Energy Research and Development Division
FINAL PROJECT REPORT

LARGE-SCALE ENERGY REDUCTIONS THROUGH SENSORS, FEEDBACK, AND INFORMATION TECHNOLOGY

The Stanford Energy Behavior Initiative

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PREFACE

The California Energy Commission Energy Research and Development Division supports public interest energy research and development that will help improve the quality of life in California by bringing environmentally safe, affordable, and reliable energy services and products to the marketplace.

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- Renewable Energy Technologies
- Transportation

Large-Scale Energy Reductions Through Sensors, Feedback and Information Technology is the final report for the PIR-10-054 project conducted by Stanford University's Center for Integrated Facility Engineering, Design for Change, H-Star Institute, Precourt Energy Efficiency Center and the Prevention Research Center. The information from this project contributes to Energy Research and Development Division's Buildings End-Use Energy Efficiency Program.

For more information about the Energy Research and Development Division, please visit the Energy Commission's website at www.energy.ca.gov/research/ or contact the Energy Commission at 916-327-1551.

ABSTRACT

Smart meters and related sensing technologies are promoted on the promise that energy information will play a key role in reducing energy use, thereby helping California meet its aggressive greenhouse gas emissions targets aimed at stemming global warming. However, poorly designed interactions with energy information jeopardize these goals and reduce the efficacy of billion-dollar utility infrastructure investments. The current problems are numerous: sensor information is complex and dull, incentives are inappropriate, interactions with energy information are poorly designed to modify behavior, and social context is ignored. These problems all involve the intersection of human behavior and technology.

This research developed a comprehensive human-centered solution that leverages the anticipated widespread diffusion of energy sensors to significantly reduce and shift energy use. The authors' major innovation was the creation of a transformative system that combines behavioral techniques with human-centered design, computation, and technology to affect energy use behavior. The work involved a collaboration of Stanford University researchers and energy industry leaders formed in 2008 to establish a new concentration in energy and human behavior. The group conducted research, built systems, and tested solutions in the field.

This research had three parts: (1) technology, including an extensible energy communications network to enable future innovation in home area networks; a software platform to enable behavioral programs to be implemented at scale through a "living laboratory"; and algorithms to advance the areas of energy disaggregation, segmentation, and automation, (2) behavioral interventions to reduce and shift energy use, and (3) data evaluation and modeling approaches that applied economic and social network analysis techniques to data collected in interventions. The behavioral interventions included media (interaction design, social networking, games and feedback interfaces), incentive (behavioral economic programs) and community (schools, utility and social organizations). The behavioral intervention projects demonstrated potential to reduce energy use in California by using various methods of displaying information to consumers, depending upon demographics, the framing of the messages, and personal motiviations of individuals and communities.

Keywords: smart grid, smart meters, sensors, energy behavior, behavior, ARPA-E

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EXECUTIVE SUMMARY

Introduction

In January 2010, the United States Advanced Research Projects Agency for Energy (ARPA-E) awarded funding to Stanford University's Precourt Energy Efficiency Center (PEEC) and Human Sciences and Technology Advanced Research Institute to forge effective ways of integrating behavioral science into smart grid technology to achieve meaningful energy savings. The California Energy Commission's (Energy Commission) Public Interest Energy Research (PIER) Program also provided supplemental match funds supporting the research. This initiative was created to address two timely energy problems. First, significant low-cost energy reductions could be made in the residential and commercial sectors by individual and collective operational changes and energy efficiency investment decisions, but these savings have been only partially achieved. Second, billions of dollars are being spent to install smart meters, yet without careful consideration of the human element, the energy saving and financial benefits of this infrastructure will not reach its full potential. By strategically approaching these problems and leveraging now pervasive internet technology and behavioral science learning, the authors believed that they could address these problems. Thus, the Stanford Energy Behavior Initiative and its associated constellation of projects were born, comprising a living laboratory.

The Stanford Energy Behavior Initiative leveraged smart meter and other sensor technologies with behavioral approaches to achieve energy savings at a large scale.

Deliverables were produced and results found in each of the corresponding cluster research or program intervention styles areas as noted in the following list. Complementary workshops and other support efforts were also conducted.

Technical Platform Technical Platform

There are several aspects of the technical platform: hardware and a communications network, an energy services platform to streamline the creation of behavioral programs, and several types of algorithms to perform segmentation, automation, and disaggregation. The authors also compiled energy-saving actions for use in recommendation engines, both those typically recommended by energy and utility organizations, but also innovative ones, for example derived from other cultures and periods. The following are the projects resulting from this research:

1. Created an open standard for Transmission Control/Internet Protocol (TCP/IP) in home area networks, as well as an open-source reference implementation of the standard for others to copy, extend, reuse, and improve. This open technology leverages the Internet and will provide greater freedom in data collection, representation, storage, and communication between devices from different manufacturers, all leading to innovations and improvements in human interfaces to sensor-actuator networks. As a second deliverable, Levis et al. created an extensible and open-source sensing hardware platform for devices that monitor the power of individual electronics, such as computers and monitors.

2. Guided the effort to create the Stanford Energy Services Platform (ESP) to support the data collection, computational, and Web presence needs of several of the behavioral interventions, as well as to benefit the future work of outside groups.

Segmentation Algorithms

3. Developed algorithms to segment customers based on their energy consumption patterns over time using large residential and commercial smart meter data sets. They used this information to strategically and cost-effectively match customers with energy-saving programs.

Automation Algorithms

4. Developed adaptive machine learning algorithms that used sensor data to improve lighting automation on the dimensions of both user preferences and energy savings.

Disaggregation Algorithms

5. Conducted three projects on disaggregation, or the separation of a whole home electricity use into appliance-specific data to guide people on where they should take action, covered the scope of foundational work necessary to jump-start significant interest and research in this space. A comprehensive technical and policy-oriented survey paper was written that has received tens of thousands downloads to date from the PEEC website.

6. Created a data set for disaggregation developers to train and test their algorithms; this data set has been extensively used.

7. Developed disaggregation algorithms using sparse coding methods to advance the state of the art.

Target Actions

8. Identified about 250 energy-saving actions, or behaviors, and created taxonomy to support recommendation engines and behavioral programs within and outside the Stanford Initiative.

9. Collected energy-saving actions from other cultures and throughout history as inspiration for modern-day energy-saving innovations, and the energy savings of these actions were quantified to provide an opportunity map for future design efforts. Many of these may require further development before incorporation into recommendation engines.

Behavioral Programs

Social-ecological models of behavior change, a dominant class of theories in public health, hold that the use of multiple types of programs or interventions are more effective than one because they complement and reinforce one another. Several of the Initiative projects developed and tested media, incentive, and community-based program interventions to assess the effectiveness of these programs and the behavior change techniques embedded within them. Some projects employed an approach typical in the field of public health or in utility pilots in which the effectiveness of multifaceted programs was evaluated. For example, a randomized controlled trial assessed the effectiveness of a program that incorporated multiple behavior change techniques versus a no-treatment or status-quo control. Other projects followed an experimental psychology approach in which there were multiple experimental conditions that were identical except for individual variables that were modified in each to investigate the specific impact. These projects:

Media

10. Created the Power House online game that incorporates real-world energy data into game play, leverages social competition, and retrains habits through reinforcement. Results of a laboratory and a field trial suggest the effectiveness of the game in saving energy and energy-related behaviors.

11. Created a basic resource consumption feedback interface that includes energy- or water-saving recommendations for two respective Northern California communities. The researcher found that framing an individual's efforts as part of the community effort could sometimes increase but other times decrease conservation efforts.

12. Created an immersive virtual shower world and measured the impact on energy-related water consumption behavior, with results suggesting that vivid visualizations of energy consumption (for example, amount of coal instead of kilowatt hours [kWh]) are more important than the personalization afforded by avatars.

13. Created three Facebook applications to match the range of motivations exhibited by individuals. Power Tower is social in that it allows one to collaborate with others in a Tetras-like puzzle where pieces are granted based on multiple participants' energy savings. Kidogo is effective in that it allows one to compute his or her real-world energy savings and then microfinance individuals in developing countries based on this savings.; Powerbar is cognitive in that it primary displays energy feedback data.

Incentive

14. Created the Appliance Calculator application, which has been used by more than 60,000 people through Google ad words. By testing changes in the interface the authors have found, contrary to expectations, that projecting cost savings over time does not appear to prompt selecting more energy-efficient refrigerators when shopping on-line, whereas simply changing the default sort order to put the most efficient appliances on top does. This suggests that simply implementing the most effective behavior change techniques may be a more effective strategy than the traditional route of analyzing the underlying cause of a problem and then trying to address it.

15. Created the Insinc lottery-like transportation incentive program, significantly shifting participants to off-peak travel or public transit, with an enrollment of more than 15,000 Singaporeans to date.

Community

16. Created the Girls Learning Energy and Environment (GLEE) Girl Scout community-based program. Such programs can scale quickly by tapping into established networks and providing close support from peers. Preliminary results indicate significant changes in reported energy-saving behaviors by children in both the home and transport curricula.Project Benefits

Evaluation and Modeling

Three projects developed methods for evaluating the effectiveness of energy programs, and modeling the effectiveness of interventions to guide future work. Specifically, these projects:

17. Applied an analysis derived from economic methods to quantify the effectiveness of Google Powermeter in saving energy. The approach could help inform approaches for legitimizing energy savings from behavioral programs within utilities and government agencies.

18. Developed the Twitter Explorer, which tracks all tweets containing any of roughly 150 energy-related words to track and map conversation changes pertinent to this topic across the online social network of the Internet.

19. Developed a simulation tool that allows one to model the energy savings of behavioral interventions according to parameters such as time, behavioral technique used, and social network distance and type. This tool could serve as a foundation for developing similar but more sophisticated tools enhanced with additional parameters and empirical data that could eventually reduce the time and cost of developing future interventions through predictive modeling.

Future Steps

20. Additional funding has been provided by ARPA-E toward an effort to scale the work of Projects 3, 10, 13, and 16. Furthermore, one new project (20) aims to develop an application that integrates many of the effective pieces from a number of the projects described above and augment these to develop a program that will disseminate broadly and achieve significant energy savings.

In summary, the Stanford Energy Behavior Initiative, which ran from early 2010 through the summer of 2013, developed the components that would support a system aimed at using smart meter and other sensor data, communication technologies, and behavioral approaches to achieve significant energy savings. The initiative can be divided into software and analytics, behavioral programs, and evaluation tools projects. The ESP software from project 2 provided the technical backbone for the behavioral programs. The analytics were developed to perform personalization, targeting, and other functions to improve uptake and effectiveness of the behavioral programs, and evaluation tools were developed to help assess the effect of the programs. Many deliverables were created from these projects that could be used to scale programs for widespread impact, and that could be used by other groups, and numerous publications were produced describing the methods, findings, and deliverables. Phase II of this initiative aims to integrate and scale these projects and disseminate findings.

Project Benefits

The majority of the Stanford Initiative's work to date has been developing software, algorithms, programs, evaluation tools, and other supporting deliverables, and testing these precursors to scaling to large populations to achieve the widespread impacts. There have been tangible energy-saving effects. For example, the lottery project included more than 20,000 participants with an average of 7.5 percent of trips shifted off peak, and the appliance calculator projects totaled more than 60,000 participants, and those exposed to behavioral "nudges" pursued appliances that used 10-20 percent fewer kWh than counterparts in the control condition.

However, the emphasis on scale will begin with Phase II work, if conducted, where the authors will refine and integrate the projects, make them commercial grade, develop scaling approaches, and scale them. The timeline of the development work emphasized in Phase I is mostly consistent with that described in the original grant proposal, with a some delay due to difficulty in getting sensor data, and other technical, logistical, and partnership issues. Once this work is achieved, the authors would expect savings could exceed the roughly 2 percent savings achieved by Opower's mailer report. The authors can start with an estimate of lower bound savings up to 12 percent and upper bound savings of 35 percent, with a middle ground estimate of 23 percent. These figures should then be tempered with the finding that large-scale programs tend to achieve lower average energy savings per household than smaller programs, and most of the programs to date have been smaller, thus these figures may be biased upward. A discussion of how these figures are derived can be found in the full report. Such reduced demand-side use has a wide array of benefits: reduced greenhouse gas (GHG) emissions, reduced environmental impact, reduced system capacity requirements, and increased energy security. Such behavioral programs also increase the consumer appeal of energy efficiency actions, and potentially increase economic activity and improve smart grid efficiency and benefits.

CHAPTER 1: Introduction

1.1 The Stanford Initiative – Innovative and Unique

The most unique contribution of this initiative redefined energy technology to highlight the critical role of human behavior in reducing energy use. The interdisciplinary group of Stanford researchers, the projects and innovations, and the resulting benefits, all has a common emphasis on the critical but frequently overlooked role of human behavior in reducing energy use. Without a complete consideration of human behavior, technical innovations will be at best incomplete and at worst misused or unused.

Here is a caricature of the current energy story that motivates the initiative:

> "I use energy in my home but it's invisible. I don't consume it directly but only via things I want like light, heat and refrigeration. I rarely think about the energy I'm using, and most of my use is habitual and unconscious. The amount of energy I use is registered on a meter that's out of sight, unintelligible, and read by someone else. I only get feedback about my energy use in the form of monthly bills that present complex data that are a month old, and are boring and impersonal. When information is provided to me about how and why I should change my behavior, it is also boring and impersonal and often not even applicable to my situation. Even when I understand it, I rarely act."

This story is common throughout the United States. It describes what may be the worst possible system for promoting reduced energy use: complex, dated, boring and impersonal information presented via inaccessible and unintelligible devices that fail to engage or be personally relevant, and that describe behaviors mysteriously linked to a global problem that is personally distant and difficult to define.

Behavior change can fail at any point in the story, and it does. Consequently, the research team believes that systematically applying theory and methods from the behavioral sciences will produce greater benefits for energy related programs. A system of behavioral strategies to collectively target each step in the process of behavior change is needed to seize a significant opportunity to influence energy and climate issues in America. The system that was developed , was made possible by feedback from new energy sensors, included motivational interventions informed by the best new research about human behavior and were designed to make energy use and energy savings visible, immediate, compelling and even fun.

