.

TABLE 16. STREAMING DEVICE SUMMARY PROFILE

	Standard (Wh)	Median (Wh)	Min (Wh)	Max (Wh)	Range (Wh)
Streaming Device	28.13	35.42	6.85	68.88	62.04

Figure 12 shows daily energy usage for each individual profile. The primary pattern reveals that low PM leads to much higher usage than moderate or high PM, regardless of the other two aspects. Active use also matters, with increases between moderate and high active use and larger increases between low and moderate active use. Patterns of additional use per day show a slight increase in energy consumption for profiles with better-than-low PM.

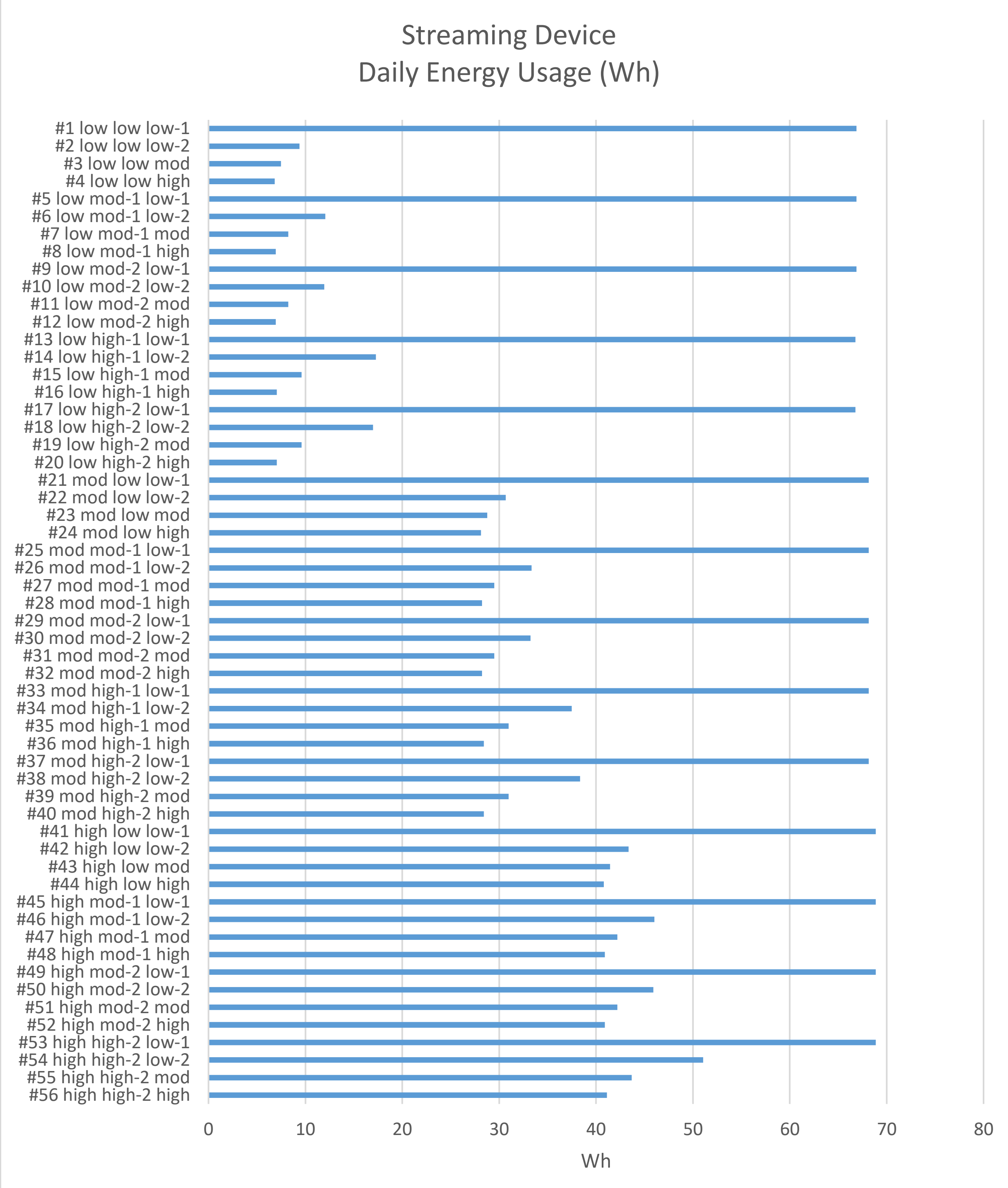

Figure 12. Streaming Device Energy Usage Profiles

VIDEO GAME CONSOLE

The evaluated device is a dedicated eighth-generation gaming console with an internal hard disk drive and wirelessly-connected controllers. The unit uses wireless connectivity and optical discs, as well as network interfacing, to allow downloading games and playing streamed media and game content. It supports HDMI CEC linking as a non-default option to allow remote-control linking when in operation.

The device has active, soft-off, and rest (standby) modes, as well as a factory default "Power Save Setting" feature for selecting the amount time until the console transitions to rest mode when not actively used. It can run games either by streaming or by disc, in which case the device transitions to the disc menu instead of the main menu when the game is stopped. As energy use differs for these two types of games and future trends lead toward more streaming and fewer physical discs, all results used here assume streaming content.

Device Usage Behavior Model

The active usage aspects for these profiles were defined based on secondary data on self-reported game console usage, collected as part of the original SIM Home report (Xia et al., 2017). The research team developed the pattern and PM aspect definitions. The pattern was based on the same aspects as for TV usage. As with the satellite set-top box, the game console might not be used every time the TV is, but in some cases, the TV may be used only with the game console, which is a maximum usage case.

The PM was based on the setting available for the particular game console tested. These definitions are shown in Table 17. As the active-low level is less than one hour, breaking it into two or four periods for the moderate and high patterns results in very short sessions; however, these were kept in the analyses on the assumption that short interrupted periods of game play were as realistic as very long periods of uninterrupted play.

Given the same aspect definitions as for TVs, the same profiles were excluded, specifically those combining high active use and high-1 pattern, due to exceeding the total number of hours in a day.

TABLE 17. GAME CONSOLE PROFILE ASPECTS

Aspect and level	Description
Active Use	
Low	0.7 hour
Moderate	5 hours
High	8 hours
Pattern	
Low	1 period
Moderate-1	2 periods, 5 hour in between
Moderate-2	2 periods, 1 hour in between
High-1	4 periods, 5 hour in between
High-2	4 periods, 1 hour in between
PM	
Low	User leaves on after use, all functions active, device switches to sleep automatically after 5 hours (longest delay time) idle
Moderate	User leaves on after use, minimum functions active, device switches to sleep automatically after 20 minutes (shortest delay time) idle; user turns off at end of day
High	User turns off immediately after each use, set to auto sleep with the shortest delay

Device Results

A summary of PLSim results for game consoles is shown in Table 18**.** The standard profile (#18, mod-low-high) produces usage of 556.90 Wh. Median falls between the values of profiles #26 (mod-high1-mod) and #29 (mod-high2-mod). The minimum profile was #3 (low-low-high) and the maximum was #25 (mod-high1-low). This produced a large range of modeled outcomes that vary by usage. For comparison, the minimum boundary level (at standby power for 24 hours) is estimated at 257.03 Wh while the maximum boundary level (active game play for 24 hours) is estimated at 1667.09 Wh.

TABLE 18. VIDEO GAME CONSOLE SUMMARY RESULTS

	Standard (Wh)	Median (Wh)	Min (Wh)	Max (Wh)	Range (Wh)
Video Game Console	556.90	644.24	303.50	1557.76	1254.26

Each individual profile’s daily energy usage is shown in Figure 13. The pattern shows higher energy consumption for low PM, and lower (but similar) energy consumption for moderate and high PM. These results suggest the amount of active use also affects energy consumption, but has little effect on the pattern.

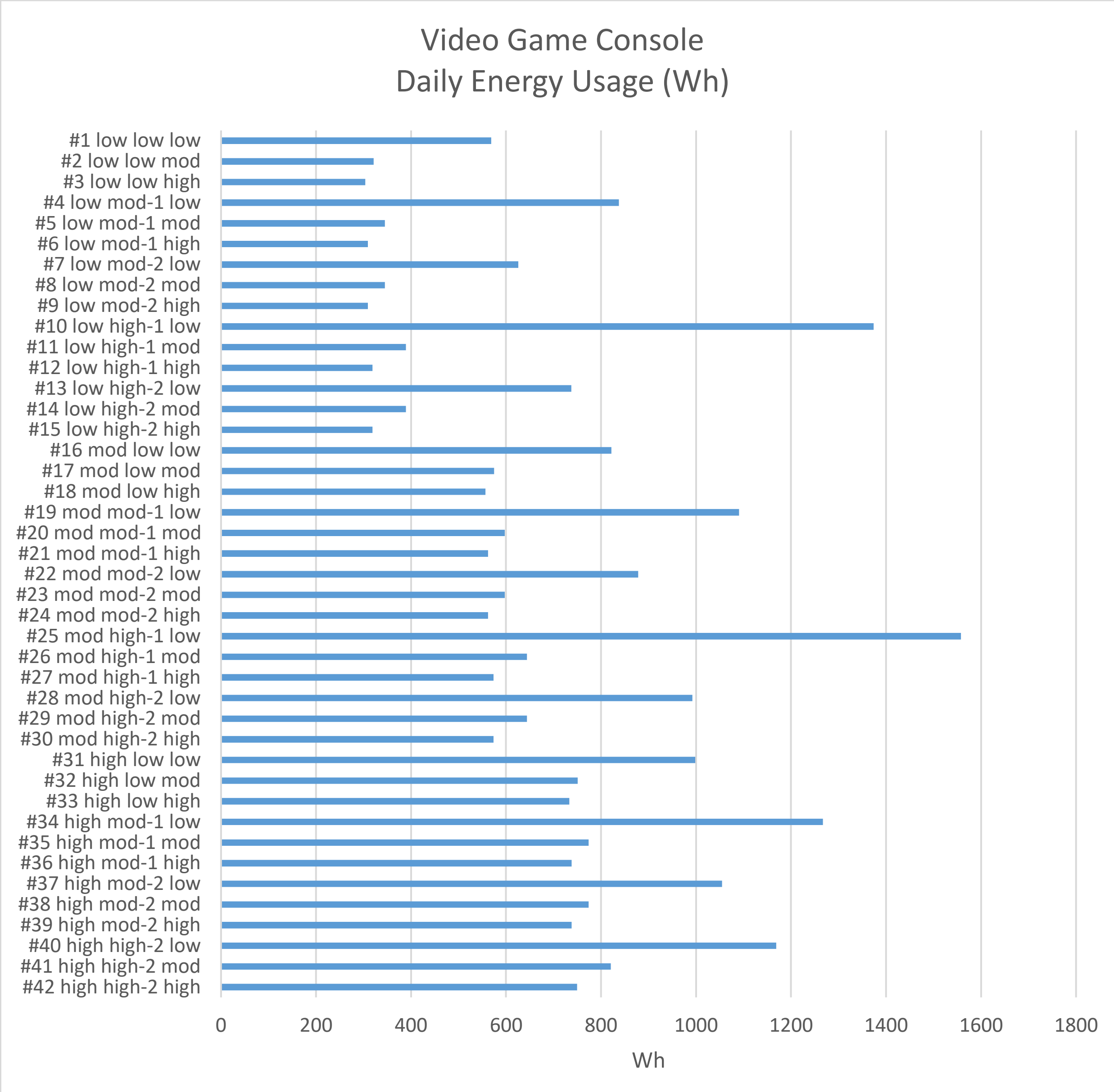

FIGURE 13. VIDEO GAME CONSOLE ENERGY USAGE PROFILES

Computer Equipment

Desktop Computer

This device is a name-brand Small Form Factor (SFF) computer running Microsoft Windows 10. It has multiple low-power modes, including soft-off (when manually shut down), sleep, hibernate, and hybrid sleep. In this test, only soft-off (shutdown) and sleep are examined. Energy consumption during active use varies, depending on how the computer is being used (for example, what programs are run). The Novabench computer benchmarking software tool provided maximum operational load as a reference. If the computer receives no user input, it transitions into a lower-power, short-idle state; after ten minutes, it transitions into deep-idle state.

This device supports standard, Advanced Host Controller Interface (AHCI)-enabled operating-system-based energy management. The standard automatic sleep settings transition the device to sleep mode after a period of user inactivity. The possible delay periods range from five minutes to five hours. The default setting is a delay of 30 minutes, which is used as the moderate PM level. The monitor is also controlled by the standard onboard PM settings, and was tested separately; results presented here are for the desktop computer only.

