# Personalized Energy Reduction Cyber-physical System (PERCS): A Gamified End-User Platform for Energy Efficiency and Demand Response

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**Abstract.** The mission of the Personalized Energy Reduction Cyber-physical System (PERCS) is to create new possibilities for improving building operating efficiency, enhancing grid reliability, avoiding costly power interruptions, and mitigating greenhouse gas emissions. PERCS proposes to achieve these outcomes by engaging building occupants as partners in a user-centered smart service platform. Using a non-intrusive load monitoring approach, PERCS uses a single sensing point in each home to capture smart electric meter data in real time. The household energy signal is disaggregated into individual load signatures of common appliances (e.g., air conditioners), yielding near real-time appliance-level energy information. Users interact with PERCS via a mobile phone platform that provides household- and appliance-level energy feedback, tailored recommendations, and a competitive game tied to energy use and behavioral changes. PERCS challenges traditional energy management approaches by directly engaging occupant as key elements in a technological system.

**Keywords:** Games · Gamification · Psychology · Energy efficiency · Human factors · Cyber-physical systems

## 1 Introduction

Smart grid systems are rapidly being deployed across the world. They provide opportunities for improving the reliability, efficiency, and adaptability of the electric grid. Among an array of hardware and software upgrades, smart grid systems include high-resolution meters to measure electricity use. For example, advanced metering infrastructure (AMI) technology involves meters that collect near real-time usage data ("smart meters"). However, the meters alone do not generate electricity savings.

Changing end-user behavior is key to an optimally functioning smart grid system. A variety of technologies and programs already exist to involve end-users in power


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systems, but consumers are often not central considerations in technology design. Technologies that consider end-users as key players in power systems are urgently needed.

Leveraging behavioral science can improve our understanding of how to partner with consumers in the smart grid to develop these technologies, and ultimately lead to more efficient uses of energy. A wealth of research supports the effectiveness of various tools in changing end-user energy behaviors. For instance, the provision of real-time energy feedback to customers has proven to be a reliable strategy for achieving conservation. Energy savings tend to be higher for more granular feedback, which has been greatly facilitated by smart meters. However, granularity in terms of specific behaviors remains on the frontier of the field: no systematic study to date has had the ability to provide real-time, personalized behavioral recommendations to reduce energy use—they have been limited to providing household-level data, leaving end users to contemplate which behavioral changes might result in large savings. Separately, recent advances in non-intrusive load monitoring (NILM) research are enabling the provision of appliance-level feedback, though training NILM algorithms has proven challenging and applications have not been widely tested. Involving end-users in the training process offers one potential for addressing NILM research challenges.

To this end, the Personalized Energy Reduction Cyber-physical System (PERCS) aims to promote energy efficiency and peak load curtailment by engaging building occupants as partners in a user-centered smart service platform. PERCS uses a single sensing point–a Wi-Fi-enabled service gateway-installed in end-user homes–to capture smart meter data in real time. Machine-learning algorithms disaggregate the household energy signal into individual load signatures of common appliances (e.g., air conditioners), yielding near real-time appliance-level energy information, and creating a smart home area network without the requirement of purchasing smart appliances. This level of customization marks a substantial innovation from the status quo of whole-house feedback. It eliminates the need for consumers to generate a mental list of what is using energy in their home, which can be overwhelming and inhibit action. Building additional opportunities for utility-customer engagement, users interact with PERCS via a mobile phone platform that provides household- and appliance-level energy feedback and timely, tailored recommendations. The user experience is tied to a competitive game that leverages social influence. The system also solicits feedback directly from end-users to improve disaggregation results. Finally, PERCS joins anomaly detection approaches with NILM to enable appliance fault detection.

In the remainder of this paper, we describe shifting priorities in energy systems, and describe how PERCS is designed to achieve future energy efficiency and demand response (DR) goals. We also discuss how this system has been informed by and makes contributions to the fields of computer science and behavioral science.