The research team redefined the energy efficiency problem by emphazing its relationship to human behavior, noting different dimensions of the problem and also similarities to behavior problems in other social science arenas. Next, additional background was provided on the link between energy technology and human behavior, describe the four major parts of the Stanford Initiative, and then describe in detail each of the projects under those four parts.

1.2 Defining Energy Technology to Include Human Behavior

Energy technology is most often defined as devices that supply or improve energy efficiency. These devices most often succeed or fail independent of human action required to make them work (e.g., more efficient solar cells). Many devices, however, are critically dependent on human behavior to make them effective. This is true for the significant national investment in smart sensors that monitor residential energy use. Smart sensors (e.g., smart meters, plug load monitors and programmable controllable thermostats) provide information to people who are expected to monitor and understand the information provided, and to change behaviors accordingly. Consequently, human behavior, along with all of the cognitive, social and emotional constraints, must be considered a critical component of designing and deploying smart sensing systems.

Much more energy information will soon be available, accentuating the importance of human behavior in determining technology success. In addition for the first installations of smart meters and plug load monitors, wireless sensing technologies will be available for gas and hot water, and for transportation as sensors that quantify miles per gallon, mode of transportation and number of trips. Clearly, the impact of energy information on behavior will play a critical role in energy efficiency in the next decade. This project initially focused on smart meter and home area network (HAN) sensing technologies because of their impending rollouts. The work, however, can be transferred to transportation, gas, and water sensors.

1.2.1 'Attention to' Versus 'Processing of' Energy Information

The increased availability of sensing information creates two different information problems, both addressed in the initiative. Information processing theories differentiate selective attention to information (e.g., choosing to pay attention to smart meter data versus something else) from information processing (e.g., interpreting, remembering and changing attitudes and behavior based on the information selected).

The research team considered both problems. The increasing availability of energy information in already crowded information environments will make attention to energy information difficult. Consequently, the initiative considered how to increase attention by using techniques that increase engagement and interest in information (e.g., multiplayer games, incentive programs and social networks).

The increasing quantification of energy use provides a complimentary opportunity to influence information processing and retention. Substantial evidence in psychology shows that quantification of behavior promotes behavior change because it makes visible what is otherwise easy to forget or ignore, and because it informs people about whether their actions have effected change.

Furthermore, interventions can usefully depend on the quantification of behavior; for example, in incentive programs, energy markets, competitions, visualizations, games and social networking, automated appliance controls and behavior change guidance. The initiative explicitly considered how the quantification of energy information can influence behavior.

1.2.2 Borrowing Lessons from Other Behavior Change Domains

Although many of the team's approaches are new to the field of energy efficiency, the consideration of human behavior for other social problems is well established. Large-scale behavior change programs, similar in scope to the projects in the initiative, have been shown to alter behavior in other areas with equally difficult information challenges, including health practices related to cardiovascular disease, smoking and drug use, community political participation, and sexual practices (Rice & Atkin, 2001; Singhal, Cody, Rogers, & Sabido, 2004). Indeed, the term "energy behavior change" comes from "health behavior change." Psychologists attribute the success of these interventions to the application of proven behavioral principles such as engagement, modeling, and self-efficacy (Bandura, 1986, 1997). A distinguishing feature of this work was the collection of researchers with extensive expertise in other behavior change areas, and a commitment to borrow expertise from the larger behavior change literature that has already been completed with significant federal research investment.

1.3 Overview of the Stanford Initiative

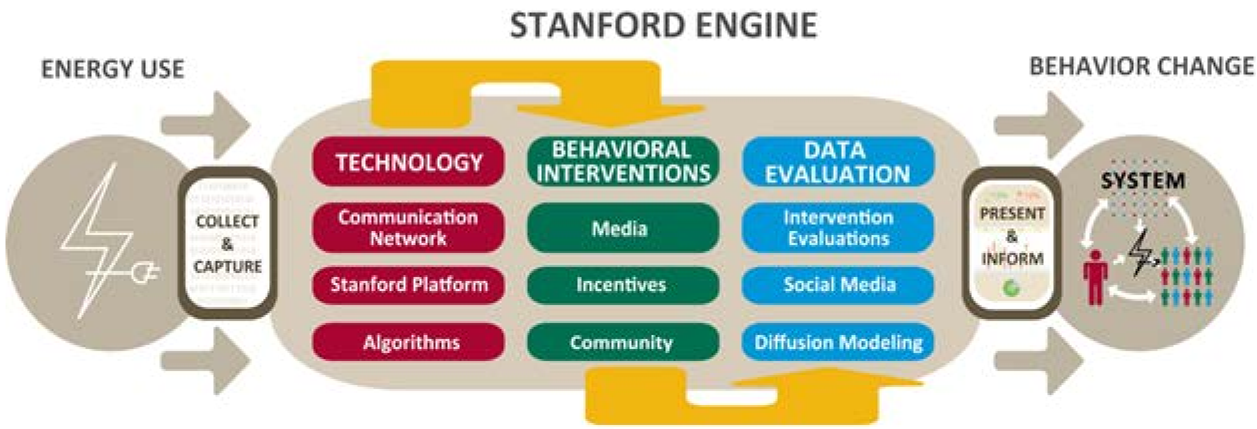
This is a unique point in history with enormous opportunity. On the one hand, wireless sensors - smart meters, home area networks, gas, transportation, and water sensors - that enable the quantification of energy usage are becoming pervasive. On the other hand, web enabled devices are also pervasive, meaning that web enabled computers and phones can deliver programs to help individuals reduce energy use.

The interfacing of these systems with an appropriate engine provides an opportunity for a Living Laboratory at a scale that has societal impact. Such an engine was funded by ARPA-E, Energy Commission, and Stanford University. This Stanford Engine is comprised of approximately 20 projects overseen by 15 faculty and spanning five schools, five centers, and ten departments ranging from computer science and electrical engineering, civil and environmental engineering, and economics, to psychology, communications, education, and behavioral epidemiology.

In summary, the initiative's goal was this: To create comprehensive human-centered solutions that leveraged the widespread diffusion of energy sensors in order to significantly reduce and shift energy use. To address this goal, the research team: (1) developed supporting technology, including an extensible energy communications network to enable future innovation in home area networks; a software platform, for use by Stanford and outside behavioral interventions; and algorithms to advance the areas of energy disaggregation, segmentation, and automation; (2) developed interventions in three categories that promote energy behavior change (media, incentive, and community based), and (3) developed data evaluation and modeling approaches that applied economic and social network analysis techniques to intervention data.

In the following pages further descriptions of the initiative's clusters are provided. Table 1 lists of all the projects by cluster, followed by more detailed descriptions of all the projects in the rest of this report. The initiative mostly focused on residential buildings, but the aim is to extend into other related areas such as transportation, commercial buildings, and water.

Figure 1: The Stanford Engine



1.3.1 Technology

The technology category of this project includes an open communications network, a software platform to support behavioral interventions, and analytics. Regarding the first, researchers expanded opportunities for flexibility and innovation in home area networks with an open and extensible communications protocol that can capitalize on unforeseen behavior change opportunities – such as the ability to provide energy feedback to users more quickly. An open technology will provide greater freedom in data collection, representation, and storage, leading to innovations and improvements in human interfaces to sensor-actuator networks.

Regarding the software platform, large interdisciplinary groups often result in a collection of thematically related projects that unfortunately do not use the technical work performed by one another. This group, however, was motivated by the prospect that a common infrastructure will allow projects to be more influential, extensible and larger than they could be if conducted independently. The common infrastructure developed included shared software, databases, and computing services that created technical economies in the conduct of large-scale field research. Through this platform, the effectiveness of interventions can be evaluated quickly, easily, inexpensively and at scale. This is possible for two reasons: (1) experimental manipulations can be generated and tracked automatically because they can be implemented and delivered via electronic media that all projects will share, and (2) objective measures of behavior change can be collected automatically by sensors, and aggregated in databases that are shared across projects.

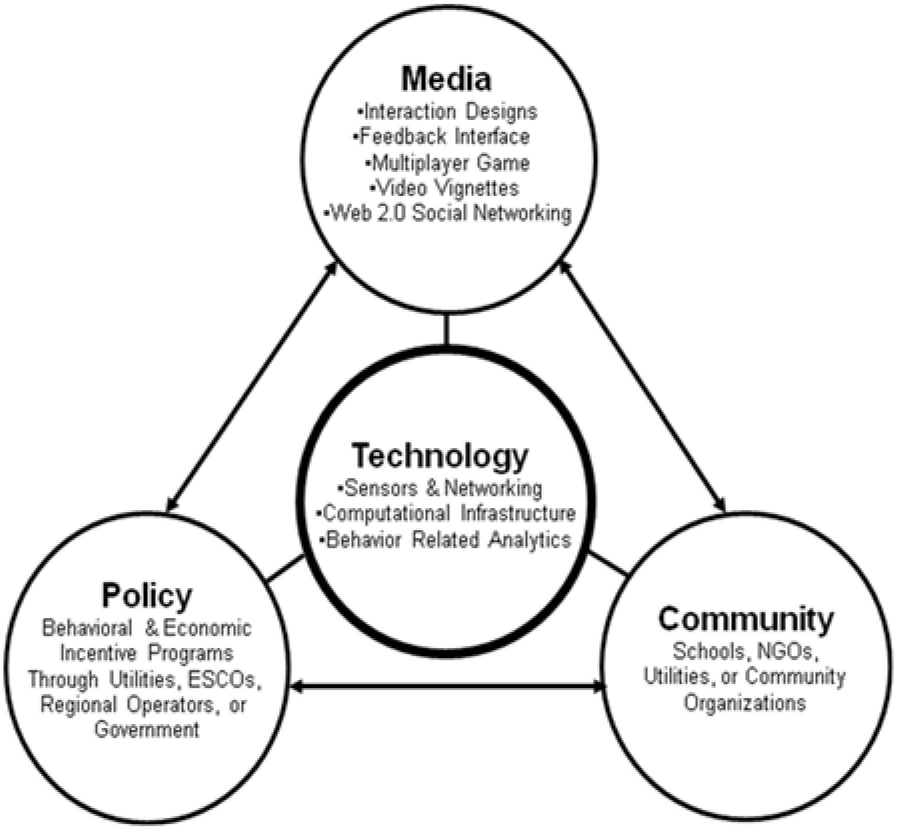
Regarding the analytics, several types of algorithms, or computational problem solving procedures implemented by us in computer software, were developed to perform segmentation, disaggregation, and automation. Segmentation (of whole house electricity consumption data) algorithms were developed to group customers based on their energy consumption patterns using large residential and commercial smart meter data sets. This information can be used to strategically and cost-effectively match customers with energy saving and demand response programs. Three projects related to disaggregation, or the separation of a whole home energy signal into appliance specific data to guide people on where they should take action; these included algorithm development, as well as a technology and policy review paper, and the collection of a dataset to speed work in this space. Adaptive machine learning algorithms were also developed that utilized sensor data to improve lighting automation on the dimensions of both user preferences and energy savings (Project 7).

There were additionally two projects that identified target actions for use in the interventions – through software or other recommendation systems. One identified and created a taxonomy of traditional energy saving actions or behaviors, based on characteristics such as cost, energy impact, who performs the action, and so forth. A second collected energy saving actions from other cultures and throughout history as inspiration for modern day energy saving innovations, and their energy savings were quantified to provide an opportunity map for design efforts and recommendation systems in the future.

1.3.2 Behavioral Interventions ("Programs")

We developed and tested the effectiveness of several types of behavior change interventions. Figure 2 names these types and example topics in each. (Specific projects in each of the categories are reviewed in Table 1.) Given technology's central role in this Initiative, it is depicted at the heart of the diagram below, and for the rest of this report Technology is broken out separately from the other types of interventions. However, note that the energy data produced by the sensors and technology projects is also used by the other three types of behavioral interventions. The arrows between the types of interventions below indicate that projects are mutually reinforcing and can both stand alone (e.g., a single test of one media strategy) and be combined in a coordinated system (e.g., different media strategies that incorporate policies). The general framework of multiple intervention types and their synergistic effects was adapted from the socio-ecological theory mentioned above which is widely used in public health.

Figure 2: Three Behavioral Intervention Categories for Energy Efficiency Projects



1.3.3 Evalution and Modeling

Three projects focused further on developing methods for evaluating the effectiveness of energy programs, and modeling the effectiveness of interventions to guide future work. One project used economic methods to quantify the effectiveness of Google Powermeter in saving energy; the approach could help inform approaches for legitimizing energy savings from behavioral programs in utilities and government agencies. A second project developed Twitter Explorer which collects and analyzes tweets, to track and map conversation changes pertinent to specified topics such as energy across the internet's online social network. A third project developed a simulation tool that allows one to model the energy savings of behavioral interventions according to parameters such as time, behavioral technique used, and social network distance and type, and served as a foundation for other tools that could eventually lessen time and cost of developing future interventions through predictive modeling.

1.3.4 The Projects

There are 19 projects summarized in Table 1, as well as the new integrative Project 20 that is underway with additional funding from ARPA-E. The table shows the project number, its category (technology, intervention, evaluation and modeling), its name, deliverables, investigators and their Stanford University departments as well as partners. The rest of the report provide more details on each of the projects, and concludes with impacts and recommendations.