Device Usage Behavior Model

The three desktop computer aspect definitions are shown in Table 19. Active use levels were based on self-reported survey data and reflect the same measures as in the original SIM Home report (Xia et al., 2017). Active typing or nonstop mouse activity for four hours is unlikely, but is still considered passive (for example, reading) or indirect (for example, periodic screen reference during a meeting) use. Because power measurements showed differences in active use (for example, video streaming) versus short-idle and long-idle, a combination of these states was used instead of assuming the computer was fully active for the entire period. Similarly, profiles in which sleep settings were enabled included some sleep time as part of the active-use period, modified based on the setting and period length.

Pattern levels were varied to reflect realistic usage patterns. The combination of low active use and a moderate pattern resulted in active periods of 7.5 minutes each. While such periods would be unrealistic for many devices, it is reasonable for computers to briefly access email or other such programs. However, it was decided that the combination of low active use and high patterns, which would result in many active periods of 3.7 minutes, was too short to be reasonable, so these combinations were not applied. Also, high active use could not be combined with the high-1 pattern aspect because it would exceed 24 hours.

The PM behaviors were based on those observed in the CalPlug Monitoring Study (Pixley & Ross, 2014) and the PMUI Study (Pixley et al., 2018), in which some subjects regularly shut down their computers in the evening, while others left them on and idle at all times.

TABLE 19. DESKTOP COMPUTER PROFILE ASPECTS

Aspect and Level	Description
Active Use	
Low	0.5 hour
Moderate	5 hours
High	12 hours
Pattern	
Low	1 period
Moderate-1	4 periods, 1 hour between
Moderate-2	4 periods, 25 minutes between
High-1	8 periods, 1 hours between
High-2	8 periods, 25 minutes between
PM	
Low	Sleep setting disabled; user leaves on after use, device left in idle
Moderate	User leaves on after use, device switches to sleep automatically after 30 minutes
High	User leaves on after use, device switches to sleep automatically after 10 minutes, user turns off at end of day

Device Results

Table 20 provides a summary of PLSim results for the desktop computer. The standard profile (#11, mod-low-mod) produces usage of 609.52 Wh. Median falls between the values of profiles #30 (high-mod1-high) and #33 (high-mod2-high). Minimum was #3 (low-low-high) and maximum was #34 (high-high2-low), resulting in a very large range. For comparison, the minimum boundary level (at soft-off power for 24 hours) is estimated as 45.70 Wh, while the maximum boundary level (active on for 24 hours) is estimated at 2957.44 Wh.

TABLE 20. DESKTOP COMPUTER SUMMARY RESULTS

	Standard (Wh)	Median (Wh)	Min (Wh)	Max (Wh)	Range (Wh)
Desktop Computer	609.52	1310.33	110.02	2472.48	2362.46

Daily energy usage for each individual profile is shown in Figure 14. Profiles with low PM show consistently-high usage, regardless of other aspects. Profiles with moderate or high PM respond substantially to the amount of active use. Pattern as defined here does not show a noticeable effect.

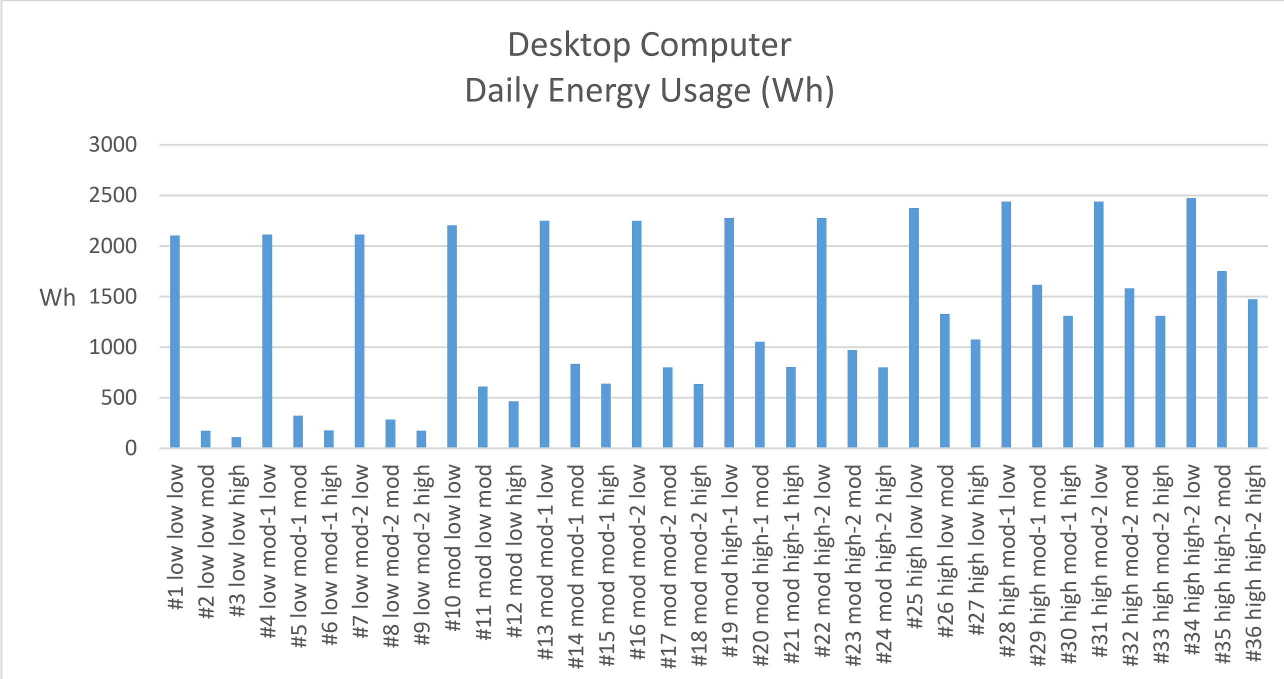

FIGURE 14. DESKTOP COMPUTER ENERGY USAGE PROFILES

LAPTOP COMPUTER

The evaluated laptop was a name-brand Personal Computer (PC)-type 14" laptop running Microsoft Windows 10, with a solid-state hard disk drive. A slight variation was observed between periods of active usage and idle. Prior to the study, the device battery was fully charged; during the study, wall-sourced power was used. To model a direct entry to sleep without the screen first becoming dark for a period of time, screen blanking was not used.

The operating system default PM settings were the same as for the desktop computer. The default setting for laptops, when plugged in, is a sleep-delay setting of 30 minutes. To simplify the simulation, the possible combinations of plugged-in and not-plugged-in usage and charging with all the other profile aspects were deemed too numerous to justify. Therefore, the energy use for all profiles is based on plugged-in tests.

Device Usage Behavior Model

For clear comparison, the same device use profiles were used for laptop computers as for desktop computers. These are shown in Table 21.

TABLE 21. LAPTOP COMPUTER PROFILE ASPECTS

Aspect and Level		Description
Active Use		
	Low	0.5 hour
	Moderate	5 hours
	High	12 hours
Pattern		
	Low	1 period
	Moderate-1	4 periods, 1 hour between
	Moderate-2	4 periods, 25 minutes between
	High-1	8 periods, 1 hours between
	High-2	8 periods, 25 minutes between
PM		
	Low	User leaves on and plugged in after use, sleep setting disabled
	Moderate	User leaves on after use, device switches to sleep automatically after 30 minutes idle
	High	User closes lid to sleep immediately after use; device switches to sleep automatically after 10 minutes idle

Device Results

Table 22 provides a summary of the laptop's PLSim results. The standard device usage profile (#11, mod-low-mod) produces usage of 112.33 Wh. Median falls between the values of profiles #26 (high-low-mod) and #30 (high-mod1-high). The minimum was #3 (low-low-high) and maximum was a tie between profiles #28 (high-mod1-low), #31 (high-mod2-low) and #34 (high-high2-low). For comparison, the minimum boundary level (at soft-off power for 24 hours) is estimated at 7.44 Wh, while the maximum boundary level (active on for 24 hours) is estimated at 595.45 Wh.

TABLE 22. LAPTOP COMPUTER SUMMARY RESULTS

	Standard (Wh)	Median (Wh)	Min (Wh)	Max (Wh)	Range (Wh)
Laptop Computer	112.33	243.11	28.87	423.29	394.42

Daily energy usage for each individual profile is shown in Figure 15. The pattern is very similar to that of desktop computers. Profiles with low PM show consistently-high usage, regardless of other aspects. Profiles with moderate or high PM respond substantially to the amount of active use, while patterns seem to have little effect.

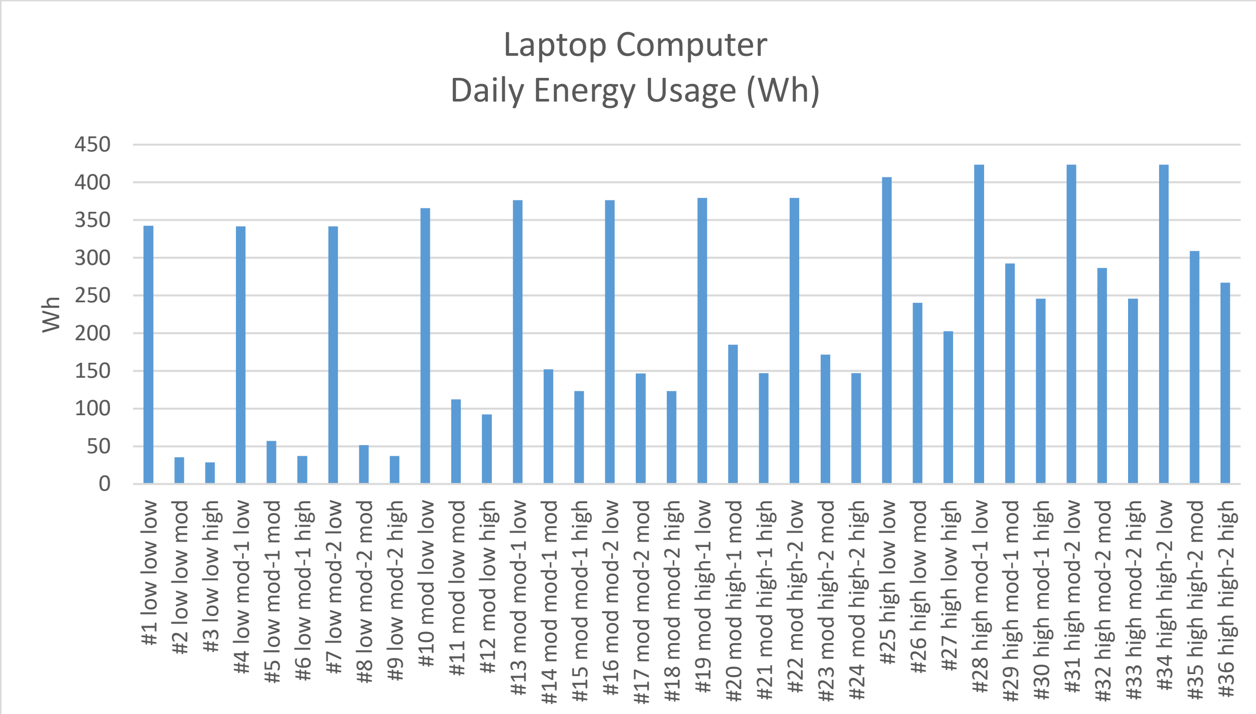

FIGURE 15. LAPTOP COMPUTER ENERGY USAGE PROFILES

KITCHEN APPLIANCES

POD COFFEE MAKERS

We tested two similar pod coffee makers from the same manufacturer. Pod coffee maker Model A is a more advanced design with a Liquid Crystal Display (LCD), while Model B has a basic design without a display. Both devices are single-cup-dispensing coffee makers, with three possible cup sizes along with adjustable brew temperatures. Tests were run using the medium cup size and standard brew temperature. Each device remained plugged in when not in use. When activated, they drew water from an on-board reservoir and heated it within an internal chamber. The temperature was maintained for this amount of water until it was dispensed through the coffee or tea pod to produce the hot beverage. After that cup was brewed, another cache of water was pulled from the reservoir and heated.

A user-enabled power-save feature was available to transition the device to soft-off mode, which was deactivated by default. The auto-off function for Model B offers only a two-hour delay period option, while Model A offers a wide array of options starting at 20 minutes and advancing in one-hour increments up to nine hours. Model A can also be programmed to turn on and off at specific times of day, but that feature was not tested in this study.

Device Usage Behavior Model

Table 23 provides definitions of the three aspects constructed for the two pod coffee makers. The active-use levels were based on self-reported survey data. The pattern levels were varied to reflect realistic usage. As with other devices, the moderate-PM level is defined as the default factory setting. However, since the default involves no PM, this leaves no room for a low-PM option that would save less energy. Instead, we constructed an additional high-PM level to provide three comparison levels, and also applied a two-hour auto-off delay in the PM aspect definitions for both models.