## 2 Literature Review

### 2.1 Shifting Priorities in Energy Systems

Despite the growing availability of renewable energy resources, current demand for electricity, particularly at peak times of day, contributes substantially to greenhouse gas

(GHG) emissions, which are associated with rising global temperatures [1] and negative public health outcomes, including increased mortality rates [2]. The residential and commercial sector is a major consumer of electrical energy and contributor to electric power-related GHG emissions: from 1990–2012, the residential and commercial sector accounted for the largest portion (35 %) of electric power-related GHG emissions of any sector [3]. In addition to environmental and health impacts, even relatively brief lapses in electric power reliability, which often occur when an overstressed grid cannot meet peak demand, have significant economic consequences. Annual losses from power interruptions range from 150 billion Euros among European Union businesses [4] to $80 billion in the U.S. [5]. Accordingly, electric utilities allocate considerable resources to avoiding such interruptions and historically, have invested in additional peak generating capacity (e.g., "peaker plants"), which generally relies on traditional, higher-polluting generation sources (e.g., coal; [6]). Although these strategies can help accommodate increasing demand, the associated economic and environmental costs are substantial. As an alternative, growing efforts are being made to manage demand by curtailing peak loads [6]. Advances in "smart grid" technologies have facilitated this approach by improving demand predictions (e.g., [7]). However, solving the problem of *how* to reduce demand merits further attention.

The U.S. Federal Energy Regulatory Commission (FERC) calls for DR programs that encourage electric customers to make behavioral changes to curtail energy use [8]. Such programs can be effective in promoting overall energy conservation, with home energy savings as high as 21 % [9]. With regards to peak demand and load-shifting programs, however, the literature is relatively sparse. Despite the prevalence of these programs, many have not been evaluated or published, and among those that have, methodological limitations suggest areas for improvement (e.g., [10]).

Achieving the load reduction objectives of the coming decades will require higher levels of customer engagement. The California Energy Commission (CEC) found that the state's DR programs have not met load reduction goals [11]. With DR program participation rates estimated at less than 10 %, and actual compliance rates likely lower [8], the CEC recommends focusing on customer engagement to move closer to DR targets [11]. Toward this end, utility-consumer connectivity must be enhanced. Programs must shift from a one-way, utility-to-consumer approach to a more interactive relationship. Research suggests that "gamified" programs may be better equipped to attract users and sustain program engagement [12] and energy savings, over time. With recent advances in human interface platforms, smart building infrastructures, and real-time mobile technology, now is the time to focus on the rapidly developing area of technology-enabled behavior change.

Building occupants need actionable energy feedback (i.e., information about their building's energy use) in order to make informed energy management decisions. Feedback has been found to be most effective when it is tailored, accompanied by specific recommendations for reductions, and delivered digitally at the appliance-level in an interactive manner [13, 14]. However, monitoring individual loads (e.g., at the appliance level) is cost prohibitive [15, 16]. Instead, a solution that gathers highly granular information while minimizing instrumentation is needed. PERCS offers these features using a single sensing point, making it cost-effective and scalable.

## 2.2 Computer Science Foundations

Energy disaggregation describes a set of statistical approaches to identify individual loads (e.g., appliances) within a whole-building energy signal. Two primary methods have been applied to electric energy disaggregation: (1) distributed direct sensing, which involves monitoring individual appliance loads; and (2) single-point sensing, also known as non-intrusive load monitoring (NILM), which uses statistical algorithms to determine the state and energy use of individual appliances based on measurements collected (e.g., voltage, current, frequency, harmonics, real and reactive power) via a single sensing point on the incoming building power feed. Because load metering requires more instrumentation and tends to be expensive, limiting its scalability, much work has focused on NILM.

NILM approaches emerged in the 1980s [17]. As power data are collected, statistical approaches identify "events", which represent state changes, and cluster them into groups, which represent individual appliances. Correctly classifying appliances with similar signatures presents a challenge. One recent advance for improving classification accuracy is to increase sampling rates, which addresses noise in the signal, thereby improving multi-event discrimination and detection of state changes [15, 16]. To this end, studies suggest leveraging data streams from installed AMI meters [15, 16], in part because such solutions can be cost-effective and scalable, given that electric utilities have deployed millions of smart meters globally that provide whole-home power measurements in intervals of seconds to minutes. Other studies have achieved improvements in classification accuracy by considering non-power data, such as time of day and temperature (e.g., [18]). It is noteworthy that approaches for advancing algorithm performance have relied on pattern detection using non-human inputs.

A major limitation of this work is minimizing the human factors element, a missed opportunity that has resulted in the limited training of algorithms [16, 19, 20]. The few studies that have considered user input and behavioral data have found a direct relationship between behavior and device usage [21] and have increased classification accuracy [22]. These findings suggest that incorporating direct user input into the NILM process can improve NILM results, and point to new research directions.

