Behavior Adaptive Scalable Energy Management for Electronics – a demonstration in Home Appliances and Displays

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ABSTRACT
Connected devices enrich user experience for a wide range of consumers. However, with an increasing number of such connected devices, improving the intelligence and coordination of energy management solutions becomes more impactful. In this paper, we propose an intelligent power management architecture for the next generation of energy efficient electronics informed by consumer behaviors. The system architecture is built upon scalable, on-demand active power and intelligent sleep/standby modes. User presence and engagement sensors are used for power management control. This system seeks to minimize both user intervention and overall energy consumption. One application of this technology is set top box (STB) power control in addition to other elements of a home entertainment setup, whether it is in a single-user or a shared-use space. For and implementation of our approach focused on STBs, during a two-month stress test, the energy consumption was reduced by over 50% in simulated usage laboratory testing. Implementation of the demonstrated approaches can occur by design integration at the OEM or be provided as low cost energy management retrofits. Direct energy savings can be achieved in existing stock by applying this behavior-adaptive management system to a wider range of consumer electronics with retrofit style solutions for existing units. A consumer behavior based intelligent power management architecture has been demonstrated as a platform for enabling energy savings in consumer plug load electronics. We extend the demonstration discussion to show application to other entertainment equipment, with specific focus on projection based displays.

INTRODUCTION
Residential electricity consumption, together with its associated generation and distribution losses, accounts for approximately 15% of the total US energy consumption as of 2010 [1]. A 2010 residential consumption survey found that about 30% of a home’s electricity is used by miscellaneous plug loads (presumably dominated by electronics), and the latest Department of Energy projections estimate that this will grow to almost 40% by 2035, while the energy demands of white goods and lighting will remain relatively stable. Energy usage for plug loads in the home is centered around home entertainment systems and home offices, with approximately 2/3 of home plug load energy being used on average for home entertainment systems [1] [2].

SYSTEM ARCHITECTURE
The system architecture for behavior adaptive energy management is illustrated in Figure 1. The consumers and plug load devices are both integral components of the decision making process for individual device energy management. The context information collected by this system includes environment (temperature, lighting, humidity etc.), network (remote access, local clients, etc.) and behavior. A number of sensors, from low level physical sensors to high level attention and “emotion” sensors, are utilized to monitor behavioral changes of multiple users. Emotion and attention can be inferred from facial expressions. A hierarchy of inputs is defined with direct user inputs taking precedence over sensor inputs and recorded patterns. This reflects the core behavior adaptive principle, where user inputs and behavior sensing can override any device level decisions.
Figure 1: System architecture for behavior adaptive energy management.

Another core concept for this system architecture is that both users and the devices are defined with finite numbers of operational “states” (Figure 2). Users, for example, are attributed with their location and activity states as they perform different daily tasks at home or work. Traditional energy management seeks to “train” users to modify their habits. On the contrary, this user-centric system treats user behaviors as primary inputs to influence device state-machines. Depending on implementation, devices may or may not be coordinated to improve system-wide integrated management. Devices managed by the system are able to shift to lower energy consuming states most effectively while providing uncompromised services to users.

Figure 2: State-machine models for both appliances and consumer cycles.

In practical implementation, larger numbers of users, lack of visibility of user action on the part of the device, and effective unpredictability of users’ interaction with a device provide challenges. To overcome these, a perturbation allowance permits optimization with allowance for differing usage.

A significant amount of research has been conducted in search of plug load power management solutions at program, incentive, components, packaging, device and system levels [3] [4]. However, consumers have always been the largest unknown factor, exhibiting unique usage behavior of their own plug load devices [5]. The concept of “Personal Energy Footprint” (PEF) was proposed at CalPlug to integrate consumers into plug load energy management. Here PEF refers to the energy needed for an individual to utilize plug load devices to support his/her daily activities such as doing the work, having entertainment, preparing food, etc. Contrary to traditional power
management where user intervention is essential, the behavior adaptive architecture (artificial intelligence) proposed in this paper seeks to liberate users from the burden of user intervention while minimizing PEF. User behavior sensing and learning modules are defined at device and system level, and their power standards specified. The inclusion of multiple users and stand-alone, unconnected devices adds to challenges in this model. When practically implemented, perturbations to actions must be gracefully handled in a manner that does not decrease device usability. In this demonstration, elements of PEF are implemented on a device used to actively seek and act on periods of non-user interactions to save energy. Scalable active power mode and intelligent sleep mode are tested and implemented on a television set-top-box (STB) with further discussion of application to projection based displays.