As the low active use level is one cup, this cannot be combined with the moderate or low pattern levels (which require making two or three cups in a row), so those profiles are not included. Additionally, profiles with high active use of 12 cups per day, and a high pattern of one cup at a time with three hours in between, exceed 24 hours and were therefore omitted.

TABLE 23. POD COFFEE MAKER PROFILE ASPECTS

Aspect and Level	Description
Active Use	
Low	1 cup
Moderate	6 cups
High	12 cups
Pattern	
Low	3 cups in a row, 3 hours in between
Moderate	2 cups in a row, 3 hours in between
High	1 cup at a time, 3 hours in between
PM	
Moderate	Auto-off disabled (default), stays in keep-warm cycle all the time
High-1	Auto-off after 2 hours enabled (keep hot cycle for 2 hours)
High-2	Auto off enabled, and user turns off after last cup (manual off)

Device Results (Model A)

A summary of PLSim results for Model A is shown in Table 24. The standard profile (#4, mod-low-mod) produces usage of 1076.87 Wh. Median falls between the values of profiles #8 (mod-mod-high1) and #14 (high-low-high1). Minimum was #3 (low-high-high2), and maximum was a tie between profiles #13 (high-low-mod) and #16 (high-mod-mod). For comparison, the minimum boundary level (at soft-off power for 24 hours) is estimated at 143.75 Wh, while the maximum boundary level ("active warm up" for cold brewing 24 cups, and "hold" for the remainder of 24 hours) is estimated at 1289.06 Wh.

Note that for the pod coffee makers, there is no low-PM level, because the default setting that defines the moderate level is with no power saving features engaged. So it is expected that the standard profile (mod-low-mod) would have fairly high energy consumption relative to those with higher (more efficient) PM levels.

TABLE 24. POD COFFEE MAKER MODEL A SUMMARY RESULTS

	Standard (Wh)	Median (Wh)	Min (Wh)	Max (Wh)	Range (Wh)
Pod Coffee Maker A	1076.87	639.85	189.03	1147.60	958.57

Daily energy usage for each individual profile is shown in Figure 16. The primary pattern is that low PM leads to much higher usage than moderate or high PM, regardless of the other two aspects, although higher active use levels make a modest impact.

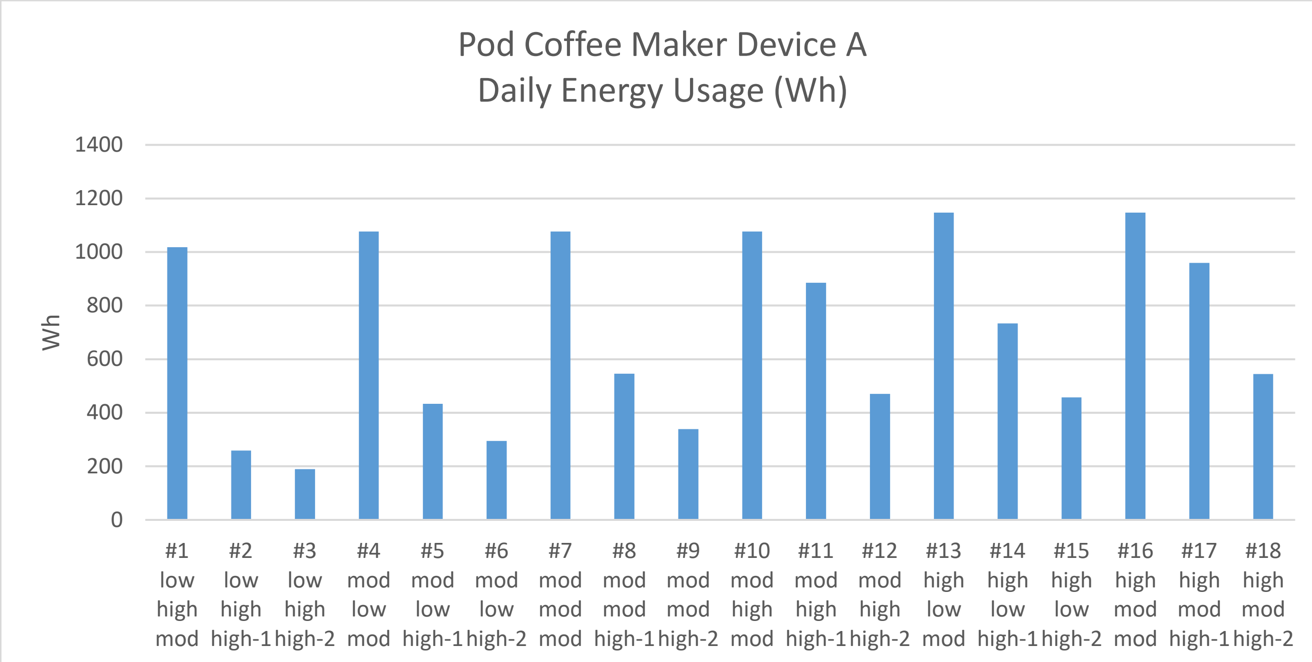

FIGURE 16. POD COFFEE MAKER MODEL A ENERGY USAGE PROFILES

Device Results (Model B)

A summary of PLSim results for Model A is shown in Table 25. The standard profile (#4, mod-low-mod) produces a usage of 1046.40 Wh. Median falls between the values of profiles #8 (mod-mod-high1) and #14 (high-low-high1). As for Model A, the minimum profile was #3 (low-high-high2) and the maximum was a tie between profiles #13 (high- low-mod) and #16 (high-mod-mod).

For comparison, the minimum boundary level (at soft-off power for 24 hours) is estimated as 87.00 Wh, while the maximum boundary level ("active warm up" to cold brew 24 cups and "hold" for the remainder of 24 hours) is estimated at 1151.40 Wh. The range of usage estimates is very similar to that of Model A, although overall, this device uses somewhat less energy.

TABLE 25. POD COFFEE MAKER MODEL B SUMMARY RESULTS

	Standard (Wh)	Median (Wh)	Min (Wh)	Max (Wh)	Range (Wh)
Pod Coffee Maker B	1046.40	535.70	123.32	1081.40	958.08

Daily energy usage for each individual profile is shown in Figure 17. The pattern is very similar to that of Model A, although for profiles with high PM, the estimates appear more responsive to the amount of active use than for the other device.

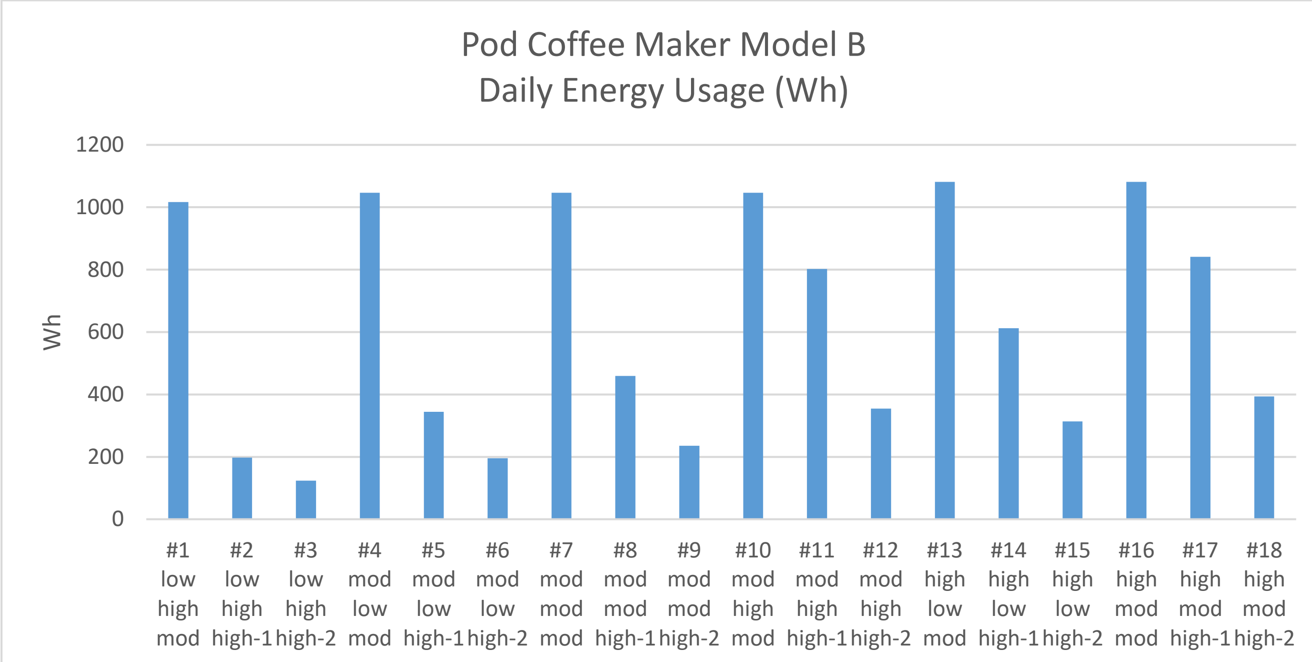

FIGURE 17. POD COFFEE MAKER MODEL B ENERGY USAGE PROFILES

RICE COOKER

The rice cooker we tested was able to prepare a maximum capacity of ten cups of cooked rice (approximately three to 3.5 cups uncooked, depending on the type of rice). This device had a delay timer for programming the start of the cook cycle, but this feature was not evaluated. In addition to cooking rice, this device also has a steaming function, but it was not tested here.

When the rice cooker function is turned on, the device heats the water to boiling, then switches to the "cook" cycle to maintain the temperature. When the temperature begins to rise above boiling, it indicates the water has been absorbed, and the cook cycle ends. Therefore, this cycle varies based on the amount and type of rice, and the amount of water added to cook. When the active cooking period ends, an alarm sounds and the device automatically switches to a "keep-warm" mode. A passive cooldown period occurs, where the temperature reduces to 65.5 C and is maintained.

There is no auto-off capability, so the device will stay in the "keep-warm" state until turned off. If left plugged in, it stays in a soft-off state at very low power. The device constantly displays the front lights, even in the lowest-power (soft-off) state.

For all tests, white jasmine rice was cooked at a ratio of 1.5 cups of water per one cup of rice. A dual thermocouple thermometer was used to measure both vapor temperature and liquid temperature.

Device Usage Behavior Model

Definitions of the three aspects constructed for the rice cooker are shown in Table 26. The active levels were based on reasonable assumptions about use patterns. Note that a single cup of uncooked white rice generally expands to about three times its volume when cooked, although this varies by the type of rice and the amount of water. The pattern levels were varied to reflect realistic usage patterns based on meal times; that is, some households will make one large pot of rice for breakfast and keep it warm all day, while others might make a separate pot for one to three meals.

The moderate PM setting reflects an anecdotally-common practice of leaving rice on “warm” during the remainder of meal preparation and over the course of the meal (estimated as one total hour). Low PM reflects the practice of keeping rice warm throughout the day, either by making new pots of rice for later meals, or by making one pot and keeping it warm all day ("all day" is defined here as the 24-hour period minus eight hours for sleeping, or 16 hours). Moderate PM is used for the standard testing profile, since the default setting transitions the device to “warm,” and that state should be included in total energy consumption. No profiles were omitted.

TABLE 26. RICE COOKER PROFILE ASPECTS

Aspect and Level		Description
Active Use		
	Low	1 cup*
	Moderate	2 cups*
	High	3 cups*
Pattern		
	Low	1 use per day
	Moderate	2 uses per day, 5 hours in between
	High	3 uses per day, 5 hours in between
PM		
	Low	User leaves on warm all day, no matter how many pots they make (user turns off at hour 16)
	Moderate	User leaves on warm for 1 hour then turns off
	High	User turns off immediately after cooking is completed

* Uncooked white jasmine rice.

Device Results

A summary of the rice cooker’s PLSim results is shown in Table 27. The standard profile (#11, mod-low-mod) produced usage of 282.19 Wh. Median is #14 (mod-low-low). Minimum is #3 (low-low-high) and maximum is #25 (high-high-low), resulting in a wide, varied range of modeled outcomes.

For comparison, the minimum boundary level (at soft-off power for 24 hours) is estimated at 18.72 Wh, while the maximum boundary level – cooking six cups of rice (twice the high active level, one cup at a time, warming in between and for the rest of the 24 hours) – is estimated at 1934.21 Wh, providing reference boundaries for excessively-wasteful/longest-possible use (maximum usage) and non-usage.