Also relevant to NILM is the issue of appliance performance degradation over time. NILM can deliver an additional service by identifying, tracking, and addressing sub-optimal appliance performance (i.e., appliance fault detection). To this end, anomaly detection, which has been extensively studied among the signal intelligence (SIGINT) community [23], offers a viable model. For example, Hidden Markov Models have proven successful in detecting changes in observed behaviors [24]. However, little, if any, of this research has been applied to the NILM context, in which there is opportunity to improve equipment operating efficiency. For instance, in a typical household, anomalies can result from innocuous changes in end-user behavior (e.g., change in frequency of opening/closing refrigerator door) or due to appliance performance problems (e.g., fan bearing failure, etc.). A primary innovation of the current study is to extend NILM research by leveraging SIGINT approaches.

Finally, little work has leveraged NILM to investigate real-world potential for energy savings. The few studies that have done so have been on limited scales (e.g.,

[16], [19]) with the exception of Chakravarty's study [25], which showed promising results of 14 % energy savings following provision of disaggregated energy feedback via web and mobile interfaces among a sample of California households. Limitations in the methodology of this latter study underscore the need for additional research.

PERCS extends NILM research in three fundamentally novel ways, by: (1) engaging users as partners, directly building user feedback into training the models; (2) integrating SIGINT anomaly detection approaches with NILM to enable appliance fault detection; and (3) mapping the output of the NILM process to actionable insights for end-users, offering a cost-effective smart service.

## 2.3 Behavioral Science Foundations

Previous behavioral science studies on residential electricity consumption have estimated that households could realistically use 5–10 % less energy without adversely impacting occupant comfort or well-being [26]. Newer technologies allow users to achieve comparable output with less energy input, and upgrading appliances or using appliances more efficiently offers an excellent opportunity to achieve reductions [3, 27]. In addition, people tend to underestimate the amount of energy required for household activities, especially those that involve major household appliances [28].

Smart meter infrastructure can be leveraged to motivate residents to increase energy efficiency through feedback. Historically, residents received only aggregated feedback on a monthly or quarterly basis, making it difficult to connect their behaviors with consumption. Behavioral research has shown that feedback can play an important role in reducing energy consumption, with high-resolution feedback associated with greater savings [13]. For instance, a recent meta-analysis of 57 residential energy feedback studies found that disaggregated, real-time feedback was associated the highest mean reduction of energy use at 12 % [9]. The same meta-analysis found a mean peak load reduction of 13 % among 11 studies that targeted load curtailment. Although these findings are promising, many of the studies included in the meta-analysis did not undergo rigorous peer-review, as is true for the bulk of DR projects.

More importantly, energy feedback by itself may not be sufficient to motivate change [29]. For feedback to generate a behavioral response, the individual must also have a goal, and creating a specific plan for achieving an energy reduction goal has been associated with greater savings [30]. In addition, research on financial framing and incentives suggest that these tools are generally not effective at motivating reductions in electricity consumption, and in some cases they result in increased consumption [31]. Among the feedback-frames tested to date, social comparison to peers has emerged as a promising strategy for motivating electricity conservation [32, 33].

Finally, in line with the Theory of Planned Behavior [34], studies suggest that energy technology acceptance is partially explained by perceived control over the technology [35]. Direct control DR programs may achieve reliable reductions, but participation rates are estimated at 10 % [8]. Evidence suggests that consumers may be deterred from these programs due to privacy and autonomy concerns. Among the most well-documented customer concerns regarding smart grid technologies are perceptions that utilities can (1) directly control a variety of home equipment without consumer permissions or opt-out; and (2) infer specific behaviors in which occupants are engaging [36]. In a similar vein, many consumers prefer choosing their own methods for curtailing consumption to direct control technologies [35]. To gain greater acceptance, smart grid technologies should provide some level of consumer choice.

PERCS provides residents with near real-time feedback about their household and appliance electricity consumption, along with specific recommendations for reductions. This allows consumers to link discrete actions with electricity data, and to decide whether they will change their behavior. The feedback is delivered in a gamified context that allows for social comparison and for a non-pecuniary reward system, a strategy that can potentially motivate users to reduce their consumption [32].

# 3 PERCS

The mission of PERCS is to create new possibilities for improving building operating efficiency, enhancing grid reliability, avoiding costly power interruptions, and mitigating GHG emissions. PERCS proposes to achieve these outcomes by engaging building occupants as partners in a user-centered smart service platform that motivates behavioral changes. See Fig. 1 for a systems diagram.

## 3.1 Objectives

Our research objectives are to (1) improve energy disaggregation classification by incorporating non-power features, most notably direct user input, into algorithm training; (2) integrate anomaly detection approaches with NILM to enable appliance fault detection along with a user alert system; (3) test the energy efficiency and peak load curtailment potentials of deploying a gamified, user-centered NILM platform at scale, with energy reduction goals of 15 % per DR event and 15 % for overall energy efficiency; and (4) evaluate the effectiveness of appliance-level feedback and behavior-contingent social rewards on electricity use among residential end-users.