Table 1: List of Major Projects of the Stanford Initiave, Project Goals, and Lead Investigators

Project # - Report Section	Project Name	Goals	Investigators	Stanford Departments & Partners
Technology				
1	Open Extensible Communication Network	Development of an extensible HAN protocol to enable innovation	Levis, Kazandjieva	CS
2	Stanford ESP	Database + analytics for experimentation at Stanford and beyond	Armel, Reeves	PEEC, Communication Jay Bartels and Andrew Davidson at Bonsai Development Corp.
Algorithms				
3	Energy Consumption Forecasts	Segmentation of commercial and residential energy use data, models that forecast building energy consumption to guide utility interventions	Fischer, Rajagopal, Albert, Kavousian	Civil & Environmental Engineering Google, Pacific Gas and Electric (PG&E)
4	Advanced Learning Automation	Software to customize HAN automation, specifically automation based on action recognition and individual preferences	Aghajan, Khalili, Chen	EE
5	Disaggregation Technical and Policy Survey Paper	Assessment of the benefits of disaggregation, state of the art algorithms and performance, and smart meter suitability for this data	Armel, Gupta, Shrimali, Albert	PEEC, FS/ISB, EE Bidgely, Venrock
6	Residential Energy Disaggregation Dataset (REDD)	Data set collected for developers to build and test disaggregation algorithms	Kolter, Chadwick, Armel, Flora	CS, PEEC
7	Disaggregation Algorithms	Development of algorithms to identify appliance level energy information from whole home data stream	Ng, Kolter	CS

Target Behaviors				
8	Energy Behavior Taxonomy	Catalog of energy behaviors, and their impact and barriers	Flora, Boudet, Roumpani, Armel	H-STAR
9	Identification of Innovative Energy Behaviors	Identification of innovative energy reducing behaviors and their potential imact	Armel, Cornelius, Ardoin, Plano, Bridgeland, Morton, Chang, Allen	PEEC, E-IPER, Education IDEO
Interventions				
Media Interventions				
10	Multiplayer Online Game	Online game utilizing team competition	Reeves, Cummings, Scarborough	Communication Kuma Games
11	Collective Action Feedback Interface	Web application that helps consumers monitor goals and compare energy use	Walton, Sparkman, Clark, Paunesku, Armel, Luo, Flora	Psychology Steve and Lisa Schmidt & City of Mountain View
12	Visual Metaphors in a Virtual Immersive Environment	Development and evaluation of metaphors to make energy vivid and personal	Bailenson, Bailey, Flora, Armel, Voelker, Reeves	Communications, PEEC DraftFCB
13	Motivationally Framed Facebook Applications	Web interfaces to motivate energy reductions	Banerjee, Flora, Sahoo, Bhansali, Greenspan, Khakwana, Liptsey-Rahe, Madres, Manley, Omer, Rajendra, Scalamnini, Wong, Stehly, Voelker	Mechanical Engineering, H-STAR
Incentive Interventions				
14	Appliance Calculator	Information and framing tools for guiding the purchase of energy efficient appliances and electronics	McClure, Houde, Armel	Psychology, MS&E, PEEC Sears
15	Transportation Lottery	Utility program that stretches the motivational value of monetary incentives	Prabhakar, Merugu, Pluntke, Gomes, D. Mandayam, Yue, Atikoglu, Albert, Fukumoto, Liu, Wischik, Rama	EE National University of Singapore, Land Transport Authority of Singapore

Community Intervention				
16	Girl Scout “GLEE” Program	Curricula that increase engagement with sensor data and diffuse sensor use and energy saving actions to families	Robinson, Ardoin, Boudet, Flora, Armel	Pediatrics, Education, H-STAR, PEEC Girl Scouts, People Power
Evaluation & Modeling				
17	Google Powermeter Evaluation	Field trial of Google PowerMeter impact using analysis tools from economics	Houde, Sudarshan, Todd, Flora, Armel	MS&E, PEEC Google
18	Social Media Analytics with Twitter Explorer	Analysis of the “conversation” about energy efficiency and behavior on the web & analytical tool for platform	Russell, Rubens, Flora	H-STAR University of Electro-Communications, Tokyo
19	Diffusion Modeling of Behavioral Interventions	A simulation model to predict diffusion in behavioral interventions	Shrager	Symbolic Systems
Integrative Project				
20	Integrative Project	An integration of some of the most effective pieces of the initial projects, as well as new components such as narrative and added diffusion strategies	Armel	Habitable, Free Range Studios, possible others

CS = Computer Science
E-IPER = Emmett Interdisciplinary Program in Environment and Resources
EE = Electrical Engineering
FS = Freeman Spogli Institute for International Studies at Stanford
H-STAR = Human Sciences and Technologies Advanced Research Institute
ISB = Indian School of Business
MS&E = Management Sciences and Engineering
PEEC = Precourt Energy Efficiency Center

CHAPTER 2: Technology

There are several aspects of the technical platform: hardware and a communications network; an Energy Services Platform (ESP) to streamline creating behavioral programs; and several types of algorithms to perform segmentation, automation, and disaggregation. Energy saving target actions were also collected for recommend systems.

2.1 Open Extensible Communication Network

2.1.1 Background

A Home Area Network (HAN) is a type of local area network that facilitates communication and interoperability among digital devices present inside or within the close vicinity of a home (through wired connections or wirelessly), such as "smart" appliances", home security systems, lights, and audio-visual consoles. Computers and smart phones receive data from and can sometimes control these devices through communication with the network. From an energy perspective, a HAN can enable control from a distance or can be programmable; it can be used to turn things on and off, reduce energy voltage, or put electronic devices in "sleep" mode to reduce energy waste when spaces are unoccupied, or devices are not needed to continually be in "active" mode. HANs can also "learn" use and occupancy patterns such that devices use energy only when necessary.

It is important to expand opportunities for flexibility and innovation in Home Area Networks (HANs) with an open and extensible communications protocol that will allow for unforeseen behavior change opportunities that can lead to energy use reduction or increased energy efficiency. For example, if research indicates that high frequency, real-time traces of energy use are effective at changing user behavior, having an open and extensible underlying technology will make it easier to provide such data. An open technology will also provide greater freedom in data collection, representation, storage, and communication between devices of different manufacturers, all leading to innovations and improvements in human interfaces to sensor-actuator networks.

2.1.2 Objectives

In order for this opportunity to be available for the next stage of research and real world applications, Professor Levis aimed to design and implement an open-source network architecture for home area networks. The first major deliverable was open-source code that could be used on a wide range of sensor hardware. The second major deliverable was an extensible and open-source sensing hardware platform for smart meters. Together, these two provide a complete hardware and software solution that users and companies can build on.

2.1.3 Methods - Deliverable 1, Open-Source Code

HANs have been plagued and limited by numerous, overlapping, closed commercial standards. As open-source implementations of closed protocols are of only limited use, Professor Levis participated in an effort to define an open Internet standard, called an IETF request for comments, or RFC. This RFC would provide an open and free definition of how HAN devices should interoperate in order to communicate data with the larger Internet. The protocol described in the RFC is called RPL ("ripple"), or Routing Protocol for Low Power and Lossy Networks. Professor Levis would follow this protocol standardization with supporting and managing an open-source implementation of RPL in the TinyOS operating system, an operating system written by Professor Levis and used by tens of thousands of people worldwide. Together, this means there is now an open standard for TCP/IP in HANs as well as an open-source reference implementation of the standard for others to copy, extend, re-use, and improve.

2.1.4 Outcomes - Deliverable 1, Open-Source Code

The major deliverables were completed. The RPL RFC was ratified in March of 2012. There are now numerous implementations and interoperability tests at IETF meetings. The TinyOS implementation of RPL supports almost all of its major features. Using TinyRPL, a developer can quickly build a large-scale, multi-hop wireless mesh that self-organizes to support TCP/IP to every device and self-heals in response to wireless signal changes, adding new devices, and devices failing. This open-source implementation has been used in several research papers as a basis for exploring ways to improve RPL and has also been used by several companies for prototyping new products.

2.1.5 Methods - Deliverable 2, Sensing Hardware

Professor Levis had proposed building an open hardware platform for smart meters that would allow scientists to access data at a scale or fidelity that is difficult to achieve with existing commercial products. The necessary lead-time for hardware development given the safety certifications needed for such a device turned out to be too long for the results to be useful to other scientists in the project who might have benefitted from the data. The reasonable time estimates for the project indicated that Professor Levis' team would have working sensors as data collection began to wind down. The team therefore decided to build a simple and easier power plug meter that would measure devices rather than whole buildings. This plug meter would use the TinyOS operating system and RPL protocol to establish and test its design.

2.1.6 Outcomes -Deliverable 2, Sensing Hardware

The team developed a wireless power plug meter that automatically joins a self-assembling, ad-hoc wireless mesh network to deliver data to collection points. They open-sourced the design, which has been used by several follow-on efforts by other groups as a basis for their own power plug designs. The team deployed a network of 200 such meters in the Gates Computer Science building at Stanford for over two years to obtain long-term, fine grained power draw measurements of the building's computing systems. This extensive data collection allowed the team to publish detailed data at a scale order of magnitude than other, similar efforts, as well as establish the basic methodologies one should follow to measure computing energy. The lead student on this project has now graduated and has been working with several green computing companies in the Bay Area to write future energy standards for computing systems.

2.1.7 Future work

This work should have significant real world impact moving forward. These efforts helped establish the first Internet standard for HANs, which is being adopted by industrial consortia such as WirelessHART and ZigBee. The open source implementation of the protocol in TinyOS provides a starting point for its demonstration and improvement, both through research and engineering. The embedded wireless plug meters demonstrated low-cost ways to densely measure computing energy and have established techniques on how to collect and analyze such data. In summary, the open-source thrust of this work should facilitate real-world impact, as a ready-made hardware and software solution that can be easily extended will reduce the cost of entry for new companies and lower the bar for innovation.

2.2 Stanford Energy Services Platform (ESP)

Investigators: K. Carrie Armel, Byron Reeves, Jay Bartels, Andrew Davidson

2.2.1 Background

Many researchers are designing and testing feedback interfaces, as evidenced by proceedings from conferences such as the Behavior, Energy and Climate Change Conference (BECC) and the Computer Human Interaction Conference (CHI), and the dozens of publications on the topic over the past few decades (for reviews see Darby, 2006; Neenan & Robinson, 2009; Ehrhardt-Martinez & Donnelly, 2010). However, the research team found through interviews that researchers typically build the various software services needed from scratch and in a piecemeal manner. As a result, valuable time and resources are wasted, and often, researchers are confined to running very small scale experiments (i.e., 10-30 people per studies, only a couple studies per year). A platform could be of great benefit to researchers, utilities, and third party developers in this space. This kind of software is not available off the shelf, and the system has not been built in full robustness because while the benefit is high, the amount of effort for any one group to build the system is very large.

2.2.2 Objectives

The Stanford ARPA-E Energy Services Platform (ESP) is an attempt to address this need for feedback interface software that is available for multiple parties to use. The platform provides software services including data collection, data cleaning and storage (e.g., sensor, click, and survey data), analytics (e.g., baselining, comparison to other users, disaggregation), graphing, recommendation systems, participant registration and assignment, and front-end display and email notifications suitable for performing experimental manipulations.

2.2.3 Method

The ESP was coded by Bonsai Development Corporation, informed by the needs of Stanford ARPA-E Initiative projects. Five Stanford behavioral programs have or are using the ESP: *PowerDown, Power House, Kidogo, Appliance Calculator, and Girls Learning Energy and Environment (GLEE).*

2.2.4 Outcomes

The ESP platform has been created, including a back-end with data and service layers, and a front-end presentation layer (see Table 1). The software engineering design emphasizes modularity, extensibility, security, and scalability.

The data layer includes data collection, storage, and retrieval. There are currently five logical data stores, containing different types of data: (1) energy data (the system currently collects, via a web collector, hourly electric and gas smart meter data being stored by utilities), (2) project-specific data (e.g., experiment details, investigator names for data access), (3) participant data (e.g., survey input, utility username/password), (4) website/application activity, (5) external data (e.g., weather, regional specific information like fuel type penetration or socio-demographic characteristics), and (5) recommendations, including energy-saving actions and also energy efficient appliance recommendations.

The services layer is anything that requires computation, logic, or analytics, such as baselining, graphing, or disaggregation; a determination of recommendations; or participant registration and assignment. Several services were developed to group data in ways that could motivate behavior change. For example, the team compared a user's energy usage to their baseline, or to a groups' energy usage, through numbers and graphs. The Appliance Recommendation System uses user inputs on characteristics of their current appliance, what state they live in, and preferences for new appliance attributes, in concert with the databases described above, in order to provide recommendations on whether one should upgrade to a new appliance, and, if so, which one.

The front-end of the system is the presentation layer, and refers to the device (e.g., computer, ipad, handheld), application type or medium (e.g., text messaging, widgets, flash animation, social media), and graphical user interface (GUI) characteristics (e.g., style and layout, type of content (i.e., which widgets?), as well as the actual content (the specific text, images, sounds)). For research and evaluation purposes, it is important that users across a broad range of technical capabilities have flexibility and control in the presentation layer. This is important because researchers need to be able to make front-end changes to the applications easily and see the results, so they can continuously iterate, and to create variations on a "parent" web-page so they can easily create different conditions for their experiments. With the ESP developers can control the presentation using various technologies, depending on their skill level and desire for customization. These technologies include:

- Software Developers Kit (SDK): The platform has an API that can be made available for users with programming knowledge that allows them near complete flexibility in designing and developing applications (e.g., mobile, website, Facebook), while accessing databases or services on the platform.
- Mash-Ups: These are easier to use than an API, but allows the same access as the API, it is so suitable for those with limited programming knowledge.

- Widgets: the platform also allows for users with no programming knowledge to create applications, for example, by selecting and then dragging and dropping pre-made modules or "widgets" in systems such as iGoogle, Google sites, and iWeb.
- Off the shelf packages: Various presentation oriented packages, also known as management systems (CMS) such as Drupal or Joomla, can be interfaced with this platform.

2.2.5 Next Steps

The code for the system is being streamlined for use by outside groups (such as research groups or start-up companies), documentation is underway, and an online licensing agreement is being set up.

2.3 Algorithms

2.3.1 Residential Energy Analytics Segmentation, Targeting, Thermal Response, & Building Energy Efficiency

Investigators: Ram Rajagopal, Martin Fisher, June A. Flora, Jung Suk Kwac, Adrian Albert, Amir Kavousian, Jeff Wong

Partners: PG&E, Google

2.3.1.1 Background

Utility demand-side programs are designed towards achieving set target kWh reductions in consumption for a given time horizon. Demand response programs aim at short time scale reductions, such as 10 min to one hour, while energy efficiency programs aim at longer time scale baseload reductions such as over the period of weeks to years. Success of a program is measured by the yield in the program: the ratio between projected reductions and achieved reductions. Typical yields in current utility programs are in the low range of 10-30 percent. The primary reason is due to customer enrollment challenges. The population of consumers can be segmented according to how the program benefits them as shown in Figure 1(a). There are four groups of customers. The customers with large positive benefits usually enroll in the program, but are a small fraction of the customer population. Similarly, the customers with large but negative benefits (group C) usually do not enroll as expected. More importantly, customers with small positive benefits (group A) fail to enroll. Moreover, customers with small negative benefits (group B) who could also achieve positive benefits by performing small and inexpensive changes in consumption patterns also do not enroll. Groups A and B form the majority of the population and need to participate if a program aims at high yields. The team's goals within the ARPAe projects were to develop and test scalable methods and metrics for customer segmentation; develop algorithms for customer targeting for demand response programs, and predicting energy consumption thermal response.