TABLE 27. RICE COOKER SUMMARY RESULTS

	Standard (Wh)	Median (Wh)	Min (Wh)	Max (Wh)	Range (Wh)
Rice Cooker	282.19	529.44	249.00	937.92	688.93

Each individual profile's daily energy usage is shown in Figure 18. The primary pattern shows low PM leads to much higher usage than moderate or high PM, regardless of the other two aspects, although moderate and high PM are very similar.

The pattern also shows an effect, with higher patterns (usage spread out more over the day) indicating higher energy use. For instance, for profiles with low active and moderate PM levels, making one cup of rice once a day (Pattern Low) uses 260 kWh. Splitting one cup of rice into two half-cup batches (Pattern Mod) results in 465 kWh, and making it in three batches results in 648 kWh. The total amount of active use also shows a modest effect.

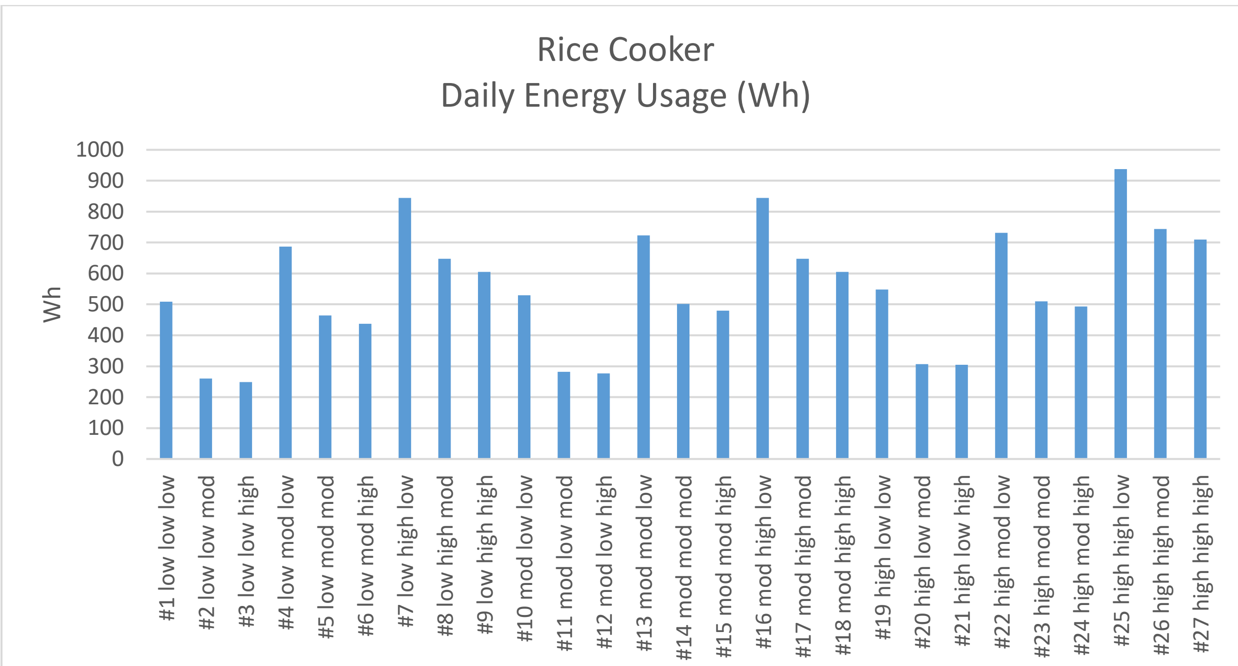

FIGURE 18. RICE COOKER ENERGY USE PROFILES

Range of Energy Consumption across Profiles, by Device

The findings so far help to answer the first research question: given a reasonable range of usage behaviors, what range of results would be seen for the devices included in these tests? That is, if we assumed all devices in all households were run according to the standard device use profile, how far off would we 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 an array of households.

However, if the device's energy consumption is not responsive to actual usage parameters, perhaps additional development of low-power states could help reduce consumption during non-active periods. On the other hand, if the range across profiles is very large, especially in terms of values much higher than the standard testing profile, it indicates possible intervention points of either reducing active use or promoting more effective PM.

The summary tables for each device in the previous section show the range between the minimum and maximum, but this 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 consumption was 1000 Wh, but substantial if it was 100 Wh. For comparison, the summary results for each device are presented in Table 28 as the absolute percentage difference between the standard device use profile (mod-low-mod or mod-low-high, depending on the device) and the profiles producing the minimum and maximum results.

For instance, if a standard profile produced an energy consumption estimate of 100 Wh and the profiles with the minimum and maximum were at 80 Wh and 120 Wh, both the minimum and maximum percentage from standard would be 20%, and the range percentage would be 40%. 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% of the standard profile, probably much less (as 100% lower would mean zero energy consumption for the minimum profile).

Among entertainment devices, the two TVs show large energy consumption ranges, but the video game console range is also high, especially compared to those of the sound bar and set-top box. The streaming device shows a large range, but the standard profile’s energy consumption is so low that it is not important.

The TV 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% of energy compared to the standard profile. By contrast, the satellite set-top box shows the lowest ranges of all the devices shown here. For most of the devices, the maximum estimates vary more greatly from the standard than the minimum estimates do.

The desktop computer used substantially more energy than the laptop computer in the standard profile. However, their relative ranges are similar. The minimum profiles for both computers saved a similar proportion of energy relative to the standard profiles, but the desktop’s maximum profile used proportionally more than 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, almost all due to the minimum usage profile being substantially lower than the standard profile. Note that the pod coffee makers have

PM features, but are shipped with those settings disabled, so the moderate PM level has no low-power mode, and all PM levels save more energy 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.

TABLE 28 SUMMARY OF RANGES AS PERCENTAGE DIFFERENCE FROM STANDARD PROFILE

	Standard (Wh)	Min % from Standard	Max % from Standard	Range % of Standard
4K TV	1305.1	94%	187%	281%
HDTV	667.4	93%	185%	278%
Sound Bar	111.7	19%	77%	96%
Set-Top Box	669.9	2%	4%	7%
Streaming Device	28.1	76%	145%	220%
Video Game Console	556.9	46%	180%	225%
Desktop Computer	609.5	82%	306%	388%
Laptop Computer	112.3	74%	277%	351%
Pod Coffee Maker A	1076.9	82%	7%	89%
Pod Coffee Maker B	1046.4	88%	3%	92%
Rice Cooker	282.2	12%	232%	244%

These results are presented graphically in Figure 19, for easier comparison across devices in terms of both standard profile energy consumption and ranges. Three general patterns are seen: 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 lean toward higher values.

For instance, the standard profiles for pod coffee makers exhibit energy consumption almost as high as that of the 4K TV, and higher than the HDTV. However, almost all the variations in how pod coffee makers are used result in lower consumption, whereas the top range for TVs is substantially higher.

By contrast, 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, but for both the desktop computer and game console, usage variation can lead to higher consumption (much higher for the desktop) whereas the set-top box has almost no usage variation.

In the multivariate analysis section, analyses are presented that indicate whether active use, pattern, or PM levels have a greater impact on the range of energy consumption across profiles for each device. This is especially important for devices with large or moderate ranges. Those results will give little insight, however, to the set-top box, sound bar, and streaming device, since the variation is so low.

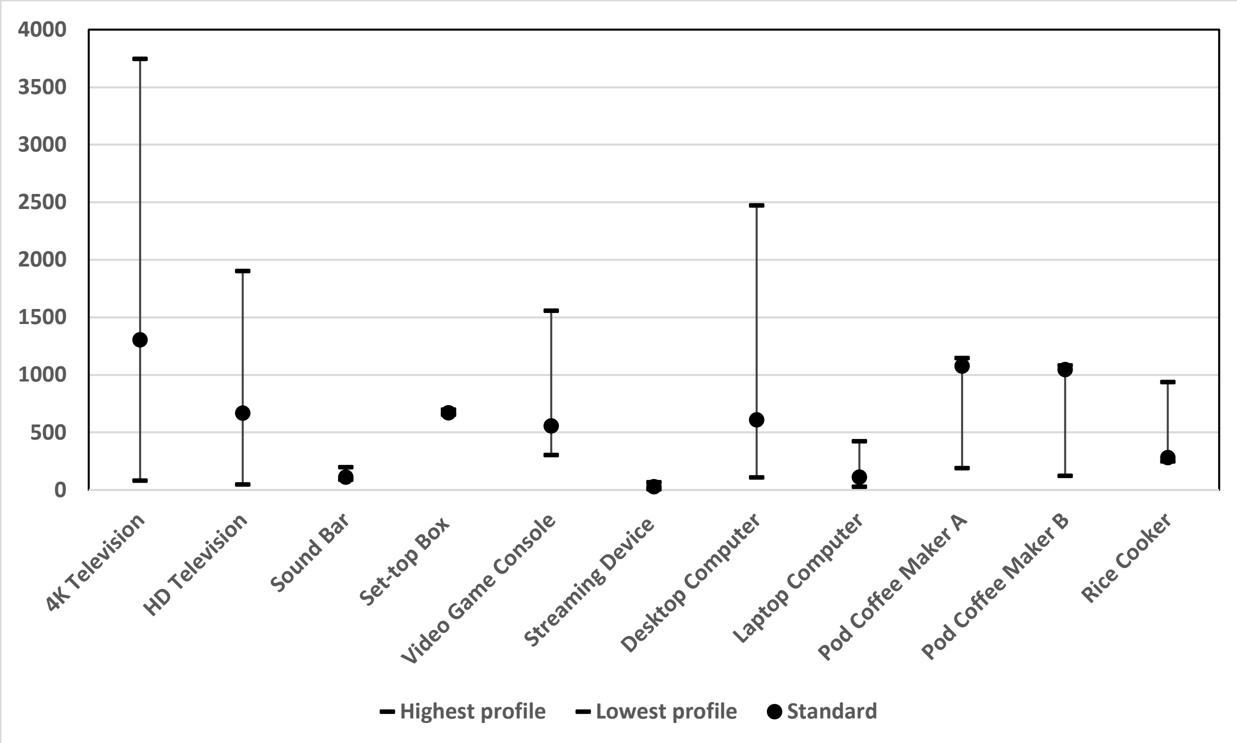

FIGURE 19. RANGE OF DAILY ENERGY CONSUMPTION OF PROFILES, BY DEVICE

MISER

For computers, because PM is complicated in nature and has variable settings, a specifically-developed tool can be used to analyze the marginal difference in energy usage across PM settings for this device class. When introducing the tool, the authors discussed how it could be used to analyze the 2014 Monitoring Study, which is the default operational dataset for assessing office desktop computers, and provide insight on similar devices.

A day-by-day simulation can be performed to identify the frequency and length of idle periods in actual usage, given the observed PM settings, and calculate the amount of energy that could be saved if different settings were used. The energy saved by replacing idle time with sleep time differs across computers, but as the sleep state uses a small fraction of the energy used in idle mode, this provides an energy savings proxy.

Analyses were performed using the Monitoring Study data where potential marginal energy savings were tabulated for different periods of default settings. This provides the total amount of idle time that would have been reduced (that is, energy saved) if the simulated new PM settings were used as opposed to the observed PM settings. The resulting output values are expressed in minutes per day of idle time that would be transitioned to the sleep state, if the PM had been set more stringently. Inputting estimates (or direct measures, if available) of power usage at each operational state determines energy saved and total energy consumption per year in kilowatt hours (kWh).

The large number of studied computers with disabled sleep settings stayed in idle mode not only overnight, but for multi-day periods over weekends and vacations. This means that even PM settings with longer delay periods break a multi-day waste cycle, producing savings. The simulated savings of idle minutes due to enabling sleep settings, depending on delay period, is shown in Figure 20.

Going from disabled sleep settings to the highest possible delay period of 300 minutes saves a substantial amount of idle time (413 minutes); reducing that to the default settings of 30 minutes almost doubles the savings (782 minutes). Shorter sleep delay settings produce higher savings compared to longer delays by not only transitioning earlier at the end of the day, but also by catching idle times between periods of activity during daily usage. Using a delay period of 30 minutes as opposed to 120 minutes can save 160 minutes per day of runtime; considering the power usage difference between active and sleep states, this results in 116 Wh/day average savings based on the model generated from the observational data.

More idle time is reduced when pushing the delay setting to 20 or 10 minutes rather than 30 minutes, but it is important to remember that shorter delay period settings are more likely to lead to false sleep periods and annoy users, especially those who previously had their sleep settings disabled. Encouraging users to enable their sleep settings at a 30-minute delay rather than a 300-minute delay will save substantial idle time (369 more minutes) whereas pushing users to begin by trying a 10- or 20-minute delay period will only save an additional 28 to 67 minutes over a 30-minute delay, but may increase the risk of them reverting to disabled sleep settings.