## 3.2 Technical Approach

PERCS uses a single sensing point – a Wi-Fi-enabled service gateway installed in a residence – to capture smart electric meter data at high resolution, and push the data through a server where it is processed. The processed data are then presented to users as novel information about their home energy use via a mobile phone application (app), providing actionable, appliance-level information without the requirement of purchasing individual smart appliances or smart plugs. The NILM process identifies "events" in the power feed that indicate a state change of an appliance, typically signifying a change of power. Machine learning algorithms then attribute non-power features to that event, such as delta-power, time of day, and outdoor temperature, which enable discrimination between similar load characteristics. Using these features, a clustering algorithm groups these events into groups of similar events. Event-groups that co-occur are then grouped into an "appliance-pattern", which is linked to specific appliances based on additional non-power characteristics of state changes (i.e., only runs when outdoor temperature is above 80 F). PERCS aims to refine appliance classifications through soliciting feedback from users as part of the training process, described below. Additionally, the system identifies patterns of suboptimal appliance functioning and alerts users when it would be advantageous to replace or service inefficient or failing appliances. PERCS features the following:

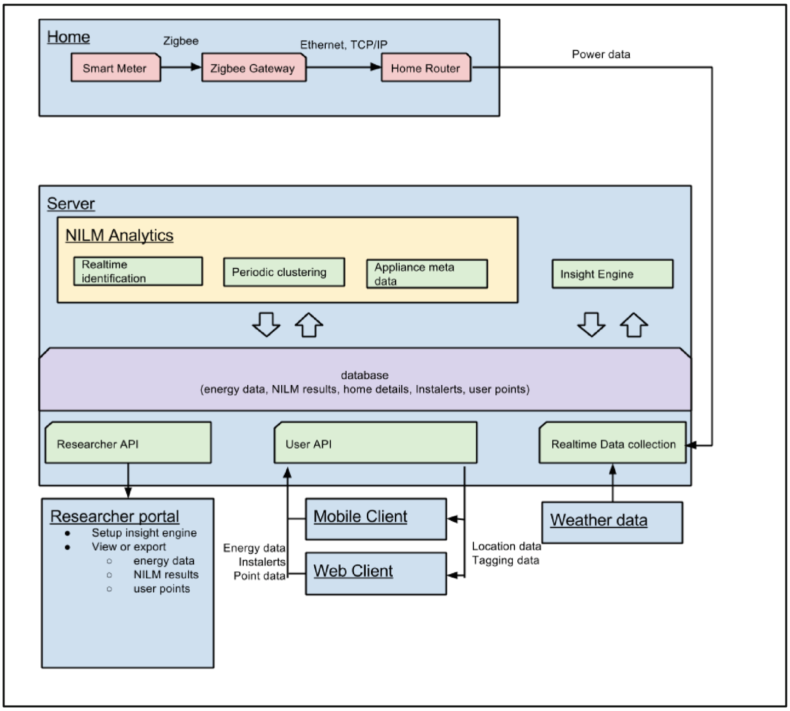


**Fig. 1.** Systems diagram

**Leveraging User Input to Improve Classification**. PERCS builds user feedback directly into the NILM workflow through a process called "tagging". PERCS prompts users to identify an appliance that changed state in real time by sending notifications to users' mobile phones. This data improves differentiation between similar appliances (e.g., stove and grill) as well as identification of appliances with multiple signals. To encourage responses to tagging prompts, users earn points for responding as part of the competitive mobile platform game, described in detail below.

**Real-Time Algorithm Training.** Running the entire NILM process continuously can be computationally intensive. In PERCS, we add a unique parallel process that streamlines the process, enabling it to run as new data are received. This real-time identification process uses characteristic appliance data to identify state changes, updating classification as appropriate as new data are received.

**Smart Appliance Insights for Users.** Perhaps the most transformational of the PERCS innovations is the insight engine, which uses NILM results to provide a valuable service to end-users by triggering user notifications. The trigger comprises a decision tree with specific conditional triggers, such as time of day, total power demand and consumption, specific appliance power and run time, appliance efficiency, and other metrics. From the insight engine, PERCS sends “Action of the Week” notifications to users every week, each of which is a request to engage in one specific behavior tailored to each user’s household based on identified appliances (e.g., “Keep your A/C off every day this week from 1–4 pm”). These notifications serve as behavioral “triggers”, which have been identified as a key component of behavior change [12]. This level of customization marks a significant innovation from the status quo of whole-house feedback. It eliminates the need for consumers to generate a mental list of what is using energy in their home, which can be overwhelming and ultimately inhibit action. By eliminating this step, PERCS provides a valuable service that enables consumers to focus on executing a single, straightforward action to save energy.