2.3.1.2 Partners and Data

We utilized an anonymized large utility provided data-set with more than 250,000 PG&E customers with at least one year worth of hourly smart meter data recordings. The research team also used TED collected data on over 1,000 Google employees.

2.3.1.3 Methods

The sum of the methods was titled Behavior Analytics. The research team began by building a basic methodology for characterizing an electricity customer. The methodology decomposes a customer's consumption into daily load shapes. Load shapes are then analyzed in aggregate to obtain a small number of typical loads shapes that characterize the whole population. These typical load shapes can be used to build behavioral models for customers which examined features such as variability, amount of kWh consumed, and thermal response. Finally, innovative methods to quantify the energy efficiency of buildings were developed.

The four projects examined methods and outcomes of customer's consumption segmentation, targeting, thermal response, and quantification of energy efficiency in buildings (See sections A-D below).

Load Shape Clustering and Customer Segmentation

The wide-spread deployment of smart meters has made available concrete information about customer consumption patterns or load shapes, including the magnitude and timing of their electricity consumption. To populate a dictionary of representative load shapes for a large data set, a hierarchical clustering algorithm has been developed to separate shapes that are "close" to each other into different groups. This massive data analytics is scalable and reveals various key information about the data, including the most frequent load shapes that characterize a customer's lifestyle, the number of peaks, peak times and peak durations. The load shape dictionary is used to segment customers according to extracted features such as entropy of shape code which measures the amount of variability or stability in consumption. Segmentation strategies can be developed to target customers for specific applications such as demand response (DR). For example, to target households for an automated DR program, the focus should be on heavy use and stable customers, in the appropriate time-based segment. So segmentation can be an effective filter to reduce the number of eligible customers. This is particularly useful when the customer size is very large in a full-scale deployment. Also it will be easier to forecast consumption at an individual level for stable customers, and harder for unstable customers since variability is larger in their usage patterns

Customer Targeting Strategies fo Improving Program Efficiency

The idea of demand side load management has been employed to help reduce energy consumption at peak hours and provide demand curtailment during periods of shortfall in renewable generation. To achieve these objectives, utilities are rolling out different energy programs, such as demand response (DR), to small and medium sized customers. Recruiting a customer into an energy program can have significant costs, including market enrollment, event notification, and very often, the setup for enabling hardware at the customer premise. Moreover, the power curtailment potential across customers varies significantly. So for utilities to achieve high yields (for example, high energy savings) in these energy programs, effective strategies need to be designed to identify and target the right customers. For instance, one should not first target customers who will unlikely be consuming large amount of energy at peak hours for a peak load reduction program. The availability of smart meter data allows a close examination of the customers' potential for an energy program, so that they are chosen adequately to balance the magnitude of response potential (reward) and the uncertainty in the prediction (risk). In this project, the research team proposed a methodology to use a large data set with 200K smart meters to select the right customers for a given level of enrollment expenditure. The focus is on the Smart AC program that curtails power consumption by increasing the temperature set-points. The method combines a customer response forecast model estimated from data with a stochastic discrete optimization program that selects customers in order to minimize risk given a desired level of curtailment response. The algorithm gives a minimum number of customers needed to achieve a certain energy reduction target and a list of customers who can achieve this goal with a certain confidence level (probability). This is a scalable selection algorithm and has been validated on a large data set.

A key measure of success for an energy program is its ability to consistently achieve its energy saving goal. So a demand response (DR) program (with incentives), combined with a targeting mechanism and appropriate promotion messages for specific customer segments, built upon a number of DR experiments, needs to eventually induce "steady-state demand response behavior". Such steady-state behavior is necessary in helping utilities measure and quantify the amount of "reliable load reduction" from demand response. This also allows a better understanding of DR availability to identify key customer characteristics (such as demographics, or environmental orientation) that drive energy sustainability in each program.

Load Flexibility and Management of Thermal Sensitive Load

Thermal-sensitive energy consumption, such as that from a heat, ventilation and air conditioning (HVAC) unit, accounts for 25% of the residential electricity usage in the U.S. and is the single largest block of the electricity budget for most customers. There has been tremendous interest and effort in developing methodologies to decompose individual consumption into a thermal -sensitive component and a non-thermal-sensitive base load. Models and algorithms for stacking individual energy consumption in such a structure provide a useful mechanism for understanding the flexibility in managing customer load, and subsequently making effective demand response and energy efficiency intervention decisions. The team developed a model of temperature response that is based on "thermal regimes" for separating the thermal-sensitive load from the thermal-insensitive base load. These "thermal regimes" are consumers' unobserved decisions to use their heating or cooling appliances. With this description of consumption, a system operator could manage the thermal usage component over the course of a planning horizon (24 hours) for a large population of consumers by communicating actions (thermostat temperature settings) to them such that the aggregate load follows a desired profile. This knowledge allows scarce operational and marketing budgets to be allocated to the right consumers when DR programs are executed. Moreover, the features computed from the temperature response model could be used to predict actual characteristics; for example, the presence of large appliances is best predicted by consumption magnitude features, and lifestyle is predicted by the rate at which consumers switch between different consumption regimes. Energy efficiency programs can also be designed to offer the right incentives, such as rebates for efficient appliances, to the consumers whose appliance stock and lifestyle patterns are likely to sustain most long-term energy savings.

Ranking Energy Efficiency of Buildings

Quantifying building energy efficiency is essential to developing and monitoring energy efficiency programs. Existing methods for energy efficiency ranking are time-consuming (thermodynamic models), based on industry averages as opposed to observed operational data (simulation models), non-adjustable to specific situation of a building (Energy Star), or too simplistic (energy intensity comparison). Frontier methods, on the other hand, quantify the energy efficiency of buildings by forming an efficient frontier (i.e., best-practice technology) and comparing all buildings against that frontier. The efficient frontier specifies the lowest energy consumption observed at any Level of Service, which is defined as the utility that the users receive from using energy. This is an indicator of the utility (service, output) that a building provides to its occupants. Stochastic Energy Efficiency Frontier (SEEF) is a performance-based method based on frontier methods for ranking building energy efficiency. It specifies the best practice combination of energy consumption and the level of service. It offers several improvements over existing frontier methods, such as recognizing the random nature of energy consumption and treating energy efficiency as a random variable. It creates a ranking process that identifies a probability distribution of building efficiency ranks, instead of declaring a building is more efficient than another deterministically. The method also uses actual data to estimate uncertainty of efficiency scores.

2.3.2 Advanced Learning Automation

Investigators: Hamid Aghajan, Amir Hossein Khalili, Chen Wu, Louis Chen

2.3.2.1 Background

While encouraging user's proactive involvement in reducing their energy use is an important goal, a complementary strategy looks at how automation can improve efficiency or reduce energy waste with minimal user input; for example, automatically shutting off lights or appliances that are not in use or adjusting the temperature control in response to outside weather conditions. This approach has the potential to reduce energy use with little direct user effort, circumventing persistence issues in user behavior. In order for these techniques to be effective, however, they need to consider behavior. The vast majority of current home automation systems operate without such consideration, using one of two insufficient paradigms: 1) either the systems operate using fixed rules that fail to account for individual differences or 2) they require that users specify the operation rules themselves which is time consuming, unintuitive and may be easily ignored.

2.3.2.2 Objectives

The first aim was to create a solution that is an integrated approach based on ubiquitous sensing of the environment, and algorithms that will predict user behavior and automatically adapt. The second goal was to evaluate the system through in vivo testing – that is, testing in a space that is being used for real work or living functions. Deliverables for this project included building and implementating a model using real world data that predicts user behavior. Predictions from the modeling system are integrated into existing user interfaces, to display predicted future behaviors in a visually accessible manner.

2.3.2.3 Product Description and Study Methods

The automation was accomplished by using machine learning algorithms that address both user models and decision-making. Modeling algorithms use sensor data collected from a variety of sources. Such a model could learn from observations such that, for example, when a user is sitting in the living room in the evening, the TV and lights in that room are likely to be on. And it could also learn the probability that the user will transition to a different situation (such as going to sleep). The team can then apply decision-making algorithms to prescribe system changes that limit energy use; for example, the system could predict that computer use is typically low while the user is watching TV, and it could power down the computer in another room. The key element is that both the modeling and decision making processes are adaptive and will adjust to a user's behavior without requiring manual entry of preferences.

2.3.2.4 Outcomes

To achieve adaptivity in providing services to the user, the system was found to need to support two functions: 1) sense the activity and state of the user, and 2) customize service to the user's profile. To achieve this, three functional modules were developed and described in published papers. In the first module, behavior analysis of the user in a home environment was achieved based on multi-camera vision processing. In the second module, a user profile was defined and hierarchical reinforcement learning was employed as a technique to learn the user profile dynamically. The third module is a decision maker which employs the user profile to control services to maximize user comfort and utility. An automated light and TV control implementation using a network of wireless switches was developed based on detecting the location of a user and his pose with a number of cameras. A web-based user interface was developed to capture the user’s input about the automation setting and build a context-aware user profile, which was used to adapt the setting according to the user’s preferences. For additional details, see publications at:
http://peec.stanford.edu/energybehavior/projects/HAN_automation.php.

2.3.2.5 Next Steps

On further development effort, algorithms can be created to detect complex but unobvious schedule regularities and automatically control devices in a home area network (HAN), and the behavior of which can change over time to adapt to the underlying changes in the user’s behavior or preferences or with seasonal changes. Other algorithms can be developed to track actual and expected energy use of appliances and suggest when appliances or electronics should be repaired or replaced. On commercialization efforts, the research team can share their findings with commercial entities involved in home automation services and collaborate with them on developing test cases for actual user deployment settings.

2.3.3 Disaggregation

2.3.3.1 Disaggregation Technical and Policy Survey Paper

Investigators: K. Carrie Armel, Abhay Gupta, Gireesh Shrimali, Adrian Albert

Background

Appliance-specific feedback may be the most effective type of energy feedback data for the purposes of reducing energy consumption. Appliance specific feedback can achieve this in numerous ways, as seen in Table 1.

Table 2: Energy Feedback from Appliances

Benefits	Domain	Explanation
Consumer	Residential Energy Use	Greater energy reductions from this type of feedback
		(a) Automated personalized recommendations (through auto-commissioning, fault detection, elucidating behavioral patterns, analysis of when and what type of new appliance to purchase based on current use, etc.), (b) personalized recommendations allow for personalized information to reduce barriers to energy efficient actions (e.g., mapped recommendations on where to purchase recommended items); enabling of additional/enhanced behavioral techniques (feedback, competition, visualizations, markets, incentives, etc.)
	Commercial Energy Use	Similar application to residential; large untapped savings here
Research and Developmen t	Appliance Innovation	Better data to (a) redesign appliances for energy efficiency, (b) improved standards, and (c) back up appliance energy efficiency marketing
	Building Research and Design	Improved building simulation models to increase design and operational efficiency (commissioning and auto-commissioning)
Utility and Policy	Segmentation for Energy Efficiency Marketing	Strategic, specific, energy efficiency marketing
	Program Evaluation	(a) Improved objectivity, sensitivity, and causal inference in program evaluation; secondary benefits of (b) improved program design from improved evaluation learnings, and (c) diversification of program types, because these can be quantified, and utilities in many states are incentivized when program savings can be quantified
	Building and Contractor Ratings and Incentives	Affords performance based metrics, ratings, and incentives of buildings which could impact real estate value, and evaluation of contractor performance
	Economic Modeling and Policy Recommendations	(a) Improved load forecasting; (b) Improved economic models to better inform policies and funding allocations

Many approaches for supplying appliance-specific feedback are costly or effortful because they depend on hardware installations. Another approach is disaggregation - the use of algorithms to break down an aggregate or whole-home energy signal into its component appliance/electronic contributions.

Objectives

In this comprehensive survey paper, the research team explain how appliance level data affords numerous benefits, and why using the algorithms in conjunction with smart meters is the most cost-effective and scalable solution for getting this data. They reviewed disaggregation algorithms and their requirements, and evaluate the extent to which smart meters can meet those requirements. Research, technology, and policy recommendations are also outlined.

Methods

In addition to reviewing relevant academic literature, white papers, and manufacturer's manuals, the team interviewed dozens of professionals across relevant sectors, and included electrical engineers with relevant expertise as co-authors. These approaches were particularly helpful in determining disaggregation algorithms data requirements as well as the type of data that is currently available through deployed smart meters.

Outcomes

The work reviewed suggests that there are compelling reasons to pursue disaggregation, and that it may be possible to leverage existing or future smart meters so that appliance specific information can provide benefits at scale. The following are several specific recommendations for moving forward, which are elaborated on in the paper.

The following research and development activities are suggested, as well as fiscal support for these:

1. Improve disaggregation algorithms, in order to improve robustness, accuracy, and number of appliances identified by the algorithms, while reducing frequency, processing, and training requirements, and develop high-yield data compression algorithms. These improvements will move algorithms closer towards in commercial grade (i.e., consumer acceptable) products, and will result in algorithms improvements that will enhance their ability to facilitate energy reductions under more diverse hardware conditions and while consuming less energy to operate.

2. Develop a common data set that captures variability over appliances as well as operating conditions. One such data set has been created at Stanford (see REDD project). Most of the algorithms that have been developed to date have utilized data from only a couple of buildings and so training and testing on this new data set should significantly improve the accuracy of the algorithms across a more representative and diverse housing stock. It would also be beneficial to: (a) Establish performance metrics, such as common definitions of accuracy to enable the comparison of algorithms, so that the

effectiveness of different algorithms can be compared. (b) Organize a competition, as has been done previously with algorithm development in other domains.