As explained earlier, the Monitoring Study data only provided device state information in 15-minute blocks, which affects the precision of estimates for shorter periods of idle. This is a limitation of the data, not of MISER; additional analyses with more robust data would be useful to verify these estimates.

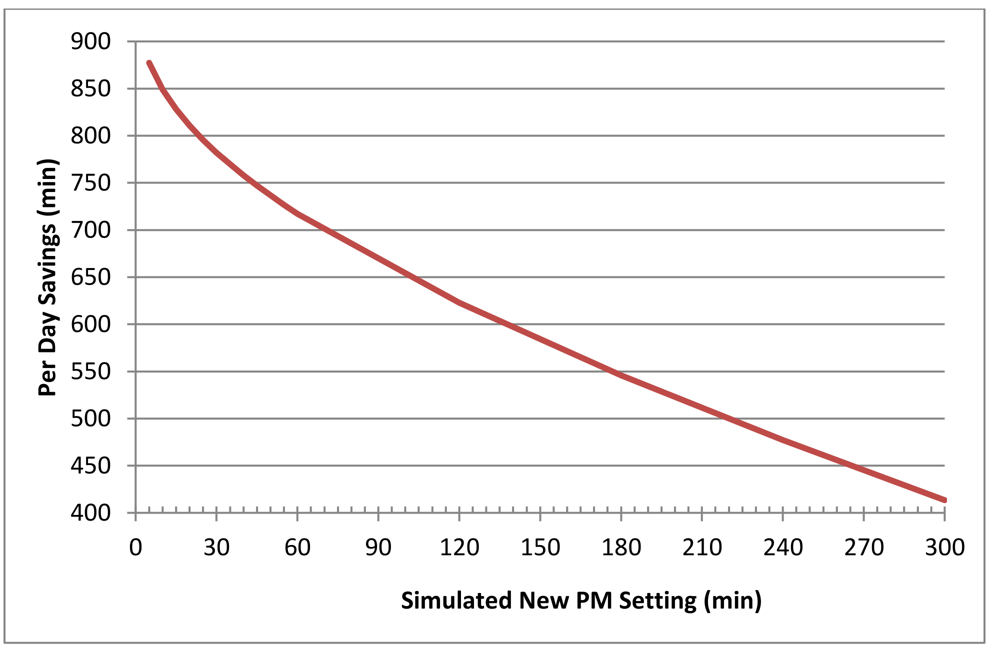

FIGURE 20. PER DAY IDLE TIME SAVINGS FOR COMPUTERS WITH DISABLED PM BY SIMULATED NEW PM SETTING

MISER's practical use is limited to computers and other devices with PM settings offering multiple delay period options. This is true for several types of plug load devices, including others covered in this report, but the desktop computer is the only device for which the necessary field study dataset was available.

The results shown here are based on office desktop computers used by staff at a university. The transferability of results for residential desktop computers is not well understood. Using MISER with laptops treats these systems like desktops, with respect to modeling. Highly-portable home laptops may not be well modeled by this approach. New datasets and better understanding of how residential computers are used can provide improved capability for this tool. The effects of sleep blocking and the prevalence of this phenomenon as caused by programs preventing entry into sleep is not well understood, resulting in MISER findings representing a more ideal solution than may actually happen during observation.

While MISER has a limited scope in this study, it can provide context to help understand the results of other evaluation approaches for these devices. Continued MISER development can help improve usefulness for other modeling scenarios, and improved modeling acuity for desktops and laptops in different usages circumstances.

EFFECTS OF BEHAVIORAL ASPECTS

The figures in the previous section illustrated patterns of results across profiles in which PM appeared to be most important for energy use in some devices, while amount of active use or pattern of use also appeared significant in others. The multivariate regression models shown in this section serve to quantify those patterns.

Regression models were used to evaluate the proportion of variation in modeled energy consumption across device use profiles attributed to the three aspects tested here, given the specific definitions of each aspect. That is, particularly for devices with a large range of modeled 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 PM 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 goodness of fit statistic that indicates 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 percent of the variance in energy consumption across the device use profiles was due to whether they had high, moderate, or low active use.

An example of a nested model regression is presented here to illustrate how the process works. The remaining regressions are omitted, as the main results can be adequately summarized by presenting the R^2 goodness-of-fit statistics. Regression results for the desktop computer are shown in Table 29. For any set of dummy variables that exhaustively describes all cases within the sample, one variable must be omitted from the model to act as a reference group.

In the Active Model, the moderate level is the reference group. If the coefficients (*B*) for active-low and active-high are significant, they are interpreted as the average difference for any profile with that aspect level compared to the active moderate. In this case, we see that active-high profiles show energy consumption that are 506.78 Wh higher than active-moderate on average (although it only approaches significance at the $p < .10$ level), and that there is no significant difference between active-moderate and active-low. Additional tests (not shown) confirm that active-high is significantly higher than active-low.

The R^2 statistic shows that 20.0 percent of the variance in energy consumption is explained by the active aspect alone. The model (F statistic) is significant at $p < .05$. By contrast, none of the coefficients in the Pattern Model are significant, the R^2 statistic is only 3.6 percent, and the model is not significant at the $p < .05$ level. This indicates that by themselves, pattern levels do not significantly affect energy consumption. It is still possible that they interact with PM aspects (that question is not assessed in the current model).

The PM Model shows a very strong effect, with a large difference between the PM-moderate and PM-low profiles (and, not shown, between the PM-high and PM-low profiles), although there is no significant difference between the moderate and high PM profiles. The R^2 statistic shows that 73.9 percent of the variance in energy consumption is explained by PM levels.

Finally, the full model includes all three aspects, and shows the effect of each variable net of the other variables in the model. The total R^2 statistic is 95.2 percent, approaching almost 100 percent. This would be highly unusual for any natural observational sample, as there ae always unmeasured sources of variation not captured in the model. However, since these profiles were calculated using only the variables contained in the model, no such outside source of variation exists.

Indeed, the only reason the model would not explain all the variances would be if there were interaction effects among the included variables – for example, if the pattern had a different effect depending on the level of PM. This type of interaction seems to account for just under five percent of the variation in energy consumption for this device.

TABLE 29. REGRESSION OF ENERGY CONSUMPTION ON DEVICE PROFILE ASPECTS FOR DESKTOP COMPUTER

	Active Model			Pattern Model			PM Model			Full Model		
Predictors	**B**	**SE**	***P***	**B**	**SE**	***p***	**B**	**SE**	***p***	**B**	**SE**	***p***
Active Low	-416.35	311.10	0.1899							-343.64	91.09	0.0008
Ref: Active Moderate	---									---		
Active High	506.78	285.77	0.0854							536.75	81.47	<.0001
Ref: Pattern Low				---						---		
Pattern Moderate-1				-139.23	393.94	0.7262				139.23	94.08	0.1505
Pattern Moderate-2				126.92	393.94	0.7495				126.92	94.08	0.1885
Pattern High-1				216.94	557.12	0.6996				281.31	141.77	0.0575
Pattern High-2				463.66	440.44	0.3006				259.66	108.63	0.0241
PM Low							1332.39	172.01	<.0001	1332.39	81.47	<.0001
Ref: PM Moderate							---			---		
PM High							-195.96	172.01	0.2628	-195.96	81.47	0.0233
Intercept	1258.18	190.51	<.0001	1161.12	278.56	0.0002	944.21	121.63	<.0001	717.95	95.05	<.0001
F	4.12			0.29			46.75			67.11		
Pr > F	0.0252			0.8829			<.0001			<.0001		
R^2	0.200			0.036			0.739			0.952		

*** = $p < .001$; ** = $p < .01$; * = $p < .05$

The results of the aspect-specific regression models are summarized for all the tested devices in Figure 21. The asterisks indicate which models were statistically significant. These results reveal major differences in the relative importance of active use, pattern, and PM for energy consumption across these devices.

These effects should also be considered within the context of how much energy consumption ranged across profiles for that device. For instance, for the set-top box, PM 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 28), so there is essentially no variance to explain. For that reason, the set-top box is not discussed here. For the sound bar and 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.

For all the devices, PM explained a significant proportion of the variation in energy consumption across profiles. Devices varied in the effects of active use and pattern of use aspects. Four patterns are exhibited: (1) strong impacts of both active and PM aspects, with active use almost as high as PM (4K and HDTVs); (2) significant impact of the active aspect but much lower than the impact for PM (streaming device, video game console, desktop computer, and laptop); (3) significant impact for PM alone (sound bar and both pod coffee makers); and (4) significant impact of pattern of use that exceeds that of PM (rice cooker).

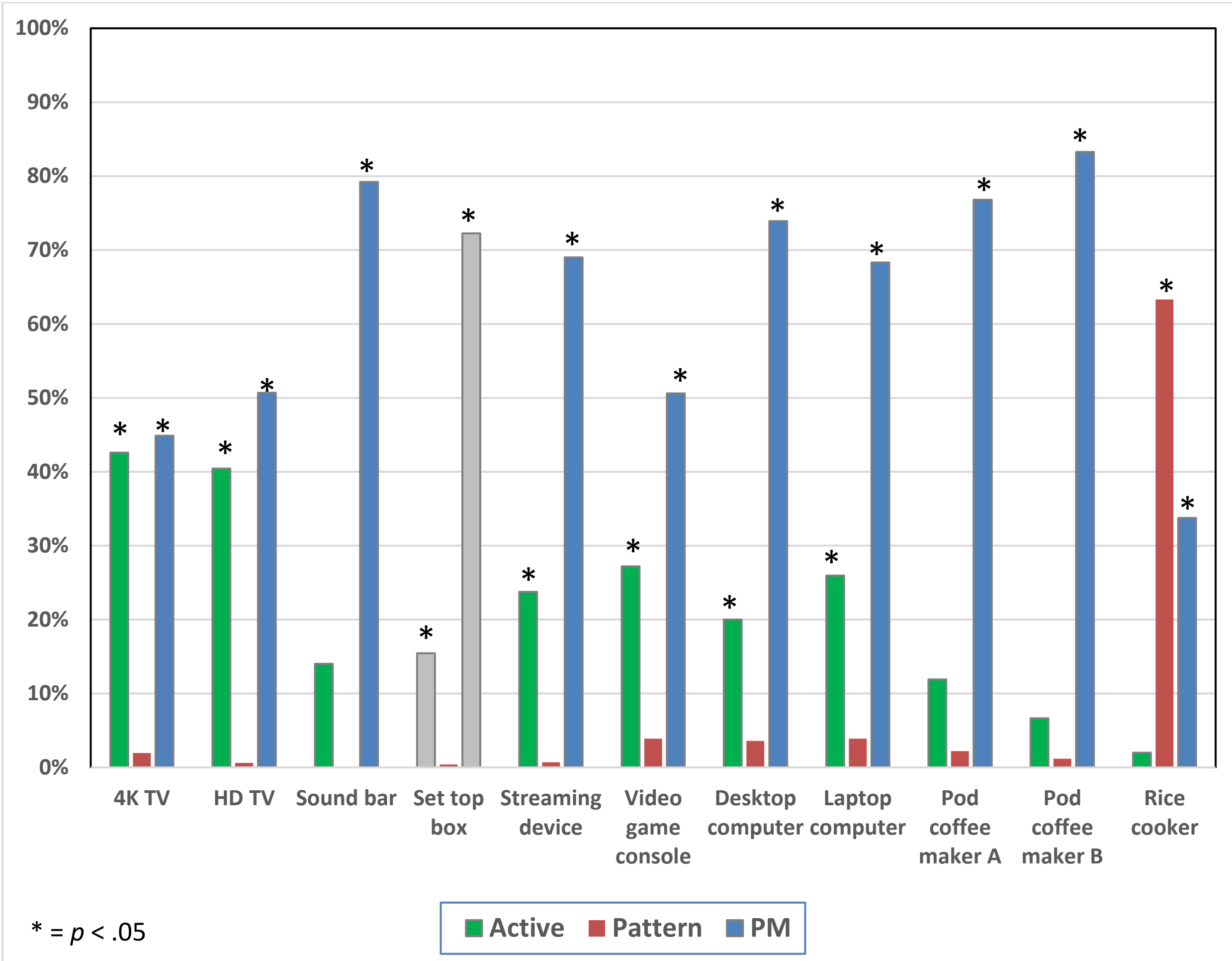

FIGURE 21. PROPORTION OF VARIANCE IN ENERGY CONSUMPTION EXPLAINED BY EACH ASPECT

DISCUSSION

The impact of behavior on energy use is a major consideration to produce an accurate evaluation of device energy consumption for modeling and mitigation efforts.
In this project, the authors demonstrated a multi-phase analysis method of evaluating the energy consumption effects of three aspects of user device behavior: the amount of active use, the pattern of use, and PM. This method was applied to assess common residential plug load device energy use across a number of major categories (see Table 2). Using carefully-defined profiles, comparisons highlighted points of energy impact to prioritize and focus efforts to address improving energy usage in specific devices related to generated profiles. Future testing and evaluation methods could expand upon this method and continue refining procedures to match devices as they evolve, considering behavior and usage.