**Enhancing User Engagement.** To produce and sustain an engaging user experience, PERCS includes a game as part of the mobile platform under which users earn points for complying with “Action of the Week” requests. Each “Action of the Week” is presented to users via a push notification sent to their mobile phones, and includes the following information: concise description of specific action to be taken, number of points that can be earned for compliance, and dates and times of requested compliance. Any given “Action” is active for a 1-week period, and users can earn points for complying each day during that particular week. To maintain user engagement over time, the platform offers opportunities to earn bonus points, which will be awarded on intermittent schedules of reinforcement (e.g., points awarded for logging in, participating in tagging process). Users compete against one another for the highest rank among the PERCS community via a public leaderboard that displays each participating household’s selected username, point total, and rank, introducing social norms as motivation to reduce usage. Point totals and leaderboard ranks are updated daily to encourage frequent participation. To enable households who join the game relatively later than others to “catch up” to households that joined earlier, leaderboard ranks are adjusted daily to account for level of participation. For DR events, users receive special push notifications one day ahead and one hour ahead of the scheduled event, with a request to engage in a specific behavior to save energy.

**Protecting User Data Privacy.** To protect users’ data privacy, energy data, disaggregation results, and other anonymous data are linked to an Anonymous User ID. All identifiable data (e.g., address) are stored separately, linked by an Identifiable User ID. Only the study team has access to both IDs to enable mapping between datasets. Select pieces of secure code in the application programming interface have access to the proper private keys required to link the Anonymous and Identifiable User IDs.

**Anomaly Detection.** PERCS expands on the disaggregation process by adding anomaly detection to the platform in order to identify failing or inefficient appliances. We leverage research from the U.S. Department of Energy-funded Building Level Energy Management System (BLEMS; [37]) and the U.S. Office of Naval Research

(ONR)-funded Geospatial Analysis of Motion-Based Intelligence and Tracking (GAMBIT) projects [38]. In BLEMS, artificial neural networks and Bayesian Belief Networks (BBNs) were trained to recognize office building occupancy patterns and to detect anomalies. This information was used to calculate HVAC set points to simultaneously optimize energy efficiency and meet occupant comfort preferences. In GAMBIT, BBNs were trained to recognize movement data (signals) and detect normal and abnormal movement behaviors. PERCS incorporates these approaches to identify, track, and address appliance degradation, using findings to trigger user alerts regarding appliance functioning along with recommendations to service or replace failing appliances at the optimal time.

**Smart Building Services.** We view energy efficiency, peak load reduction, user satisfaction, and equipment performance as services – each often competing with the other. A smart service platform that is designed to add capabilities over time, PERCS currently offers the following: (1) detect and differentiate energy usage anomalies from appliance performance degradation, including identifying the economic and environmental "cross-over" point at which it is advantageous to replace an appliance; (2) tailored to each participating household, suggest specific behaviors to improve energy efficiency and reduce peak demand; (3) provide an engaging experience to occupants using relatable information and social incentives.

If successful, future extensions of PERCS would enable remote appliance control, integrate with DR forecasting to improve peak demand management, and/or offer redemption of points earned as part of the game (e.g., gift cards, utility bill rebates).

## 4 Conclusions

PERCS introduces new possibilities for improving building operating efficiency, enhancing grid reliability, avoiding costly power interruptions, and mitigating GHG emissions. Using minimal instrumentation, we provide a cost-effective and scalable solution for intelligent sensing. Additionally, PERCS offers a new model for engaging utility customers, which may prove to be valuable for meeting DR and energy efficiency goals. The platform allows end-users to monitor their behavior, receive personalized feedback, and motivates behavior change via competition. If successful, PERCS could be expanded to promote behavior change for other applications.

Using an interdisciplinary approach that combines social psychology, machine learning, energy informatics, and network computing, PERCS challenges traditional energy management approaches by directly engaging end-users as key elements in a technological system, and provides a solution to the problem of *how* to achieve reductions in peak demand. PERCS advances behavioral science and computer science research by creatively mapping the output of the NILM process to actionable insights via a relatable user platform; it improves the NILM training process without burdening, but rather by engaging, end-users. Coupled with DR forecasting, PERCS holds promise for reshaping the energy landscape.

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