SET TOP BOX IMPLEMENTATION

To the surprise of many, the quiet, inscrutable, STB that sits next to their TVs are among the largest energy users in the plug load category [6]. It has caught national attention since the combined annual energy consumption of all STBs across the US is estimated to be four nuclear power plants’ annual output [7]. There are technical and non-technical issues that may impede further power reductions. The most popular pay TV service infrastructures, including cable and satellite, must maintain high quality and security of the content delivered through the network. To introduce effective energy saving solutions, such as various sleep mode(s), one needs to consider both potential interference with user experience and upstream communication.

A CalPlug prototype solution code named “5W5s” is introduced as an implementation of the behavior adaptive architecture. The device can retrofit most modern STBs and put connected STBs into light and/or deep sleep at less than 5 watts of power consumption, and recover for full service within 5 seconds. Internal power savings modes (preferable if available) and power cuts to the STB (using an additional power controller) can both be leveraged for control. A USB prototype which was demonstrated is pictured visually and diagrammatically in Figure 3 and Figure 4, respectively. In Figure 3, a commercial STB under 5w5w management is shown in the background. This module prepares the STB by getting ready ahead of time by sensors built-in and usage patterns recorded.

Figure 3: External view of the 5W5S prototype device.
To base an estimation of how much energy can be saved, we first make a set of assumptions about basic patterns of daily user activities. Albeit with more uncertainty, patterns such as these can apply to families or multiple users on a similar schedule. In the example case, the user gets up at 7:00am and leaves home for work at 8:30am. The user returns at 6:00pm and is interested in watching TV between this time and approximately an 11:30pm bedtime (after this time the user is assumed to be asleep until 7:00 am). Using elements of a programmed (or learned) schedule, actions can be anticipated and acted upon. For example, anticipating the user has left the home, the power control box turns off the STB at 9:30am (user expected to leave the home). The STB stays completely off until the user comes back home at 6:00pm. Then, the user watches TV or walks around until 11:30pm, during which the STB is on all the time. One hour after the user goes to sleep the box turns off the STB at 12:30am. A time-based scheduling is augmented by sensor controls to permit early wakeup and overriding (or delay) of shutdown events. Based on the example case above, the STB stays off for 15 hours a day, i.e. 62.5%. Operational cycling is recorded on the onboard EEPROM of the 5w5s device for later inspection. If the 5W5s device consumes 1.5 watts inherently and stays on permanently, assuming the STB consumes 12 watts in operation, and 10 watts when idle, the energy consumption would decrease by at least 40% through intervention. The non-intervention case assumes no power management in use.

Figure 4: The 5w5s prototype hardware block diagram.