The analyses in this report address two main questions. The first is how large a range of energy consumption outcomes the device use profiles generate for each device, based on reasonable assumptions about the range of real-life usage. A subset to this question is whether the range is primarily higher or lower than the standard profile representing what would be 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 device's energy use is not responding to the amount of time the device is actively being used, and that any PM features are ineffective at saving energy.

The second main question is how much of the variation, within the range of energy consumption outcomes across profiles, is explained by differences in active use versus pattern of use or PM behaviors. Energy consumption is expected to vary by active use – if it 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. Likewise, PM is expected to affect energy consumption – if engaging PM options fails to save energy, it suggests those options are ineffective.

However, if much of the variation attributable to PM behaviors results in higher energy usage, it suggests a different type of problem – that PM 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. As described earlier, the device usage profiles are based on observed or self-reported behaviors as much as possible, but several assumptions had to be made when defining the levels of each aspect. Therefore, any conclusions are limited by the extent to which the assumptions about average, and also extreme, behaviors (those 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.

SPECIFIC DEVICES

TVS

The 4K TV tested here uses almost twice as much energy in its standard profile as the HDTV (1305 Wh versus 667 Wh). However, the results patterns are otherwise similar. Both TVs 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 TV, 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 profile). This suggests that, to the extent these device use profiles reflect real-life behavior patterns, estimates based on standard usage would underestimate total usage across households.

The high energy consumption of the standard profiles for these devices (especially the 4K TV) and the very high range in energy consumption 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 TVs show a pattern not seen in other devices – the active use aspect is almost as strong a predictor of variation in energy consumption as the PM aspect.

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

As active use and PM are both important contributors to TV energy use, 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 TVs, if the length of time some households actively use their TVs were more strongly weighed in deliberations. Options that adjust 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 PM options and their use could potentially save as much energy with less extensive modifications to the devices themselves. Both of these TVs have very low-power standby modes; the challenge is to transition the device into standby mode whenever feasible. Both TVs 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 TV has three delay settings from 15 minutes (default) to 60 minutes, while the HDTV has only one delay setting (10 minutes). This feature can potentially save substantial energy, but only in specific circumstances – when the TV is receiving content from an external device (rather than through apps in a smart TV) or 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 will not activate due to lack of signal.

The 4K TV 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 four hours, which is the default setting. The HDTV has no such auto-off feature. One relatively simple improvement would be to provide such a feature in all TVs, offer shorter delay period options (as short as 1 hour) and set a two-hour delay as the default. Informative user interfaces, such as motivating explanations on the PM setting screen or signals to warn of an impending sleep transition easily bypassed by pressing a remote control button, are essential for encouraging users to enable (or not disable) PM settings and understand how to use them effectively.

Video Game Console

The video game console tested here showed results closest to that of the HDTV 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 HDTV (1254 Wh versus 1855 Wh). Compared to TVs, 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 HDTV (and much less than the 4K TV) but a larger proportion of its estimated use is higher than (versus lower than) the standard profile.

Like several of the other devices, the video game console showed a large impact of PM 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 TVs in this respect. As such, the results support a similar approach to that described above for TVs, in which approaches for reducing consumption during active use are warranted, and those focused on improving PM are as well.

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 minutes to a maximum of five hours.

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 their progress will be lost, even if this concern is unfounded; added security and reassuring communication may be helpful here. Another point is that the main system menu page, if not interacted with, functions similarly to a standby mode, and yet consumes almost the same power as active gaming and continues to do so no matter how long the device goes unused. This suggests exploring the possibility that a "deep idle" mode, similar to that of computers, could save additional energy by pausing certain processes after a shorter period of inactivity.

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 condition range for this device, which consumes 699.7 Wh at the highest possible use state (active video) for 24 hours 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, and 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 active all day). This reflects the fact that set-top boxes must maintain continuous connections for program and encryption services; even in their lowest-power standby mode, they use substantial power. As a result, users are limited in how much they can affect this device’s energy savings.

Given the lack of variation in energy consumption across profiles, multivariate analyses explaining which use aspect caused that variation are moot. A closer examination of this device's operation shows the PM features 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 actively used. The only PM option is a four-hour delay time; this leaves the device in idle mode, which uses the same power as 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 in active-use mode.

Streaming Device

Of all the devices tested here, the streaming device uses the least amount of energy for its standard profile, and shows one of the narrowest absolute ranges of energy consumption estimates across the profiles, at 62.04 Wh between the lowest and highest. This is only somewhat larger than the set-top box range (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.

As shown in the pattern of results for the streaming device's energy usage profiles (see Figure 12), all profiles with the PM-low-1 level produce a relatively high energy consumption estimate (around 67 to 69 Wh) which almost reaches the boundary maximum of 70.6 Wh. So it is not surprising that PM explains the majority of variation in energy consumption across profiles (69%). However, active use also explains a significant amount (24%).

The streaming device benefits from having an aggressive PM 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 (where the device is paused on a 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.

Sound Bar

When presented in comparison to other devices in Figure 20, 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 more than twice as large as that of the streaming device, indicating more potential room for substantive energy savings.

The sound bar is one of the three devices for which the majority of variation in energy consumption across profiles is explained by PM, and neither active use nor pattern are significant factors. The overwhelming influence of the PM low level is shown in the graph of energy usage across profiles for this device (see Figure 10). Indeed, if all profiles using PM low are removed, the maximum profile usage drops by 48 Wh, cutting the range by almost half. Additional analyses that omitted PM-low profiles (not shown) reversed these findings: no differences were seen across the moderate and high levels of PM, while the majority of the remaining variance was explained by active use. This example 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.

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 TV. 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.

Turning to which aspects predict greater variance in energy usage across profiles, the desktop and laptop computers follow the same pattern as the video game console, streaming device, and set-top box: both active use and PM aspects are significant contributors, but PM 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 ten minutes, 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.

PM options and low-power states are well-developed in both desktops and laptops. As both the PLSim the MISER 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 agreement is how to get more users to enable (or not disable) their computer sleep settings. As there are valid reasons why a subset of users would need to prevent their computers from entering a low-power mode, either permanently or occasionally, it would be problematic to remove the option of disabling sleep settings and make them involuntary. Instead, efforts to reduce energy in computers would be more fruitfully targeted to research into how users behave toward computer PM. This should be aimed toward designing more effective and convincing user interfaces, and toward understanding and addressing the barriers that lead to users disabling or otherwise underutilizing computer PM options.

POD COFFEE MAKERS

The two pod coffee makers showed very similar standard profile energy usage estimates (1076.9 Wh and 1046.4 Wh), which are higher than any device other than the 4K TV, 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 two minutes to heat the water cache from the cold state, and one minute to dispense each cup. As such, the added energy needed to brew six cups instead of one (Active Moderate versus Active Low) is overwhelmed by the energy used over the rest of the 24-hour period.

Instead, PM accounts for the majority of the energy consumption variation across profiles. As shown in the energy usage profile results for these devices (see Figure 16 and Figure 17), energy consumption is very similar across profiles using the high-1 and high-2 levels of PM (in which auto-off is enabled and set at two hours, and the user turns the device off after use, respectively) but much higher for profiles using the moderate level of PM, in which auto-off is disabled. There is no low level of PM, as the standard PM aspect – the factory default – is already as inefficient as possible.

The first solution to saving energy with pod coffee makers then seems straightforward: change the factory default so that auto-off is enabled. This assumes users are less likely to disable the setting if it is enabled by default, than 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 – as is already done for the more advanced Model A device – would also save energy and may be considered a default setting. This could work well for households where only a few cups of coffee (or tea) are brewed within a short timeframe every morning.

Unlike many other devices discussed (especially in the entertainment category) these devices are not intended to run for an extended duration, as their utility comes from producing a product (a cup of coffee) quickly rather than providing screen time. Accordingly, it is wasteful to leave these devices on for extended periods beyond what is necessary for producing coffee. The benefit of PM turning devices off when left on is that it prevents unnecessary thermal maintenance of the brewing water, in turn saving substantial energy. At the same time, users may become frustrated if pod coffee makers take what they perceive as "too long" to warm up from a standby state when they want coffee, especially since speed and convenience are expected pod coffee maker benefits. One possible reason users disable sleep settings is impatience waiting for devices to resume from sleep mode. Speeding the warm-up period and providing a user interface showing its progress may help prevent this annoyance, allowing a shorter sleep delay time to be effective without reducing user satisfaction.

RICE COOKER

Although the rice cooker, like the pod coffee makers, 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 consumption estimate of 282.2 Wh, and although the range is somewhat smaller in absolute terms than that of 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 resulted in higher energy consumption.

The rice cooker is unique among the devices tested, because its pattern of use explains a significant proportion of variance in energy consumption across device use profiles. The amount of active use – in this case, how much total rice is cooked in a 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, for example, 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, it took 32.5 minutes to cook one cup of rice, and only an additional eight minutes to cook three cups of rice.

However, changing the pattern and cooking three cups of rice in two or three separate, fresh batches over the course of the day (for example, for lunch and dinner) requires a new baseline cook time level. 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 TVs and computers, where the amount of time actively watched or used is synonymous with the amount of service received. As such, although the pattern aspect reveals additional energy consumption, it is the consumption during active use that must be reduced 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 coffee makers, under-sink or table-top water heaters, hot pots, and electric pressure cookers – and some conclusions can be cross applicable.

While PM 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 PM – 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 differs in another way from other devices tested here, in that the device being left on in the keep-warm state is seen by users as deliberate and functional. An online search reveals many people prefer to make a large pot of rice and keep it warm all day, claiming it tastes better than rice that has been stored in the refrigerator and reheated. In fact, there are warnings against a common practice of leaving rice in the keep-warm state for two days or longer, due to risk of bacterial growth if rice is kept warm this way for 12 hours or longer.

According to the current results, it uses more energy to make a new, smaller pot of rice three times a day (and turn the warmer off after one hour) than to make one large pot and keep it warm all day. For instance, profile #19, high-low-low (three cups of rice made once and left on "warm" all day) uses 548.3 Wh, compared to profile 26, high-high-mod (three cups of rice total, made in one-cup increments three times, turning the keep-warm function off after one hour) which uses 743.5 Wh. So if a user perceives these as the competing options, the "worse" PM strategy would actually use less energy. That said, it is still the case that all else being equal, turning the rice cooker off immediately after use, or within one hour, still saves more energy than leaving it in the keep-warm state all day long. And users should certainly be discouraged from keeping rice warm longer than 12 hours, given the health risks.

OVERALL

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, 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 for energy efficiency or standard test protocol accuracy. It is reasonable that devices would use more energy if actively used more hours, and that devices would save more energy if more aggressive PM features were used. Likewise, a very small range is not necessarily a good sign, as it indicates the device does not effectively reduce energy use for shorter active periods or in response to PM.

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, because it depends on how common these device use behaviors are, and understanding this would require a much greater amount of field research on consumer behavior than is available at this time.

The larger the range in possible energy consumption outcomes, the more likely it is that the real-life pattern of outcomes is skewed, which is especially concerning when results show energy consumption levels much higher than the standard profile. For most of devices tested here (TVs, video game console, desktop and laptop computers, and rice cooker) the upper range was much larger than the lower range, indicating 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 it, which is due to the PM settings being disabled by default for those devices.

ACTIVE USE

The duration or frequency of active use is a significant factor influencing energy consumption for many of the devices. Indeed, were PM not being tested, the effects of active use would be more pronounced for most devices. The effect of active use across profiles can be seen in each device's energy usage profile figures, which also illustrate how the effects of low (inefficient) PM can easily outweigh differences due to active use.

Even considering the weight of PM, active use explained 40 to 43 percent of the variation in energy consumption for the 4K TVs and HDTVs, and 20 to 27 percent of variation for the desktop, laptop, video game console, and streaming device. Of these devices, the TVs, video game console, and desktop computer used a relatively large amount of energy in their standard profile compared to others. It is especially troubling how much more energy was used by the newer 4K TV than the HDTV. These results add weight to efforts to reduce power draw during these devices' active states.

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 PM fails (that is, automatic low-power settings are disabled and the user neglects to manually turn off the device). Therefore, the high power draw of the active state contributes to the energy waste attributed to the PM aspect in these results. More aggressive improvements to energy efficiency during the active state would 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 the operational duration typically involves reducing energy use for 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 self-regulates to passively save energy. After testing multiple generations of computers for this project, improvement in idle energy usage was easily observed. Considering the flow diagram in Figure 3, it helps to promote alternate solutions, when possible. For example, a substantial energy penalty is paid to stream online content on a video game console versus a dedicated streaming player.