3. Facilitate testing of compression and disaggregation algorithms on actual smart meters, to evaluate performance.

4. Perform key behavioral research: Identify popular use cases and their information requirements, as this has relevance to data handling and consumer display requirements.

The following steps should be taken to improve data on existing meters. Regarding firmware upgrades, these are similar to software updates, and can be performed remotely and can be appended to routine updates so as to minimize cost.

1. Upgrade firmware to make reactive power available in addition to real power. This allows algorithms to disaggregate more devices.

2. Upgrade firmware to support data compression. Transmitting events/transitions instead of raw load profiles could significantly improve the frequency of data available to HAN devices, as band-with is currently the bottleneck.

Regarding future smart meter hardware and firmware, it is recommended to:

1. Be capable of 10-15 kHz frequency, which would only cost $5-10 more, but would likely enable a jump in accuracy and the number of appliances recognized. Also, improve wattage granularity. These modifications could garner additional energy saving opportunities from additional identification of devices (electronics are the fastest growing energy consumer in the residential sector) and recommendations.

2. Be capable of supporting disaggregation inside smart meters through firmware toupgrades; this would avoid AMI or HAN network constraints on the amount of data that can be transmitted and thus disaggregated (resulting in identification of fewer devices).

3. Add or replace 802.15.4 based radio (used by ZigBee) with 802.11 (WiFi or low power WiFi) so that meters can communicate directly with the broadband routers, rather than require additional hardware.

Additional policy recommendations include:

1. Disaggregation developers should contribute use case specifications and requirements to the standards process so that other forthcoming communications technologies are better suited for disaggregation.

2. Institute policies to ensure that utilities enable the HAN communication interface (example ZigBee radios in the meters deployed in CA) soon, at a minimum beginning with pilots.

3. Institute policies, such as rebates, to make HAN gateways (that enable consumers to get real time data from their smart meter) effectively free to consumers.
4. Institute policies to ensure that utilities select HAN devices during pilots that allow consumers to access or share their data with any third party.
5. Federal agencies and PUCs should demand improved transparency about meter specifications, and enable universities to test real meters to establish actual constraints.
6. Utilities and regulatory agencies should expediently approve guidelines for addressing privacy issues, if they have not already.

Future Work

Smart meters, given their widespread roll-outs, and ability to circumvent cost and effort barriers, offer an opportunity for quick, sweeping market penetration of sensing hardware required for disaggregation in a relatively short time frame. Given the benefits, it is anticipated researchers, policy makers, and manufacturers will work together to realize the application of disaggregation with smart meters. To date, significant interest is evidenced by tens of thousands of downloads of this survey paper. Further, this work could clear the way for similar energy disaggregation work on gas, water, and transport, and the work could have significant implications for demand response program development and outcomes in the commercial as well as residential sector.

2.3.3.2 Residential Energy Disaggregation Dataset (REDD)

Investigators: J. Zico Kolter, Sarah Jo Chadwick, Larsen Plano, K. Carrie Armel, June Flora

Background

The previous project outlined the importance of disaggregation, as well as other energy data analytics, and identified the need for further algorithm development. Despite its potential, there are a number of obstacles that have hampered academic work on energy data analytics. Data for energy domains is typically collected by companies or utilities themselves, often at substantial cost, and there are several factors that make sharing this data difficult: 1) energy data at the level of individual homes or buildings has intrinsic privacy concerns: connecting even moderate frequency power measurements to a specific home or individual has the potential to reveal substantial information about that person; 2) the value of sharing data freely with the entire body of academic researchers can be unclear, especially when the data itself has substantial business value; and 3) the volume of raw data for many systems can often be quite large, and it is not clear how to widely share the data in a manageable fashion. Due to these factors, academic studies on energy data have often followed a less-than-ideal pattern: a study or analysis is conducted using data gathered from by a third party, but the data is not released and cannot be obtained by researchers looking to build on the data. The specific line of work that originally spawned the research team’s work, energy disaggregation and non-intrusive load monitoring, has followed this rough trajectory: despite work in this area for over 20 years, no independent studies prior to the initial release of REDD that used a common data set is known.

Objectives

The Reference Energy Disaggregation Data Set (REDD) project collects such a data set and standardizes the data collection process. REDD is a free and publicly available energy data set, with common evaluation metrics, to be used by researchers and algorithm developers to develop algorithms designed to separate an aggregate or whole-home energy signal into its component appliance/electronic contributions, as well as in the development of other energy related analytics.

Methods

Four weeks of data were acquired from approximately 40 homes in the Boston and San Francisco metropolitan. In the West Coast data collection, monitoring devices were installed in up to seven homes for three to four weeks at a time; 30 homes were monitored over eighteen months. All of the below data was collected for 48 different circuit breakers, in 30 total homes, with the collection period for each home typically ranging from 2-4 weeks.

We developed and refined a multistep protocol for data collection that details recruitment, consultation, hardware specifications, equipment installation and removal, data evaluation, and a one-hour energy debrief with participants. The REDD protocol was streamlined to work around complex issues that arose.

The REDD monitoring devices were designed to record aggregate home power consumption signals at high frequency and granularity, as well as collect individual circuit-level and plug-level power consumption signals. More specifically, in each home the research team monitored:

1. Whole-home voltage and current monitored at high frequencies (16kHz), to record the actual AC waveforms of the aggregate electricity signals in the homes. Because the raw 16kHz data is quite large, and consists mainly of repetitions of identical waveforms, the data was temporally compressed, and only report those times where the waveforms change (according to the criterion of a multiple changepoint detection algorithm).

2. Per-circuit electrical power monitored at medium frequency (approximately one measurement every three seconds). Whenever possible, the circuit with a human-readable description was labeled, and also identified some of the major loads present on the circuits.

3. Per-plug electrical power consumption, monitored at medium frequency (often once a second, though some homes have only once-a-minute monitoring) for about 20 select plug loads in the home. In all cases the appliance being monitored is labeled in the data set.

Taken together, such data gives a powerful snapshot as to what has happened regarding the energy in the house over this period: the whole-home signals provide high frequency data where devices can be identified the waveforms themselves, while the per-circuit and per-plug signals provide the "ground truth" labeling as to what was actually occurring the home.

Figure 3: REDD monitoring device collecting data from a circuit breaker panel.

Source: Stanford University

Outcomes

The Reference Energy Disaggregation Data Set is available at: http://redd.csail.mit.edu. Here you can download an initial version of the data set, containing several weeks of power data for 30 different homes, and high-frequency current/voltage data for the main power supply of two of these homes. The data itself and the hardware used to collect it are described more thoroughly in the Readme on the main page and in the papers: Kolter, J. Z., Chadwick, S.J., Armel, K.C.; REDD 2.0: The Expanded Reference Energy Disaggregation Data Set. (2013). In press; and J. Zico Kolter and Matthew J. Johnson. REDD: A public data set for energy disaggregation research and in proceedings of the SustKDD workshop on Data Mining Applications in Sustainability, 2011. [pdf]. Those wishing to use the dataset in academic work should cite this paper as the reference. Although the data set is freely available, for the time being the authors still ask those interested in downloading the data to email us (zkolter@cs.cmu.edu) to receive the username/password to download the data. See the available readme.txt file for a full description of the different downloads and their formats.

In addition to this work providing data for algorithm developers and testers, it is anticipated that this database and protocol will allow professionals in other geographic regions and climate zones to collect and store data to facilitate the continued advancement of disaggregation algorithms. Of relevance to continued work is the lesson to date that even in homogenous suburban areas, home energy systems, appliance stock and consumption patterns are extremely diverse.

Future Work

This work is aimed at spawning the development of algorithms, more standardized testing of algorithms, and the collection of new datasets. Further, such a database could provide a foundation for open competitions to seed innovation. Finally, in the future, the research team would like to tightly integrate these types of data collection procedures into commercial devices developed by companies.

2.3.3.3 Disaggregation Algorithms

Investigators: Andrew Y. Ng, Siddartha Batra, Tommi Jaakkola (MIT), Matthew J. Johnson (MIT)

Background and Objective

The potential of energy disaggregation algorithms - computer language instructions that do specific calculations, to accurately determine electricicy consumption for individual devices- holds promise for eliminating the need for costly equipment and installation processes typically required to monitor individual devices for power use. Algorithms that can accurately determine this level of discrete information have signifigance for potential application to utility demand response programs. Demand response programs seek to reduce demand on the electric grid to avoid the need to build new electricity capacity, and to avoid power blackouts , damage to transformers or disruption to power frequency. These types of events can be very costly and degrade the reliability and safety of the power system. However, algorithmic approaches to energy use disaggregation (a topic also referred to as non-intrusive load monitoring (Hart, 1992), have traditionally been very simple, and focused solely on just detecting "device state changes" in a power signal; unfortunately, such detection alone does not actually give a breakdown of power in homes, and is fundamentally limited to monitoring frequencies where such "events" are obvious: the methods would be unusable, for example, using just hourly data from smart meters. Thus, the algorithmic goal of this project has been to develop new algorithmic techniques that can breakdown energy more accurately than previous approaches, using data at a variety of different resolutions and times scales.

Methods

Formally, the algorithmic work pursued through this project approaches energy disaggregation as a source separation problem. That is, given an observed aggregate time signal:

$y_1, y_2, y_3, \dots, y_T$

the goal of energy disaggregation is to find a breakdown of this signal into multiple components

$$\begin{matrix} y_1^{(1)} & y_2^{(1)} & \cdots & y_T^{(1)} \\ y_1^{(2)} & y_2^{(2)} & \cdots & y_T^{(2)} \\ \vdots & \vdots & \ddots & \vdots \\ y_1^{(N)} & y_2^{(N)} & \cdots & y_T^{(N)} \end{matrix}$$

where each y_t^((i)) term denotes the energy consumed by appliance i (for example, a refrigerator, dryer, computer, etc) at time t, with the additional constraint that at each time the power consumption of all the appliances must add to the observed total aggregate power. Although mathematically straightforward this problem is rendered very difficult by the fact that, without significant restrictions, there are any number of appliance powers that could add to a given total. Thus, the algorithmic fundamentally focuses on two elements: specifying models of what appliances "typically" look like, as well as developing algorithms that can take such models and the aggregate signal, and predict the best breakdown of consumption.

Outcome 1: Energy Disaggregation via Sparse Coding

The first study used a collection of about 10,000 individually monitored devices, with average power recorded each hour, and applied a method known as sparse coding to learn models for appliances and separate the signals. The basic principle is to look at a fixed period of time (in this study, a single week was used), and express each appliances entire energy trace over that week in terms of some linear combination of "basis functions". That is:

$$\begin{bmatrix} y_1^{(i)} \\ \vdots \\ y_T^{(i)} \end{bmatrix} \approx \begin{bmatrix} | & \cdots & | \\ b_1^{(i)} & \ldots & b_n^{(i)} \\ | & \cdots & | \end{bmatrix} \begin{bmatrix} a^{(i)}{}_1 \\ \vdots \\ a^{(i)}{}_n \end{bmatrix}$$

Where $b_{1:n}^{(i)}$ are a set of basis functions that capture "typical" usage patterns for the ith device, and $a_{1:n}^{(i)}$ are "activations" that specify which of these basis functions makes up any given signal. Given a collection of example usage patterns for an individual device, researchers can learn both the bases and activations using a method known as sparse coding (Lee et al., 2006); for this particular project additional algorithmic extensions were developed that tailor sparse coding to this source separation setting (Kolter et al, 2010).

This study with this approach used data provided by Plugwise, a European manufacturer of plug monitors. The team built models using appliance-level data from 413 homes, and then evaluated the learned models to separate appliances in the remaining 117 homes. Typical results of this method are shown in Figure 1, and on average the method is able to correctly assign 55 percent of the energy correctly into one of 10 device categories (evenly divided, so that random guessing would give about 15 percent accuracy). Furthermore, the method requires only hourly data, which can be readily obtained from smart meters, and thus provides a method for approximate disaggregation that can use the existing monitoring infrastructure

Outcome 2: High-frequency disaggregation via hidden Markov models

Although the previous approach is promising in its ability to use the existing monitoring infrastructure, new sensing modalities offer the promise of much higher frequency data. Thus, the team's second project used the previously discussed REDD data set (Kolter and Johnson, 2011) which was collected in conjunction with the algorithmic development presented here), to disaggregate energy in a home using ~1Hz data. In particular, the research team used a model known as a factorial hidden Markov model (Ghahramani and Jordan, 1997), a graphical representation of which is shown in Figure 2, that captures a time varying process with several devices that can take on some discrete number of power states (e.g. on, off, standby). While not all devices have discrete power levels, several common appliances do, and the method is able to accurately model most of the devices in a common home. The particular algorithmic contribution for this work was to develop an "inference" procedure (an algorithm that determines the state of appliances given an aggregate signal) that was many times more accurate and faster than existing approaches (Kolter and Jaakkola, 2012).

The main goal of this particular study was to evaluate the potential of higher-frequency data (in this case, 1Hz whole-home power) and compare to more traditional event based detection methods. Data from an initial release of the REDD data (including 6 homes) was used to build models for appliances and then separate out the different end-uses. Figure 3 shows a typical example of the algorithm's output, along with the output of an event-based approach. In total, the algorithm correctly assigns about 87 percent of the energy in a home (again, assigning to one of 10 categories of end-use), whereas the event-based approach assigns about 49 percent correctly. This highlights both the potential benefit to higher-frequency sampling, as well as demonstrates the advantage of using more advanced algorithms over the previous simple approaches.

Future Work

Next steps and future/ongoing work for these approaches include: developing methods that can build models using only unsupervised information (i.e., aggregate data alone), rather than both aggregate and individual device level; combining small numbers homes monitored at high frequency with large data sets of smart meter data; integrating the approaches into deployed systems in building energy management solutions.