From the above discussion, it becomes clear that detecting and predicting the state and activity of the consumer is of paramount importance to provide a satisfactory Quality of Experience (QoE) while reducing energy consumption. The audio sensor (a low-pass sound envelope detector) uses changes in room sound as an indicator for user presence. The sudden appearance of sound with voice envelope modulation can indicate the presence of users in the vicinity of the device. Similarly a light and motion sensor set provides environmental operational cues due to device user induced local environmental changes. Other, more subtle environmental patterns that change with user presence are currently being investigated as extended user interaction prediction mechanisms. Direct human interaction is inferred through detection of Infrared (IR) remote control signals. Detection of user activity in periods where none is expected can lead to temporary device power control overriding in the short term and new usage pattern learning to improve control for similar future events. Temporal correlation is used as an element of the self-learning algorithm. Sound and motion triggers are used to identify usage activities prior to device interaction. These can permit preemptive device startup to ensure the device is operational by the time the user requests content. The STB device control is accomplished either through USB mediated control of a power management API or by device power cutting. Herein, we propose a Finite State Machine (FSM) model capturing the joint consumer-STB state. The consumer is characterized in terms of presence, attention to the device, and current device usage activity. The model enables the use of mathematical tools such as dynamic programming and Hidden Markov Model that empowers the
system with classification, analysis and long-term optimization (self-learning) capabilities [8]. Based on the sensors’ output, the statistics of the state transitions are matched to elements of a predefined reference set. The estimated statistics then allow the 5W5s control algorithm to perform maximal likelihood detection of the current state, and to implement techniques to optimize the long-term performance measured in terms of energy consumption and waiting time.

A two-month stress test of the prototype is carried out between two identical operating STBs, one with 5w5s and one without. During the two-month period, daily activities in the engineering laboratory of CalPlug are used as user behavior inputs. Students (15 total) were invited to watch TV during the day and into the evening for both the control and experimental setup which were operated simultaneously. The pay TV service remains uninterrupted throughout the testing period for both STBs. The final savings using the 5w5s solution reached 57.9% in this usage testing scenario.

![Figure 5: Stress test of energy savings potential with and without 5w5s solution.](image)

**PROJECTOR IMPLEMENTATION**

Control of projection based televisions (TVs) remains challenging due to the startup and shutdown periods required for the projection bulb to warm up and cool down. While this type of device has low penetration in homes, this technology is in common use in educational and office environments and provides a test model for devices requiring soft-shutdown control in challenging usage environments. Projectors also are commonly video muted – the active projector may not be identified by a user as remaining on and never actively turned off. If prevented from internal power management control, the device can be left on indefinitely. Energy saving solutions such as Tier 2 Advanced Powerstrips do not typically provide the control needed to provide proper shutdown of loads that cannot be directly unpowered as a means to turn off operating equipment. To apply and extend 5w5s technology CalPlug developed a control system codenamed “Projector Buddy” for the management of projection displays. This system uses control elements of 5w5s for energy management along with IR emitter to mediate shutdown of projectors. Similar to 5w5s, this solution uses multiple detectors focused on discerning relevant user behavior to intelligently manage the connected device. This system uses a modulated light, sound envelope, and motion detection in addition to monitoring connected device power load with respect to time. The motion sensor identifies local motion in the area of the device while the modulated light sensor is used to infer if the projection screen is active and if images are changing – an inference metric for active usage. For Digital Light Processing (DLP) color wheel based projectors, this is accomplished by tracking the color refresh rate and overall changes in image intensity. In Tier 2 APS devices, a one to two hour timer is commonly used for shutdowns. If an onboard sensor does not detect occupancy in this period, then a shutdown is initiated. The Projector Buddy device uses a variable timer duration that uses sensor...
input to identify likelihood for interaction, similar in approach as the 5w5s solution. Beyond the 5w5s, if projectors are used in a work or school environment, patterns in sensory input can be used to infer the users’ activities and use inferred intent to improve power management. Key sensor inputs allow for immediate task detection and permit improved inference if a mediated shutdown for power savings is likely required in the near future. For specifically detected situations activities where shutdown is likely (a quiet classroom with a still image projected) the delay to shutdown can be hastened.

Figure 6: Projector Buddy prototype external view.

Commonly, projectors are used in classrooms and conference rooms - outside of residences and in shared work environments. In such shared environments, the intuitive nature of controls becomes even more important for maintaining user satisfaction for this type of solution, and inferring the type of usage (i.e. the task performed in the classroom or conference room) can lead to less obtrusive power management control actions and improve overall user satisfaction. Identification of user tasks and correctly inferring if intervention is required is key for proper operation. In some cases (such as an educational environment) inferring tasks of the occupants provides a powerful means of power management decision making. There are challenges with this approach – common sensor readings can be used to reasonably infer different usage scenarios. The addition of additional relevant sensor inputs can help distinguish scenarios. The use of task based decisions helps guide sensor selection and prioritization as well. Laboratory demonstrations have shown the feasibility of the task based usage for classroom environments as described, but power savings potential measurements are still under investigation based on real world usage of projection based displays.