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, have a separate boot-up and/or shut-down process, with a relatively high power draw. However, as these processes are short in duration, the resulting contribution to overall energy consumption by restarting the device multiple times during the day is not substantial.

A more significant issue for pattern of use is the type of cool-down period represented by automatic sleep or auto-off settings with long delay times. If a device's auto-off setting is set for a two-hour delay, and the device is used for three hours in one sitting, an additional two hours of idle or wasted active state is added to its total energy consumption. However, if the device is used for one hour at a time spaced across three instances, up to six hours of idle time would be added. In this case, pattern of use can be seen as an example of a PM 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, such as the streaming device, exhibited a small effect of pattern due to spending more time idle before the device automatically switched into a lower-power mode. All other things being equal, pattern does matter in such situations. However, this effect was overwhelmed by other factors not being equal: specifically, variation in active use and PM 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. Specifically, the rice cooker requires a fairly small amount of additional time and energy to cook three cups of rice as it does to cook one cup of rice. This means that cooking three cups of rice at one time takes substantially less energy than cooking one cup of rice at a time over three instances (say, at each meal). 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 already largely addressed the problem: 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 PM settings are disabled.

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

POWER MANAGEMENT (PM)

The PM definitions used for the device use profiles combined two factors: settings that automatically transition devices into sleep or soft-off states after a specified delay time of inactivity, and whether or not the user turns the device off immediately after use. For every device, a moderate level of PM is defined with factory default automatic setting (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 PM 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 PM setting.

Given this wide range of behaviors, it is not surprising that PM 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 PM is important, this study helps show the importance of systematically examining when and how much specific PM behaviors (both settings and manual shut-downs) affect energy consumption.

The devices studied in the current project revealed three main PM failure points: (1) when automatic settings are disabled or otherwise ineffectively utilized; (2) when low-power modes do not save much energy; and (3) 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 PM 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 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 PM 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 PM behaviors to counteract 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 they were not enabled, and figure out how to enable them. For some devices, it may be possible to take away the users' ability to disable PM 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 PM 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 user 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 setting 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 TV gave users a certain signal that it was going to switch off in five minutes so they could easily forestall a false auto-off, it could be possible to set the default auto-off delay time to one hour instead of four hours 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 standby 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 PM settings were enabled. The solution here is simple, at least in concept: reduce the energy consumption of the supposedly low-energy state. For the set-top box, PM completely fails due to this problem. But at some level, this is a productive approach for all devices where the sleep or standby state uses substantially more energy than the soft-off 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 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" then "long-idle" states in the absence of user input; to save energy, these states pause certain processes, yet leave the device ready to quickly resume full activity when the user returns.

While worthwhile efforts are still being made to further reduce energy in computer idle states, the same should be done for other devices. One example noted here is the video game console. When the device is not actively running a game, it switches to a main menu state that uses almost as much energy as active gameplay, and remains in that high-power state until it transitions to sleep or is turned off. Specifically, the power draw is 69.5 W for active game play and 63.7 W for the main system menu state, compared to 10.7 W for the standby mode. Given the amount of time the device can stay in the main system menu state, reducing consumption to something closer to the standby mode rate would be a substantial improvement.

Finally, for the sound bar, using linked devices for guiding PM was an effective approach. Specifically, an input-specific PM option switches the sound bar off when a device sending audio input to the sound bar (such as a TV) sends no input for five minutes. 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 required the TV to display content could be set to transition to standby or soft-off mode if the TV were turned off or transitioned to sleep mode.

Other devices could be set up as a single system, with any device activating the power-down or standby mode of another. Using CEC commands over HDMI, a TV or connected devices can trigger the PM action of the other, leading to the strongest link in the chain managing PM for all local devices. In this manner, a streaming device can force a connected TV to power off, if this device has more stringent PM settings (or vice versa).

This same paradigm can be linked, expanding PM to use other nearby, trusted devices to provide energy management cuing. Currently, only HDMI-linked devices that are properly configured can use this power linking. For some devices, using an input sensing feature (provided there is a low implementation overhead) may be a consideration for controlling devices over an optical or Bluetooth link as well as CEC-based communication over HDMI. A related alternate approach would be to use a Tier-2 APS to turn off devices and reduce the burden of their standby loads.

In sum, evaluating the effects of PM 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.

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 PM – was defined with at least three levels of behavior: low, moderate, and high. Moderate is intended to reflect the median usage, or the standard testing protocol. The high and low levels are intended to approximate the 10th and 90th percentiles of behavior, showing a large range while omitting the most extreme outlier cases.

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 PM, by the options the devices offered. Self-reports of the amount of active use per day are available for a few of the devices, but even for those, many survey questions use categories (for example, a range of hours of TV use) rather than point estimates.

CalPlug has observed PM behaviors for office desktop computers, but it is unknown how well these extend to home desktops or laptops. No reliable data could be found on how people actually use PM 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 device use profile analysis results are only as good as the assumptions that underlie its measures. Even assuming 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 limitations of the MISER system mirror those of the device use profile approach, in that the quality of the input data defines the quality of the output results. The main contribution of MISER is to calculate the energy savings if observed device PM settings were changed to more efficient settings. This limits the use of MISER to devices with variable PM settings, and to those with sufficient observational data on real-life usage.

The findings demonstrate the utility and potential of the PLSim tool that was developed and described here. In the present version, each parameter was entered into a file template to create a PLSim usage schedule. The PLSim output data was analyzed for each device's profile for basic range and descriptive statistics. Clearly, this manual process serves as an effective demonstration, but can be tedious at the present stage of development.

Evaluation Method Potential Extensions

The methods demonstrated in this project can be extended beyond their demonstration and limited analysis scope. As mentioned in the previous section, the demonstration version of PLSim is functional, but could be improved. Further development is warranted to streamline the code to speed up the process, reduce the chance of error, and facilitate a larger number of profiles per device. Automation and elements of advanced data analysis can be applied to PLSim's energy calculation. Currently, profiles are individually generated, creating a full set based on limited parameters. Elements of Markov Chain Monte Carlo (MCMC) can be used based on probability of choice, and seeded with likelihoods to generate numerous profiles to evaluate for energy usage with increased granularity. Field test data can be used to provide boundary conditions for profiles based on known usage profiles and variances based on observed behavioral actions.

Streamlining the dataflow process, the generated profiles can be injected directly into PLSim as schedules, with the corresponding energy outputs matched to a set of parameters. Automated analyses, combined with results thresholding and clustering, can be used to sort and prioritize profile factors for subsequent analysis and reporting. Elements of this process may be applicable to supervised Artificial Intelligence (AI) analysis processes (possibly Linear Supervised Machine Learning – LinearSVM or neural networks based on Long Short-Term Memory [LSTM]) yet the general deterministic nature of the data likely makes this approach excessive for profile analysis purposes.

In 2017, CalPlug demonstrated LinearSVM is applicable (and useful) for analyzing field trial test data to develop cyclic use behavior models (Klopfer et al., 2019). This process implicitly solves hidden-chain Markov problems, essentially building a potential chain based on device action states. This is similar to the inverse problem we are solving, and can be used to pull the basis factors to build up new profile chains. Accordingly, AI techniques may have a potential role in pre-processing field trial data to see profile generation.

A more robust PLSim suite could facilitate testing additional aspec levels (for instance, the 75th and 25th percentiles) faster, leading to larger sets of device profiles. This would enable assessing a broader range of PM behaviors and settings, and further illuminate the effects of interactions between PM and patterns of use.

With improved test data, MISER can be used even more. The current report used Monitoring Study data, with limitations described in the Evaluation Methods section of this document. CalPlug's more recent PMUI Study provides extended real-world usage data to improve marginal estimations for office desktop computers. A data connector has already been written to allow this data to be used. To extend the application of this utility beyond office computers, more test data would be required. Given the appropriate data input, MISER could provide models of granular power savings management actions, including modeling Tier 1 and Tier 2 APS systems in addition to linked PM devices. Until structured field trial data is available, this tool is relegated to computer use only.

EXTENDED PROJECT CONSIDERATIONS

Estimating, managing, and reducing energy use in plug load devices requires a multifaceted approach that encompasses elements of device design as well as understanding how the devices are used in actual operation. A device use profile approach is used in this evaluation, to identify and quantify profiles that are especially wasteful. The results provide key implications for prioritizing the direction of improvements in device design.

Device state-based modeling has direct applications in demonstrating emerging technologies, designing field trials, and prioritizing new or extended design features. This approach to evaluating energy use allows a more dynamic way to characterize device operation, and with judiciously-chosen profile configurations, allows a statistically-based evaluation of the sources of variability and points to consider. The results also highlight aspects of behavior that have a significant impact on energy consumption, and yet remain largely unknown due to the lack of research dedicated to this area of the field.

TESTING AND PROGRAM DEVELOPMENT

Many modes of promoting energy efficiency hinge on decisions made based on modeling. Standardized testing protocols create models from a single profile of the amount of active use, which is treated as a median or average usage. These results are then extrapolated to estimate annual usage across all households containing such devices. The profile approach used here suggests a useful extension of such testing, providing a distribution of likely behaviors across users, to provide a more realistic range of expected energy usage. This approach can be a potential added feature in new energy modeling suites and best practices for energy planning. For new devices, field trial data can be used to simulate operational performance on devices with different operational patterns, to assess differential energy use and determine the potential spread of savings values.

Quantifying energy usage variations for device classes can help guide efforts to improve efficiency and inform consumer choices, including government programs such as ENERGY STAR (DOE/EPA) and EnergyGuide (Commerce Department). Further extended testing for updated and new device categories in these programs, whether required or voluntary, could be focused using the outlined methods provided. Similarly, such a methodology can guide the extended application of energy usage bands to better contextualize real field performance. Estimating the energy consumption effects of various parameters of operation can help focus test expansion and refinement on areas of largest potential waste or high variance in energy usage, based on differences in how devices can be used.

The method outlined in this report was demonstrated to strategically rank modeled usage scenarios across devices to prioritize impact, cost, and priority in a dynamic balanced model. Identification of specific modes of waste from testing can help justify regional and federal device efficiency codes, where applicable. For the aforementioned reasons, identification of better real-world energy usage helps develop more informed and better-targeted programs, with more knowledgeable decisions in the process.

The results of the current analysis quantify the extent to which ineffective, misused, or disabled PM options can substantially increase daily energy consumption (or fail to substantially decrease that consumption) compared to the standard usage profile. Some devices are subject to manufacturers' voluntary agreements, based on goals set by careful modeling technology in the field.

Similarly, external regulation of features and the identification of groups of devices sharing common performance capabilities requires a clear understanding of how the devices and their feature sets operate. However, voluntary goals, as well as regulatory allowances, are based on the *existence* of energy-saving features, regardless of the actual performance of these features in real-life usage. If saving energy is the goal, it is important for manufacturers and the industry to emphasize that these features are effective in the field, and conduct more testing, research, and development to improve user interfaces and thereby encourage greater adoption.

Load Shifting

There are two ways to get household devices to respond to DR events: (1) control them so they automatically reduce energy use during the event (as in a smart thermostat reducing an air conditioner temperature setting); or (2) ask users to voluntarily power down devices as possible during the event. Automatic control is more reliable and thus preferable, but it is problematic for most plug load devices, including all the entertainment, office, and kitchen devices tested in the current report. The reason is simple: there is no lower-power active state to which a DR command could shift devices, and cutting power while in use would be an unacceptable disruption. Even when certain settings could be modified to save energy while maintaining active use (for example, by reducing TV screen brightness), such changes could cause users to suspect malfunction.

Devices may be on and wasting energy when they are not being actively used, perhaps without user knowledge; the results reported here show poor PM behaviors can lead to substantial energy consumption. However, high energy demand due to poor PM practices should be addressed through improved energy efficiency: that is, with measures that save energy all the time, not just during DR events.

The current project cannot address the inherent challenges of remotely controlling these plug load devices during DR events. However, the device use profile approach combined with PLSim estimates could be used to predict and understand the effects of *voluntary* load-shifting behaviors, either in response to DR requests or TOU pricing incentives. Analysis of different DR strategies could predict savings potential in different implementation cases. The current analyses did not specify the time of day devices were used, but began the 24-hour clock at the point of first use and cycled through the profile patterns until the period ended. However, the methodology could easily be adapted to model specific time of use, comparing profiles in which usage in peak hours was shifting to off-peak hours. PLSim could be extended to include pricing to indicate how the total cost of electricity would vary depending upon the chosen time-specific profile.