2.4 Target Behaviors

2.4.1 Energy Behaviors Taxonomy

Investigators: June Flora, Hilary Boudet, Carrie Armel, Maria Roumpani

2.4.1.1 Background

Energy actions or behaviors, such as purchasing a refrigerator, turning off lights, and cleaning a heating filter, are driven by various factors, and can be described along different dimensions. In trying to explain environmentally responsible behavior, Stern (2000) lists four major types of causal factors: (1) attitudinal, (2) contextual, (3) personal capabilities and (4) habit or routine. Numerous researchers — including Kaiser, Wölfing, and Fuher (1999); Barr, Gilg, and Ford (2005); Corraliza and Berenguer (2000); Oskamp (2000) and Shove (2010) — contend that psychosocial characteristics such as attitudes, beliefs, perceived norms, and perceived risk are not primary drivers of energy behaviors. Rather, they maintain it would be more useful to study the structural or personal capability causes of environmental behavior such as household location, frequency (or repetitiveness), skill required to conduct, and cost (Wilson & Dowlatabadi, 2007, p. 182)

In this vein, different researchers have collected lists of energy behaviors and proposed different taxonomies or ways of classifying them according to subsets of contextual or personal capabilities dimensions. For example, a review of energy-reduction feedback interventions categorized energy behaviors by cost and frequency of performance (Ehrhardt-Martinez, Donnelly, & Laitner, 2010). Similarly, in reviewing how energy reduction behaviors were characterized in 28 studies, Karlin, Davis, Sanguinetti, Gamble, Kirkby, and Stokols (2012) distinguished curtailment behaviors from efficiency behaviors. Curtailment behaviors (Black, Stern, & Elworth, 1985) are generally habitual (Stern, 1992), low-cost, require little cognitive effort, can be undone, have lower savings impact, and can be performed by a wider range of actors (e.g., children). They amount to "usage-related adjustments" (Van Raaij & Verhallen, 1983b; Dillman, Rosa, & Dillman, 1983) that require minimal or no structural changes. Whereas curtailment behaviors are simple and routine, efficiency behaviors require structural changes, are infrequent and expensive, require conscious decisions, are more permanent, and require more time (Karlin et al., 2012). Such behaviors go by several names, including technology choices (Stern, 1992), conserving behaviors (Dillman et al., 1983), purchase-related behavior (Van Raaij & Verhallen, 1983b), and energy efficiency choices (Black et al., 1985).

This work has similar goals to that body of literature; however, the research team collected a more comprehensive set of behaviors, identified ten different attributes or dimensions for classifying the behaviors, developed a rigorous and graded rating classification scheme and methodology, and explored how the behaviors clustered together based on the ratings on these attributes.

2.4.1.2 Objectives

The first goal of the energy-reduction behaviors project developed a data set of searchable actions that directly reduce stationary residential energy consumption and their behavior change attributes, the latter derived, in part, from behavioral science theory (Flora et. al. in preparation).

The second goal of the project used the data set created in the first phase of the project to develop a framework for the systematic study of behavior attributes and how they cluster (Boudet et. al. under review).

2.4.1.3 Methods for Behavior Set Selection

The sample of energy efficient behaviors is an integration of lists of behaviors from public sources such as U.S. Department of Energy (DOE, 2012), Flexyourpower@CA.gov, and a comprehensive list produced by the city of Townsville, Australia (www.townsville.qld.gov.au/Pages/default.sapx) (full documentation of the source of every behavior is contained in the database). The original behavior set was a collection of energy saving behavior lists compiled from the above publicly accessible materials. More than 500 behaviors were in the original set. However, once redundancies were eliminated, inclusion and exclusion rules applied, large general actions were subdivided into smaller independent actions, the specificity of each behavior was standardized, and energy savings were identified or calculated, the behavior set was composed of 261 energy efficient behaviors (a 48 percent reduction).

2.4.1.4 Outcomes

In two papers, one in preparation another under review, the behavior attributes, their distributions in the behavior set, and the results of a cluster analysis or a grouping of behaviors into homogeneous groups were examined.

Frequency of occurrence. Many behaviors (38 percent) in the set are performed only once every three or more years. These include such behaviors as major appliance purchases and home weatherization. Another 15 percent of behaviors occur every one to three years, such as small appliance purchases and appliance maintenance. The second largest set of behaviors (20 percent) occurs with very high frequency (multiple times a day), such as turning off lights and unplugging/turning off computers and entertainment devices.

Required skill level. Some 52 percent of behaviors in the set require very little or no skill, such as closing shades or drapes to keep heat in or out, turning off lights, or installing a CFL. Medium skills — e.g., reading instructions and/or having tools — are required for 21 percent of behaviors. Another 28 percent of behaviors demand significant skill such that an expert may be needed to perform the behavior, e.g., to install insulation or high efficiency windows.

Household function. Actions that increase thermal comfort comprise 38 percent of the behavior set. These behaviors involve space heating and cooling, from installing "Energy Star" air conditioners to changing thermostat settings. Another 19 percent of behaviors have a housekeeping function (e.g., cleaning and maintenance). The smallest categories were behaviors associated with hygiene (i.e., showering) (8 percent) and outdoor recreation (i.e., pool maintenance) (2 percent).

Locus of decision. A third of behaviors (33 percent) were coded as having men or women as the locus of decision, meaning that two adults typically decide whether to adopt the behavior, such as large purchases or household organization and maintenance. Slightly fewer behaviors (31 percent) were actions for which primarily men make adoption decisions (e.g., insulating hot water heaters). For 14 percent of the behavior set, primarily women make adoption decisions (e.g., emptying/replacing vacuum cleaner filter bags regularly). Teens can perform 13 percent (e.g., unplugging the charger once a phone is charged), and young children can perform 9 percent of the behaviors (e.g., turning off lights).

Observability. Over a third of the behaviors (34 percent) are highly observable, both by household members and by outsiders and household members. Just under a third of the behaviors (31 percent) are observable by household members only. Interestingly, 35 percent of behaviors are invisible even to household members and observable only by the person who performs the behavior. Such invisible behaviors include, for example, adjusting the hot water heater temperature.

Home topography. The most common location for behaviors is in the shell of the house: 35 percent of the behaviors involve its walls, floors, ceiling, or roof. The second most common locations for behaviors are kitchen/dining areas (16 percent), multiple areas (e.g., lighting fixtures) (15 percent), and storage spaces (e.g., hot water heater closet) (14 percent).

Appliance topography. Most behaviors involve large electric appliances (33 percent) or no electrical devices (36 percent). The remainder of the behaviors involves small electrical appliances (10 percent), electronics (10 percent), lighting (9 percent), and craft and recreation (2%).

Energy savings. Almost half of the behaviors (46 percent) are projected to save more than 750 kWh/yr. About 20 percent of the behaviors have marginal energy savings of 1 to 25 kilowatt hours per year (kWh/yr). The remainder of the behaviors fall into the categories in between — 15 percent of the behaviors save 25-100 kWh/yr, 12 percent save 101-250 kWh/yr, and 10 percent save 250-750 kWh/yr.

Cost

More than half of behaviors cost no more than $20 — 43 percent cost under $5, and 11 percent cost $5 to $20. About 20 percent of the behaviors cost between $100 and $1,000, and 11 percent cost more than $1,000.

Behavior Clusters. Five clusters resulted from a K-means analysis. Each cluster was named as follows, based on the attribute means for the clusters and the behaviors represented in each cluster: Call an Expert (73 behaviors, 28 percent of the sample); Family Style (66 behaviors, 25%); Household Management (49 behaviors, 19 percent); Go Shopping (47 behaviors, 18 percent); and Behind the Scenes Work (25 behaviors, 10 percent).

2.4.1.5 Future Work

The research team planned to extend the Behavior Change Attribute Framework and analytic techniques to transportation and food. In addition, the research team is currently examining population ratings of behavior use, intentions to use, confidence in long term use, and barriers to use.

2.4.2 Identifying Opportunities for Dramatic Energy Reductions in Residences

Investigators: Carrie Armel, Marilyn Cornelius, Nicole Ardoin, Larson Plano, Brett Bridgeland, Luke Morton, Martin Chang, Amy Allen

2.4.1.6 Background

The magnitude of energy savings achieved by any of the Initiative's projects is limited by the technical potential of the practices and technologies that are currently feasible for widespread adoption in our society. A very high technical potential for savings is needed to meet proposed targets of recommendations by the Intergovernmental Panel on Climate Change (IPCC) (60 percent to 80 percent cuts in greenhouse gas (GHG) emissions below 1990 levels by 2050) . Eighty percent reduction of GHG emissions below 1990 levels[1] by 2050 is also the goal for California established by AB 32 of 2006 (the Global Warming Solutions Act). California also has established goals for new residential and commercial buildings to be zero-net energy by 2020 and 2030 respectively.

Energy use reduction in buildings is a critical component of meeting these goals and targets. Unfortunately, current estimates of cost-effective energy savings across existing residential and commercial buildings range between 15 percent and 35 percent in the United States (McKinsey & Company 2009; APS 2008; Hand et al. 2012). Low cost savings from operational changes include a range of options such as regular appliance maintenance and replacement, turning down the thermostat settings, turning off lights when spaces are unoccupied, and eliminating energy waste (e.g. unplugging electronic devices (Nair et al. 2010; Laitner, Ehrhardt-Martinez,

[1] In 1990 CO_2 levels were about 350ppm, which is considered the safe upper boundary; the 2012 figure is 394 ppm.

and McKinney 2009; Gardner and Stern 2008; Parker et al. 2006; Black et al. 1985; Kempton et al. 1984).[2]

However, there have been cases of people achieving energy savings as high as 90 percent (Ninety Percent Reductions Group Website) primarily in less developed nations. Many non-western cultures in other parts of the world use or have used dramatically less energy to achieve daily living needs. Insights into the nature of these practices and low-technology approaches have potential application in western cultures for significant energy savings.

2.4.1.7 Objectives

This project compiled a list of practices and technological insights, from other cultures, time periods, that have the potential for producing substantial residential building energy savings in California's culture (if adapted to be culturally appropriate). The research team also quantified estimates of energy savings potential of these practices and technologies.

2.4.1.8 Methods

Combining approaches from the fields of anthropology and design, data was collected from secondary sources such as books and articles, and conducted in-depth interviews with twenty "extreme users" including energy experts, historians familiar with how people in the past have met their daily household needs, do-it-yourselfers aiming for steep energy reductions; and people from a variety of cultures, in particularly those from harsh climates. Interview data was augmented with secondary research, drawing from cultural anthropology, history, and biology to collect examples of social and biological change and adaptation.

2.4.1.9 Outcomes

These results include approximately 100 energy-saving options covering actions, products, and home adjustments organized by end uses: space heating and cooling, water heating, cooking, and refrigeration. The results were also organized according to the physical mechanism or property by which they operated: (1) eliminating energy waste; (2) insulation and sealing; (3) air flow and evaporative cooling; (4) reflection and shading; (5) absorption, storage and thermal mass; (6) alternative and latent energy; and (7) acclimatization and adaptation. For example, it was found that cultures in hot dry climates achieved significant evaporative cooling effects by using porous drinking vessels (which sweat and evaporately cool), hanging moist cloth in well ventilated areas such as doorways or in wind towers, and using light colored loose clothing to facilitate air flow through the cloth which is moist with captured perspiration; they also used underground rooms to cool their bodies in the hot afternoons and preserve their food (root cellars are one example of this). Energy savings potential within each end use and principle are quantified. The team also reported barriers that interviewees identified at the individual and institutional level. This work offers an approach to identifying and prioritizing energy-saving options that are currently uncommonly applied in mainstream culture, with the intent of

[2] Note that behavioral changes do matter and one residential electricity reduction study showed behavioral changes accounting for 59 percent of the energy savings, compared to 41 percent savings from structural changes (Wu 2012).

guiding further development such as redesign, overcoming barriers, and promoting widespread adoption.

2.4.2.0 Future Work

The research team is currently collecting additional energy saving options. When complete, this work will be shared with designers and policy makers in an attempt to disseminate the practices or principles identified that could be adapted for our culture to facilitate deeper energy savings. This approach may also be extendable beyond residential buildings in areas such as, for example, the food, transportation, and small and medium commercial building sectors.

CHAPTER 3:
Behavioral Interventions

A dominant theory in public health holds that the use of multiple types of interventions (also referred to as programs or treatment approaches) is more effective than one, because they complement and reinforce one another. Several of the Initiative's projects involved developing and evaluating media, incentive, and community-based program interventions. While some projects evaluated the effectiveness of multi-faceted programs which is a typical approach employed in the field of public health or in utility pilots, other projects followed an experimental psychology approach (i.e. using control and treatment groups) and systematically changed variables between conditions to investigate the impact of specific variables on energy behavior.

3.1 Media Interventions

3.1.1 Multiplayer Online Game

Investigators: J Byron Reeves, James K. Scarborough, James J. Cummings, Leo Yeykelis

Partners: Kuma Games, Inc.; Bonsai Corp.

3.1.1.1 Background

Energy information for consumers can be complex and uninteresting. Games offer a compelling new context for home energy information that may engage consumers and change behaviors. Multiplayer games, for example, are sprawling online communities where players interact with and compete against one another in real time within visually rich, three-dimensional virtual worlds that persist and evolve even while a player is away. These games may be the most engaging, sophisticated, and collaborative media ever to be applied to campaigns to change behavior in serious contexts (Reeves & Read, 2009). The audience is big, with as many as 400 million people worldwide that operate avatars in virtual environments (Gartner, 2007). And the audience is surprisingly diverse; for example, gamers average 33 years old and there are more of them in their 40's or 50's than in their teens, the majority of them have full time jobs and kids, and the gender ratio ranges from equal to 3:1 depending on the genre. Furthermore, people are coming to expect engagement in workplace settings as well – IBM and other corporations are beginning to incorporate game-like elements and virtual meetings into work tasks.

3.1.1.2 Objective

The objective was to leverage the popularity of online games to promote energy efficiency. The deliverable for this project was a website, which included a multiplayer game and supporting social media (such as facebook connect), that is suitable for use in experiments and deployment in utility smart meter trials. Empirical experiments on selected features of the media will guide future generation media.