By using projector operation current and the status of onboard sensors, the Projector Buddy (Figure 6 and Figure 7) can identify the operation environment and the power state of the projector. The user(s) must be made aware of an imminent shutdown event. In the prototype, a laser based indicator provides an infinite focused alert logo for a pending shutdown event. This logo is projected on the screen. Users can abort an attempted shutdown by providing sensed motion to the control system after an alert is issued.
Figure 7: Projector Buddy prototype block diagram.

**DISCUSSION**

The PEF model permits tracking and optimization of energy usage. While valid on a user-by-user basis, the predictive power of this model for intervention based power management begins to become more difficult to implement practically with an increasing user base with less predictable actions. Inherently anticipating patterned interaction with some degree of random variability permits a more flexible model that improves the balance between user satisfaction and energy savings. This is maintained via self-learning by referencing past usage via pattern correlation to provide a model for predicted current and future usage. This model can work for single and small groups of commonly oriented users (a family), yet begins to break down with a large volume of uncoordinated users, low connectivity or poor data from external sensing/user tracking sources, and/or changes in regularly observed patterns. Expansion of this model to allow for tracking patterns of group user interaction can add to the robustness of a practical approach at the loss of predictive precision. In this case, probability of interaction is used to adjust the length and depth of savings measures and activity/pattern based correlation control needs less specific user information to be effective. The usage of task-based inference based on sensor inputs provides an additional element of granular control to reduce the period of time where a device is in operation and waste is occurring. This can be performed with or without past operational control. When the sensors indicate a condition where user presence is unlikely, the period of delay for sensing inputs can be shortened. This may be scaled based related to the probability of interaction or by fixed amounts. If this usage fits a pattern based on past usage, this information can be used conceptually as another sensory input to improve decision acuity. CalPlug is also investigating positive and negative reinforcement mechanisms that allow users to indicate when the control system behaved inappropriately. This “scolding” behavior can be accomplished passively or actively. In a passive implementation, a rapid repowering of the device can be interpreted as an unwanted shutdown and knowledge of this event can be used to improve future control decisions. In an active implementation, the user can provide an input to the control device indicating an inappropriate action was taken. If a proper action was taken that the user noticed, a positive feedback could be given to reinforce and increase the aggressiveness of current control schemes.

Extending the capability of sensor pre-processing and fusion can expand capabilities for control. For example, an audio system that can interpret footsteps or a door opening could potentially improve user experience. With expanded sensing capability always follows privacy concerns. These must be managed, especially for connected devices.

Intelligent sensor based, user-centric power control approaches can be expanded beyond minor power control for other classes of plug load devices. The current state power usage of some devices can be modulated. An example
of this is automatic brightness control (ABC) in TVs, or manipulation of display brightness by a power control system as an alternative means of energy control beyond a power cut or the activation of standby modes. In this way a TV left on but not used for a short period can be dimmed rather than shut off. This approach could help save energy for TVs where the TV is left on for companionship but not directly watched. This control approach also has potential for control of commercial displays where flat panel displays are used. Further evaluation of this approach is merited.

CONCLUSION

A behavior based, adaptive energy management architecture is proposed for energy management at home and work. The behavior of users and device usage preferences are factored in as the most important inputs for decision making. Devices are managed for maximum energy savings without compromising the quality of service and experience. A STB management system was implemented to test the architecture. Over 50% of energy savings was achieved with a prototype system. An extension of user behavior control was demonstrated for projectors. The approaches to user-centric power control could find a promising future as internal controls or external retrofit modules to affect deep energy savings in residential and commercial plug loads. Further investigation is in progress to evaluate and extend a number of the control approaches discussed.

REFERENCES