That said, the nature of use poses challenges with enacting successful load-shifting strategies on many classes of plug load devices, such as those studied here. Activities like watching TV, making coffee or rice, or using a home computer tend to be tied to specific times of day, such as meal times and evenings when other family members are present. Some households may be willing to forego watching TV and choose another evening activity instead, such as going out to the movies or playing board games, if sufficiently motivated by emergency DR events. However, the activities associated with these plug load devices cannot be easily shifted to other periods, as might be possible with running the dishwasher or laundry machines, or charging an electric vehicle.

Incentives

One strategy for promoting energy-saving devices is incentives, including customer rebates, retail or midstream incentives, and manufacturer-facing programs. Deemed savings and market transformation efforts offer the potential to reduce the population of inefficient devices by promoting higher-value alternatives with improved energy efficiency. Such efforts have historically focused on larger appliances such as refrigerators, incentivized through rebates and promoted with labeled efficiency ratings.

Incentives are less often used for plug load devices such as consumer electronics, generally due to their short device lifetime and the need to classify the savings performance of specific features, often on a per-device basis. Although plug load devices use relatively little energy compared to major appliances, HVAC, or lighting, most households contain a large number of plug load devices, and their cumulative amount of idle load waste is substantial.

The baseline problem is similar to that of lighting: any one light bulb uses very little energy, but all the light bulbs in a house add up.

However, the problem is further complicated because plug load devices are so variable, and each class of device requires its own analysis, testing, and incentive program. This motivates a judicious approach toward incentives to promote energy-efficient plug load devices. The device use profile analyses presented here can be used to identify and prioritize devices with particularly-problematic ranges of energy consumption, especially those with ineffective PM schemes.

Incentivizing improvements in user design and energy-saving features for devices with poor performance in these tests has great potential, as does incentivizing the purchase of devices whose device use profiles show more positive results. Specifically, in evaluating measures, field trial data can be collected and extended across different devices to assess energy use spreads. Similarly, quotas for active features contributing to energy use in different states of operation can be assessed as a means of feature incentivization. Clear modeling and establishment of savings potential helps provide useful ex-ante values to expedite measure and program development. Better assessment of device operation in real-world conditions would improve predictions of incentive program performance for benefits, and provide guidance on points for increased cost.

APPENDIX A

After the publication date of the original SIM Home report in 2017 (ET14SCE1170), a previously-unreferenced dataset became available (RECS 2015). Some elements of the RECS 2015 questionnaire did not match that of the RECS 2009. An extended comparison is shown in the tables below.

ENTERTAINMENT DEVICES

The RECS 2015 results are largely similar to those for RECS 2009, with the exception being the larger proportion of LED TVs and fewer CRT TVs.

TABLE A1. TVs

N	CLASS 2012 1982	RASS 2009 8717	RECS 2009 12064	RECS 2015 5680
Number of TVs				
0	1%	5%	1%	2%
1	17%	25%	20%	25%
2	29%	30%	33%	33%
3	26%	25%	24%	23%
4	15%	10%	13%	10%
5	9%	3%	6%	4%
6 or more	3%	3%	3%	2%
Type - Primary TV				
LCD	49%		42%	40%
CRT	23%		44%	9%
Plasma	11%		9%	14%
LED	9%		1%	35%
DLP (Projector)	7%		5%	2%
Flat Panel, Unknown	1%			
Other	0%			
Type - Secondary+ TV				
LCD	45%		29%	12%
CRT	40%		64%	31%
Plasma	6%		5%	8%
LED	4%		1%	23%
DLP (Projector)	3%		2%	1%
Flat Panel, Unknown	1%			
Other	1%			
Type - One or More				
CRT		71%		
LCD Smaller than 36 in.		31%		
LCD 36 in. or Larger		32%		
Plasma		13%		

Their size categories increased substantially, as did the percentage of households reporting larger TV screens.

TABLE A2. TV FEATURES

	CLASS 2012	RASS 2009	RECS 2009	RECS 2015
N	**1982**	**8717**	**12064**	**5680**
Screen Size for Primary TV				
Up to 19 in.	3%			
20-35 in.	33%			
36-40 in.	13%			
41-45 in.	15%			
46-50 in.	17%			
51-55 in.	11%			
56 in. or More	8%			
Up to 20 in.			10%	
21 to 36 in.			47%	
37 in. or More			42%	
Up to 27 in.				11%
28 to 39 in.				28%
40 to 59 in.				52%
60 in. or More				9%
Average Estimated Age of TV (in years)				
Primary	5.1			
Secondary+	6.7			
Features of Primary TV				
HD	75%			
HDMI	61%			
3D	2%			
Backlit LED	2%			
Smart TV	2%			
WiFi/Internet	5%			
ENERGY STAR	38%			

The RECS 2015 questionnaire used some different categories for audiovisual equipment than it did in 2009 (see Table A3) but some trends can be seen. Game consoles are more prevalent, and most households have some type of VCR, DVD, or Blu-ray player. The questionnaire did not distinguish between cable or satellite boxes, only whether the set-top box had DVR capability. Half of households (52%) reported at least one set-top box without a DVR, and another half (48%) reported at least one with DVR. Additional analyses combining these two answers (not shown) indicate that 77% of homes have at least one cable or satellite box, with 49% having two or more. A substantial minority of household reports having streaming devices and home theater or audio systems.

Table A3. Audiovisual Equipment

N	CLASS 2012 1982	RASS 2009 8717	RECS 2009 12064	RECS 2015 5680
Accessory on Primary TV (any TV for RECS 2015)				
Game Console	26%		27%	38%
VCR	25%		18%	28%
DVD	54%		52%	
VCR/DVD			26%	
DVD or Blu-ray				64%
Blu-ray	19%			
DVR/Tivo	7%		10%	
DVR				7%
Digital TV Converter	5%		23%	
HD Satellite	17%			
HD Cable	18%			
HD Cable Multifunction DVR	19%			
Cable Multifunction DVR	3%			
Standard Cable Box	12%			
Standard Satellite Box	6%			
Cable Box w DVR			20%	
Cable Box no DVR			37%	
Satellite Box w DVR			12%	
Satellite Box no DVR			13%	
Cable or Satellite Box w DVR				48%
Cable or Satellite Box no DVR				52%
Media Computer	1%			7%
Internet Streaming	5%			29%
Sound System	1%			
Stereo Component	1%			
Home Theater			19%	
Home Theater or Audio System				26%
Amplifier	3%			
Other	9%		3%	

(table continued on next page)

Table A4. Audiovisual Equipment, Continued

N	CLASS 2012 1982	RASS 2009 8717	RECS 2009 12064	RECS 2015 5680
Accessory on Secondary+ TV				
Game Console	17%		16%	
VCR	17%		12%	
DVD	35%		31%	
VCR/DVD			13%	
Blu-ray	6%			
Digital TV Converter	3%		14%	
DVR/TiVo	3%		5%	
Media Computer	0%			
Internet Streaming	2%			
Sound System	1%			
Stereo Component	0%			
Home Theater			5%	
Amplifier	1%			
Other	5%		1%	
HD Satellite	12%			
HD Cable	15%			
Cable Multifunction DVR	2%			
HD Cable Multifunction DVR	8%			
Standard Cable Box	16%			
Standard Satellite Box	8%			
Cable Box w DVR			8%	
Cable Box no DVR			41%	
Satellite Box w DVR			6%	
Satellite Box no DVR			17%	
One or More AV Devices in Home				
DVD / VCR		72%		
Cable or Satellite Box (no DVR)		38%		
Cable or Satellite Box w/DVR		36%		
Gaming System		25%		
Converter Box		21%		
Stand-Alone Stereo, iPod, etc.		21%		
Stand-Alone DVR		13%		
Sound System for TV		31%		
Stereo System			43%	

The RECS 2015 data on time use for the primary TV shows no change from RECS 2009. RECS 2015 does not provide data granularity at the level of TV usage for particular applications such as using the TV while gaming versus not gaming. Specific usage for these devices must be inferred as a subset of TV usage and additional third party literature.

Table A8. Device Use for TVs

	N	Mean	s.d.	Min	Distribution of number of hours per day 10th	25th	50th	75th	90th	Max
CLASS 2012										
All Types	5416	3.1	3.3	0.0	0.1	0.7	2.1	4.3	7.1	24.0
LCD	2526	3.3	3.3	0.0	0.3	1.0	2.1	4.3	7.1	24.0
CRT	1826	2.6	3.3	0.0	0.1	0.4	1.4	3.6	6.0	24.0
Plasma	411	3.6	3.2	0.0	0.6	1.4	3.0	5.0	7.4	24.0
LED	324	3.4	3.1	0.0	0.4	1.1	2.9	5.0	7.1	20.0
Projector	254	4.1	3.5	0.0	0.6	1.7	3.6	5.7	7.1	24.0
RECS 2009										
TV 1 Weekdays	11916	5.6	3.5	0.5	2.0	2.0	5.0	8.0	13.0	13.0
TV 1 Weekends	11916	6.2	3.8	0.5	2.0	5.0	5.0	8.0	13.0	13.0
TV 2 Weekdays	9486	2.9	2.9	0.5	0.5	0.5	2.0	5.0	8.0	13.0
TV 2 Weekends	9486	3.3	3.2	0.5	0.5	0.5	2.0	5.0	8.0	13.0
RECS 2009										
LCD TV 1 Weekdays	4969	5.5	3.4	0.5	2.0	2.0	5.0	8.0	13.0	13.0
LCD TV 1 Weekends	4969	6.2	3.7	0.5	2.0	5.0	5.0	8.0	13.0	13.0
LCD TV 2 Weekdays	2782	3.0	2.9	0.5	0.5	0.5	2.0	5.0	5.0	13.0
LCD TV 2 Weekends	2782	3.5	3.2	0.5	0.5	2.0	2.0	5.0	8.0	13.0
RECS 2015										
TV 1 Weekdays	5544	5.7	3.6	0.5	2.0	2.0	5.0	8.0	13.0	13.0
TV 1 Weekends	5544	6.6	3.7	0.5	2.0	2.0	5.0	8.0	13.0	13.0
TV 2 Weekdays	4142	3.2	2.9	0.5	0.5	2.0	2.0	5.0	8.0	13.0
TV 2 Weekends	4142	3.7	3.2	0.5	0.5	2.0	2.0	5.0	8.0	13.0
ENERGY STAR Testing Protocol										
TV										
Active		5.0								
Off		19.0								

COMPUTERS AND OFFICE EQUIPMENT

The updated RECS 2015 data shows a similar number of computers per household, and a similar number of households with no computers (see Table A5). As expected, households are shifting toward a greater likelihood of having laptops and a lower likelihood of having desktops, but there remains a substantial proportion of households using desktops.

TABLE A5. NUMBER AND TYPES OF COMPUTERS

	CLASS 2012	RASS 2009	RECS 2009	RECS 2015
N	**1982**	**8717**	**12064**	**5680**
Any Computers	92%	84%	78%	
Number of Computers				
0	8%	16%	22%	20%
1	32%	38%	41%	36%
2	39%	27%	23%	26%
3	9%	12%	9%	12%
4 or More	10%	7%	5%	7%
Primary Computer				
None	8%		22%	
Desktop	49%		44%	
Laptop	39%			
Notebook	1%			
Laptop or Notebook			35%	
Computer w Integrated Monitor	1%			
Tablet	2%			
Other	2%			
Secondary Computer				
None	42%		63%	
Desktop	26%		15%	
Laptop	29%			
Notebook	1%			
Laptop or Notebook			22%	
Computer w Integrated Monitor	0%			
Tablet	2%			
Other	0%			

(table continued on next page)

Table A6. Number and Types of Computers, continued

	CLASS 2012	RASS 2009	RECS 2009	RECS 2015
N	**1982**	**8717**	**12064**	**5680**
Of Up to Two Most Used Computers:				
One Laptop Only	16%		20%	
Two Laptops	15%		14%	
One Desktop Only	26%		33%	
Two Desktops	14%		8%	
One Desktop and One Laptop	29%		26%	
Of All Computers:				
No Desktops or Laptop				20%
Only Laptop(s)				37%
Only Desktop(s)				15%
Both Laptop(s) and Desktop(s)				28%
Number of Desktops				
0		31%		57%
1		54%		36%
2		12%		6%
3		3%		1%
Number of Laptops				
0		50%		35%
1		35%		39%
2		12%		18%
3		4%		8%

RECS 2015 does not provide data about individual types of office equipment. The revised question asks for the total number of the following plug load devices: printers, scanners, fax machines, or copiers (see Table). Over a third of households have no such devices connected to their computers, and the majority who have any have only one.

Table A7. Office Equipment

	RECS 2015
N	**5680**
Number of Printers, Scanners, Fax Machines, or Copiers	
0	37%
1	54%
2	7%
3	2%
4	0%
5	0%
9	0%

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