3.1.1.3 Game Description and General Methods

Based on research showing the effectiveness of game elements used in serious contexts (Reeves & Read, 2009), the team built a professional quality social game about energy use in a virtual home. An experienced entertainment software development company, Kuma Games, Inc., was contracted to ensure a professional and meaningful media experience to players. In the game, playable at https://www.freeenergygame.com/portal/ , energy sensors in homes are linked to multiplayer interactions that promote changes in energy use as compelling play and community participation. More specifically, the game uses real world energy use data from smart meters and converts energy savings to rewards and advantages in the game. For example, one can challenge their friends to a "lights out night" and then see who won based on the actual energy consumption data. Embedded within the overall game is a smaller game. In one mini-game (depicted in the screen shot above), the user races around a virtual house over the course of several "days", trying to achieve all the goals of the household members while turning appliances on and off so as to use the least amount of energy. In this manner, the game helps condition energy efficient behaviors in the player's actual home by modeling and reinforcing those behaviors in the virtual setting. By speeding up time and providing feedback promptly in the form of points, the game helps players to more easily develop particular energy habits. Additional features considered in the overarching game include: (a) multi-player game play (permitting individuals as well as virtual and intact groups); (b) multi-period game play (accumulating across multiple play sessions over weeks or months); (c) launched via social networking sites (e.g., friend groups on Facebook that can encourage viral distribution); (d) episodic content (new challenges can be introduced regularly that match regional or seasonal energy goals and can be implemented through video vignettes); (e) competitive (use of point-based leader boards and energy data tracking that allow competition between existing real world groups e.g., companies, classrooms, geographic neighborhoods, community organizations); and (f) portable (game play, scoring and notifications can be tracked through social networks on mobile devices). The primary thesis is that an alignment of personal motivations (e.g., increased involvement encouraged by timely reinforcement, achievement recognition, and a sense of belonging), and community environmental goals (e.g., reduced electricity usage and time-shifted energy use) will result in sustainable behavior change that is personally rewarding as well as socially responsible.

Figure 4: Multiplayer online game landing page (foreground inset) and action game (background)

Source: Stanford University and Kuma Games

3.1.1.4 Methods, Laboratory Study

In the laboratory experiment, 40 people were randomly assigned to play Power House or a similar but thematically different entertainment game (Diner Dash) for 30 minutes in a 10′ x 10′ office. Subjects were told that researchers were testing the popularity of a new game and would be asked to answer questions about how much they liked the game at the end of play. Fifteen minutes after play started, an experimenter entered the room and told subjects that she needed to leave the building before they would finish. The experimenter requested that subjects "close the office" when they were finished with the game and questionnaire. Before subjects entered the room to start playing, there were five appliances turned on in the office. There were two overhead lights controlled by a wall switch, a floor lamp, a desk lamp, and a computer and monitor. After subjects had finished playing the game and closed the office, the team returned to the room to count how many appliances had been turned off after play ended and before subjects left the room.

3.1.1.5 Outcomes, Laboratory Study

Playing the game for 30 minutes resulted in significant increases in energy efficient behaviors after play ended, compared to playing the comparable non-energy focused game. In the energy game condition an average of 2.55 (out of 5) appliances were turned off when subjects left the room; in comparison, an average of .55 where turned off after playing the non-energy game. These show that the energy game was capable of inducing energy efficient behavior after only brief exposure to the game content. More, subjects reported no conscious connection between game play and the measured energy behaviors, suggesting that this behavior was primed through mere exposure to the game content.

3.1.1.6 Methods, Field Study

In the field study participants played the game in their homes over the course of one week to one month while their smart meter provided home energy consumption data for analysis. Participants in this study would typically play the game within a real social context. For example, while playing the game via Facebook, players were able to post in-game achievements and energy savings for their Facebook friends to see. Additionally, some participants would see a detailed energy consumption chart for the previous day while others see only their monthly energy bill. This allows researchers to determine if a higher frequency of feedback can motivate players to save more energy and develop stronger energy conservation habits. Participants also completed a home energy intention survey before and after playing the game to measure any impact on energy conservation intentions that playing the game might affect.

3.1.1.7 Outcomes, Field Study

Results from the field study suggest that participants use significantly less energy while they play the game. Energy use reduction was stronger for those participants who started with a lower energy baseline than those with a higher energy baseline. This difference might be explained by the presence of a high energy consuming device such as a pool or hot tub or by a higher number of occupants in the home. These results indicate that well designed entertainment software can make a significant difference in home energy sustainability.

3.1.1.8 Next Steps

In the near future it is planned to seed a commercially viable version of the game by acquiring users on Facebook – that is, release it with a small population with the aim that that will trigger it going viral. Specifically, some elements of game will be revised; acquire a large population of users by leveraging online social networking and viral recruitment, including hiring a community manager to initiate game play and recommend the game to new players; and develop and implement commercial business model around this version of the game. Possible considerations include directed advertising for recruitment, corporate sponsorship and utility licensing. Future research efforts may isolate and investigate the relative contribution of particular game play elements (e.g., leaderboards, team-based play, energy challenges, virtual currencies) to the effects currently observed.

3.1.2 Collective Action Feedback Interface

Investigators: Greg Walton, Gregg Sparkman, Julia Clark, Dave Paunesku, Steve Schmidt, Lisa Schmidt, Carrie Armel, Tammy Luo, June Flora.

3.1.2.1 Background

Increased home energy conservation may be accomplished by framing efforts to save energy as part of a community effort to provide residents with a motivating sense of togetherness when they perform energy saving behaviors. Past research found that the opportunity to participate in a collective endeavor can be a powerful source of motivation. For example, academic motivations and achievement increase when students feel socially connected to peers and teachers or when they can work together with others on a task (e.g., Furrer & Skinner, 2003; Goodenow, 1992; Roeser, Midgley, & Urdan, 1996; Wentzel, 1997; Walton & Cohen, 2007). The importance of collective goals has not been specifically tested in the context of environmental behaviors, but a related phenomenon — the effects of descriptive norms — has been. Descriptive norms are perceptions people hold regarding which behaviors are commonplace. For example, people will more likely reuse hotel towels, reduce energy consumption, and keep petrified national park artifacts intact if they're informed that others are also performing the behaviors than if they are given pro-environmental or monetary incentives. This is true even though people believe that the latter two appeals will be more effective (Goldstein, Cialdini & Griskevicius, 2008; Schultz and colleagues 2007). One reason norms may be effective is because they convey group intentions to individuals, and being a part of these collective actions provides a desirable and motivating sense of togetherness.

3.1.2.2 Objectives

Many studies present descriptive norms and clear group intentions together to movitative actions or changed behavior, making it difficult to tell if norms alone are helpful, and whether invoking a sense of community is more powerful motivator than basic descriptive norms. The following two studies separated descriptive norms and clear group intentions to determine if they have unique effects.

3.1.2.3 Methods, Study 1 Energy Upgrade Mountain View Experiment

This fist study involved providing energy related information and collecting data from over 800 residences (mostly single family homes, but also some duplexes, townhouses, apartments/condos) in Mountain View, California. Energy use data was collected for each residence that participated for a continuous six month period, sometime between March 2012 and July 2013 depending on when the resident signed up for the program. Participants were recruited, through a variety of methods, including displays and signup lists at community events, door-to-door canvassing, and sending flyers with energy bills as part of the Mountain View Energy Upgrade California program http://www.energyupgrademv.org/. The most successful method of recruitment was to include low budget flyers with the utility bills of all the residents of Mountain View. These flyers advertised the program, offered workshops for learning about home energy reduction and also provided a free smart power strip as an incentive to sign up.

Participants viewed feedback about their energy consumption as well as energy saving recommendations and messaging in emails sent every other week, and they could also access this information through awebsite. Experimental conditions allowed for the comparison of the effects of providing energy use feedback and energy saving tips to households (through the differential framing of feedback data through comparison with others, pictures, and text-based messaging between versions of the emails/online interface) when saving energy was framed 1) as an intentional community effort done together (social togetherness condition; e.g., "We're doing it together!…Mountain View residents have reduced their energy use by 3% in the last few years."), 2) simply as a descriptive norm (norm condition, e.g., "Here's a fact!…Mountain View residents have reduced their energy use by 3% in the last few years."), or 3) without any normative information as a control (control condition). Additionally, this study compared the effects of presenting energy savings information in different ways by randomizing half of the participants in each of the three conditions above to either receive energy saving tips with or without a generalizable theme that readers may extend to other energy savings behaviors. For example, participants in the tips condition might see tips regarding plug loads, heating, and refrigerators all in one email (e.g. "Unplug devices you never use, like an old VCR or fridge."), while participants in the theme condition would also see three tips in one email but these would all relate to heating and an introductory comment on their common energy consuming mechanism would be included (e.g. "Off isn't off"…off is still on. When you just press the off button on an electronic device, it may still be dripping electricity like a leaky faucet.").

3.1.2.4 Outcomes, Study 1

We found that home energy reports in general reduced energy use, and thematic information about energy savings framed as a community effort in the social togetherness condition produced a statistically estimated energy use reduction of 7.7 percent (1 kWh/day) in home energy use when compared to the basic descriptive norm and control conditions after 6 months. This reduction was significantly better than those in thematic information with a descriptive norm only and thematic information under control conditions. Paradoxically, it was also found that the control group given only tips (without themes) also reduced their energy use by 6.2 percent - significantly more than the social togetherness tips only condition, or descriptive norm and tip only condition. One possible explanation is that the togetherness condition provided sufficient motivation to read through the lengthier thematic information and implement the ideas presented to them, while those in the control tips only condition may be more motivated to read the contents of the email given its brevity (as this condition has the least text, allowing tips to be seen at a first glance).

3.1.2.5 Methods, Study 2 City of Hillsborough Water Use Experiment

The goal of Study 2 was similar to that in Study 1 – to measure how different types of framed messages would affect future consumption. In this study, water was targeted because reducing water consumption also reduces energy use through the embodied energy consumed to extract, treat, distribute, and as applicable to heat water. The study took place in the town of Hillsborough between May 2011 and May 2012 and included data from all city residents; over 10,000 people living in over 4000 households (there are no apartments or condominiums in Hillsborough). Residents were sent paper inserts with their monthly water bills through the postal system, and everyone also received a waterproof vinyl tag with irrigation information to hang on their outdoor faucet or elsewhere to serve as a reminder prompt. The experimental conditions and means of achieving these through data, pictorial, and text manipulations on the paper inserts and vinyl tag were similar to those used in Study 1, although the tips/themes question was not investigated. Instead, each of the three social togetherness, descriptive norm, or control groups – no message were divided further into three subgroups based on percentile ranking (highest third, middle third, lowest third) relative to the community (resulting in a 3 by

3 design: social togetherness /descriptive norm/control x highest/middle/lowest energy consumption). The community or norm based motivational text differed within each percentile rank. Water email alerts were also provided to the 286 households that signed up for this after the initial mailing. Participants were also assigned to fill out one of twelve different online surveys (3 by 2 by 2: social togetherness/descriptive norm/control x survey with writing/survey no writing x adult/child) which were in keeping with the experimental condition they were assigned to, and also had the added experimental manipulation testing whether the process of writing about one's behavior increases behavioral change (through a paragraph response box on the survey), as it has in previous psychological research.

3.1.2.6 Outcome of Study 2

Researchers found that the interventions worked differently than expected. Households in the social togetherness condition used more water than those in the norm or control conditions. Interestingly, customers in the control condition used the least water, compared to both the norm and social condition customers. There are a few possible explanations for the unexpected results. It is plausible that political orientation moderated the effect given that conservation and sustainable behaviors have been greatly politicized, though this was tested and there is no empirical support of such an effect in this study. Instead, Hillsborough may not be enough of a close-knit community for the message of togetherness to be effective. Perhaps if the messages had been localized to neighborhoods rather than the whole town, it would have been effective. It is also possible that Hillsborough is a close-knit community, but residents already feel that they belong in the town, and therefore do not particularly feel the need to join in with the community. Additionally, in a recent paper, Hamedani, Markus, and Fu (2013) found that emphasizing interdependences undermined European American's motivation to learn about environmental sustainability, and led to decreased funding allocated to the cause (though this was not the case for Asian American participants). Therefore, it is possible that the message of community togetherness in fact backfired, and decreased residents' motivation to save water.

3.1.2.7 Future Work

Going forward, research on the effects of norms will focus on understanding when norms, particularly social norms invoking togetherness, are successful in motivating behavioral change, and when they are likely to cause negative reactions for intervention participants. There is potential for applying what was learned from this and similar studies to the design and nature of messages created for the purpose of recruiting participation in larger scale conservation programs.

3.1.3 The Impact of Vivid Messages on Saving Behavior related to Hot Water Use

Investigators: Jeremy N. Bailenson, Jakki Bailey, June Flora, K. Carrie Armel, Dave Voelker, Byron Reeves

3.1.3.1 Background

Virtual environments may offer a unique opportunity to facilitate cognition through embodied experiences that are personal and vivid. Immersive virtual environment technology (IVET) engages people in a three-dimensional (3D) virtual environment with a first person point of view, and it provides real-time multisensory feedback via visual, haptic, auditory, and olfactory cues. IVET also allows users to participate in actions that could not be accomplished in the real world; for example, passing time quickly, experiencing impossible physical spaces (e.g., geographically remote or fictitious), or experiencing behaviors that are novel, impossible or undesirable (e.g., harmful to the self, others, or the environment). Allowing people to experience undesirable behaviors is especially pertinent to environmental behavior changes because it allows people to observe directly far-reaching negative outcomes associated with their actions (e.g., burning of coal, smog emitted, trees felled).

Independent of IVET, vividness and personalization have been particularly effective in promoting behavior change. Personalizing or customizing information increases attention and has improved the effectiveness of numerous public health interventions. Vivid messages are emotionally interesting and imagery-provoking in a sensory or spatial way; for example, auditors have been more successful in signing up homeowners for retrofits that reduce energy use when they vividly described the cumulative air leaks in a house as being the "size of a football" or a lack of insulation like having a "naked attic" (Gonzales, Aronson, & Costanzo, 1988). The impactful effects of personalization and vividness can be explained by the theory of embodied cognition (EC) which suggests that cognition is a grounded experience that occurs in relation to states of one's body and perceptual simulation. If cognition is closely related to perceptual experiences, vivid messages that utilize strong imagery appeals, and personalized messages, may simulate sensory information in the brain that leads to changes in behaviors.

Although many researchers agree that pro-environmental interventions may be more effective if they contain vivid and personal elements, few interventions have successfully combined the two. Further, IVET has the capability to create vivid and personal interventions to a degree rarely seen in previous work. To date there has been only one study to use IVET to raise awareness on global warming, and it did not study changes in energy behavior (Zaalber & Midden, 2010).

3.1.3.2 Objectives

This study used IVET to investigate the impact of vivid and personal messages on energy use behavior specifically related to hot water use.

3.1.3.3 Methods

In order to select a vivid visualization or metaphor for energy consumption (e.g. CO2 balloons, energy vampires) in this study, dozens of metaphors were collected from public service announcements and online materials (e.g., a penguin bicycling to show how much energy was required to light a lightbulb), and also partnered with the marketing firm DraftFCB on an international competition among their offices to collect another approximately 100 ideas for visualizations. After reviewing them, the metaphor of one actually eating the fuel they use in an activity to represent energy consumption was selected, because it is a salient metaphor and IVET lends itself well to representing one's self performing impossible or implausible actions.

During the experimental study, seventy participants were placed in a virtual shower for approximately six minutes – that is, they received 3D visual and audio cues, and were asked to move their hands over their limbs and head as though they were showering – to simulate a shower experience. In addition, they received feedback about how much energy was used to heat and transport the water in their virtual shower. Participants in different experimental conditions received different feedback on the dimensions of message vividness (vivid or not vivid) and personalization (personal or not personal), as described below. Specifically, the four conditions included the following (see Figure 5). In the avatar-coal condition (top left) the treatment was both vivid and personal, and participants saw a 3D digital representation of him or herself called an avatar, standing outside of the shower window eating once piece coal for every fifteen seconds of virtual shower time. In the coal-only condition (top right) the treatment was vivid but not personal, and where the visual feedback was individual pieces of coal piling up on the table every fifteen seconds. The two non-vivid conditions provided feedback through the use of a counting ticker on a billboard sign shown outside the window (increased every 15 seconds). In the personal-sign condition (lower left) the treatment was not vivid but was personal treatment; the billboard sign used personal language when counting the number of pieces of coal consumed: "you have consumed 1 piece of coal." Finally, the impersonal-sign condition (lower right cell) was the not personal and not vivid - participants saw a billboard sign that used impersonal language that used the passive voice to count the number of pieces of coal consumed: "1 piece of coal has been consumed."

Figure 5: Visual metaphors implemented in a virtual reality environment

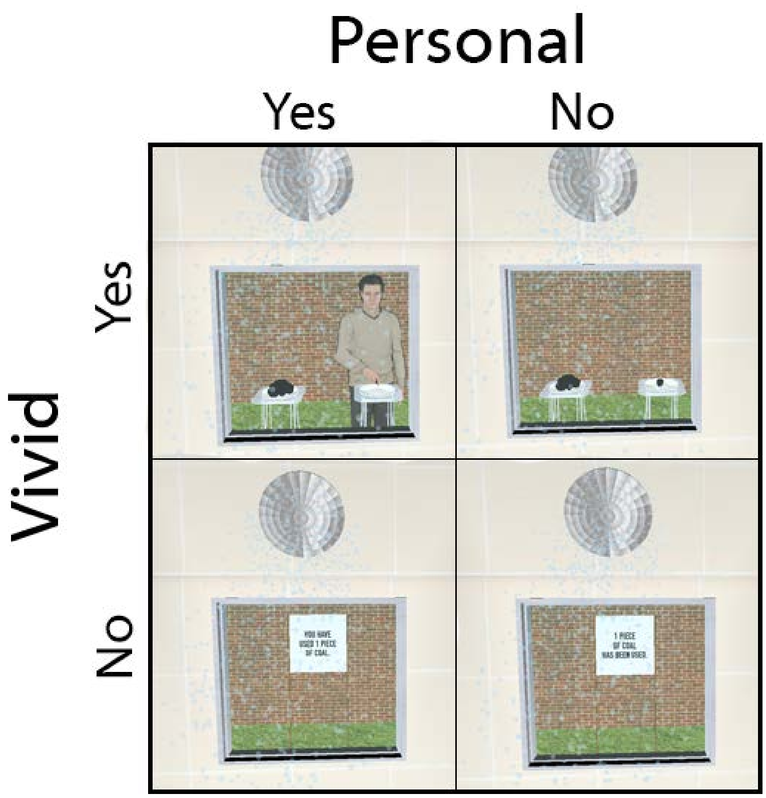


Figure 5. Each cell shows the participant's view of the virtual shower. Participants were randomly assigned to one of four experimental conditions: (1) avatar-coal condition, (2) coal-only condition. (3) personal-sign condition, and (4) impersonal-sign condition

3.1.3.4 Outcomes

Results showed a main effect of vividness. Before and after the IVET treatment, the amount of hot water people used was measured while washing their hands in a real sink placed near the laboratory. Participants exposed to vivid messages in the virtual shower experience generalized their learnings to hot water consumption in general and changed their behavior - they used less hot water when washing their hands compared to people exposed to non-vivid messages. There were no significant effects for the different levels of personalization and no interaction effects. The results suggest that new media-technology like IVET can leverage vivid sensory experiences to change environmental behavior.

3.1.3.5 Future Work

The value add of IVET should be explored; for example, how much does energy savings behavior decline (if at all) using less sophisticated but higher market penetration virtual technology like Microsoft's Kinnect, or without using any IVET technology at all. Specific energy saving metaphors/visualizations in addition to those used here could also be tested to determine which are most effective in motivating energy saving behaviors. Additional benefits of IVET could also be explored for their effectiveness: speeding up climate impacts over time, experiencing impossible physical spaces (e.g., geographically remote or fictitious), or experiencing behaviors that are novel, impossible or undesirable (e.g., harmful to the self, others, or the environment).

3.1.4 Motivationally Framed Facebook Energy Applications

Investigators: Banny Banerjee, June Flora (Research Director), Team: Nishand Bhansali, Nicole Greenspan, Ollie Khakwana, Alexandra Liptsey-Rahe, Brett Madres, Ann Manley, Issra Omer, Nikhil Rajendra, Ansu Sahoo, Annie Scalamnini, Brian Wong, Shaun Stehly, Dave Voelker

3.1.4.1 Background

The researchers at the Stanford ChangeLabs created new methodologies to apply to large real world audiences that combine principles of Design Thinking with those of Behavioral Sciences and Diffusion Theory [3, 4, 5, 7]. The researchers performed ethnographic research (research to explore the cultural processes and context within which energy is consumed), developed several Facebook energy applications, and performed associated research in part through using the ChangeLabs methodologies. Initial ethnographic research founded on the grounded theory approach [7], which uses collected data to develop hypotheses rather than vice versa, explored peoples' motivations for engaging with their energy use. Building on the ethnographic findings and guided by the Comprehensive Behavior Determination Method [1], which holds that interventions that use multiple frames appropriately paired with peoples' motivations are more effective at changing behavior than a single frame, three key motivations for energy engagement were identified: affective, cognitive, and social. Standardized measures of those concepts were used – need for positive affect [8, 9], need for cognition [10], and need for affiliation [11] – in these experiments on tests of images to be included in the applications, recommendations, and manipulations of application prototypes. This guided the final form of the Facebook applications.

3.1.4.2 Objectives

Our objective was to build, test, and diffuse Facebook energy reduction applications as well as stimulate a body of work that uses design and behavioral principles to advance innovations regarding energy reduction.

3.1.4.3 Methods

Early ethnographic work revealed that when asked about energy, consumers responded:

- "Comfort, convenience and peer comparison are important to us and our family."
- "Our family deserves the best."
- "Our family believes in volunteerism and public service."
- "We try to model our values for our children."
- "We are not sure how our small energy reduction efforts help the environment."
- "I am not engaged with my energy use."
- "Energy use and conservation is just no fun."
- "Energy is inexpensive so why should I bother."
- "We do not know what to do."
- "We will buy new appliances when the time is right."

Using the results from this ethnographic research, three motivationally framed energy reduction applications were developed, Cognitive, Social, and Affective (altruistic).

Power Bar, the cognitive app, is designed for people who are motivated by data about their home's energy expenditure. The driving motivation underlying this is the "cognitive" frame, whereby, the behavior change mechanism is data about the home's energy usage coupled with goal setting for energy savings and feedback regarding whether the target is likely to be met.

Kidogo is an application built around the motivation frame of "affect". It works with the presumption that it is possible to map energy savings to some issue other than energy that the consumer might be more emotional about, such as global poverty. This enable creating a bridge between their high motivational level in one issue to a behavior in another, in this case energy. This application allows energy savings to be converted into the emotional satisfaction of having contributed towards micro-finance loads in developing countries, rather than the relatively insignificant amounts saved in the monetary terms.

PowerTower, the social app, is a tetris-like game in which individuals get blocks based on how much energy they've saved. If you do not have electricity input into the system then you get blocks from behavior commitments and reported changes. You can also create a team and compete with other teams – building your blocks into a tower to see who can get the highest. The premise behind this game is that rather than trying to get households to change their energy behaviors in radical and improbable ways, this game leverages the large number of people in a social network all of whom commit to achievable amounts, but the large number of people who might get involved due to network effects contribute to a large cumulative savings in energy.

In addition, formative empirical studies were used to test design components to validate aspects of each of the applications. the research team conducted four online pilot tests (with over 600 young adult community college students) examining Affective application images of social entrepreneurs, Cognitive graphic feedback types, and two studies examining the role of individual motivation orientation and behavior change potential after viewing video prototypes of the energy reduction applications.

Figure 6: Motivationally framed facebook applications, including the Kidogo "affective" and Power Tower "social" applications

Source: Standford University. Kidogo and Power Tower

3.1.4.4 Outcome

Findings from the formative empirical studies include: (more detail is available here http://peec.stanford.edu/energybehavior/projects/facebook.php)

(1) Affective image test: Sad (rather than happy) images of humans (rather than animals) were most effective for the Affective application (within subject design with N=67);

(2) Cognitive graph test: Bar graphs (rather than line or radial graphs) displaying either a single day of information or a comparison of two days were most liked and understood (mixed design with N=207);

(3) Affective orientation and affective and cognitive app prototype experiment: Individual positive affect motivation was associated with higher behavior intentions and self-

efficacy (a main effect) and that affect orientation interacted positively with the affective application (one way between subjects design with N= 158)

(4) Affective, Cognitive, and Affiliative orientation and three protype apps experiment:We replicated the main effect of affective orientation on behavioral self-efficacy but found no effects of cognitive or affiliation orientation, while there were no behavior change intention change differences among the three applications; the affective app showed marginally significant greater behavior changes on easy behaviors and both the affective and social app were rated higher than the utility control (one way controlled between subjects design with N=224)

Using these results, the research team developed applications for use in the Facebook environment to ensure an "ambient" presence. These applications are now functional and data is in process of being collected and analyzed with respect to assessing the impact on electricity consumption.

Also, given these weak outcomes of association of individual orientation to application type, researchers are currently examining the role of choice in application selection using a randomized controlled experiment. The randomized experimental design had two levels; first participants were randomly assigned to an assigned or a choice condition. In the assigned condition, participants were randomly assigned to one of the three applications. In the choice condition, participants choose which app they want to use (based on a short description of the application) to view their energy information.

3.1.4.5 Future Work

The design work has implications for the practical scalability of energy applications. When confronted with three applications, utilities, energy service providers or non-profits or other potential adopting organizations typically would choose one application. Yet, these applications were conceptualized as a motivational frame map, where users can be matched or choose how they want to engage with and change their behavior. Thus, a test of these applied options will provide valuable information for adopting organizations and researchers aiming to use the applications as motivational frame prototypes. This test will have significant implications for best practices in the creation and deployment of energy reduction applications.

3.2 Incentive Interventions

3.2.1 Nudges for Energy Efficiency through an online Appliance Calculator

Investigators: Sam McClure, Sebastien Houde, Carrie Armel, Samuel McClure

Partners: Bonsai Corp.

3.2.1.1 Background

To encourage purchase of energy efficient appliances there are three primary types of policies in the US: minimum energy-efficiency standards, voluntary standards, and labeling. In the US, most appliances are required to have the EnergyGuide label, which was first introduced in 1979. The EnergyGuide label provides detailed information about energy costs. In 1992, the US Department of Energy introduced the ENERGY STAR program, a voluntary certification program that complements the EnergyGuide. The goal of the ENERGY STAR program is to facilitate the identification of the most energy efficient models and overcome the complexity inherent to energy information. The ENERGY STAR program is quite straightforward. For a given type of product, a threshold above the minimum energy efficiency is defined, if a product meets or exceeds this threshold, the product can earn the ENERGY STAR certification. The ENERGY STAR program has proven to be effective to influence consumers and firms (Houde, 2012, 2013). Some consumers, however, appear to trade-off energy efficiency with other attributes using the EnergyGuide label, while others do not pay attention to ENERGY STAR and EnergyGuide (Houde, 2012). These results suggest that there are opportunities to provide better energy information to consumers.

Furthermore, energy labels were designed with a focus on a shopping experience in brick-and-mortar stores. In the last decade, shopping habits have drastically changed. When it comes to appliances, online shopping is an important part of the shopping experience. In 2011, although only 8% of appliances were sold online, more than 38% of consumers that bought in-store said that online shopping influenced their decision (Traqline 2011). How energy information should be presented online, however, is unclear.

3.2.1.2 Objectives

The goal of this project is to investigate how and which type of energy information can nudge consumers to purchase energy efficient appliances when searching online for energy intensive durables, such as refrigerators. The nudges and frames used are guided by principles of behavioral economics, such Prospect Theory (Kahneman and Tversky, 1979) and intertemporal choice (Lowenstein and Prelec, 1992), as well as simple principles that have proven very effective to date, such as defaults (Levav et al., 2010).

3.2.1.3 Methodology

To study online purchasing behaviors, an online appliance recommendation website (Figure 1) was developed. The website has three components. The first component allows users to learn about the electricity consumption and cost of the appliance (refrigerator) they currently own. This information is used to determine whether it is desirable for users to switch to a more energy efficient models. The second component allows users to search for a new appliance. The third component presents search results. Researchers created different versions of the website to test how to present the search results to induce more energy efficient purchases. These different versions are discussed below.

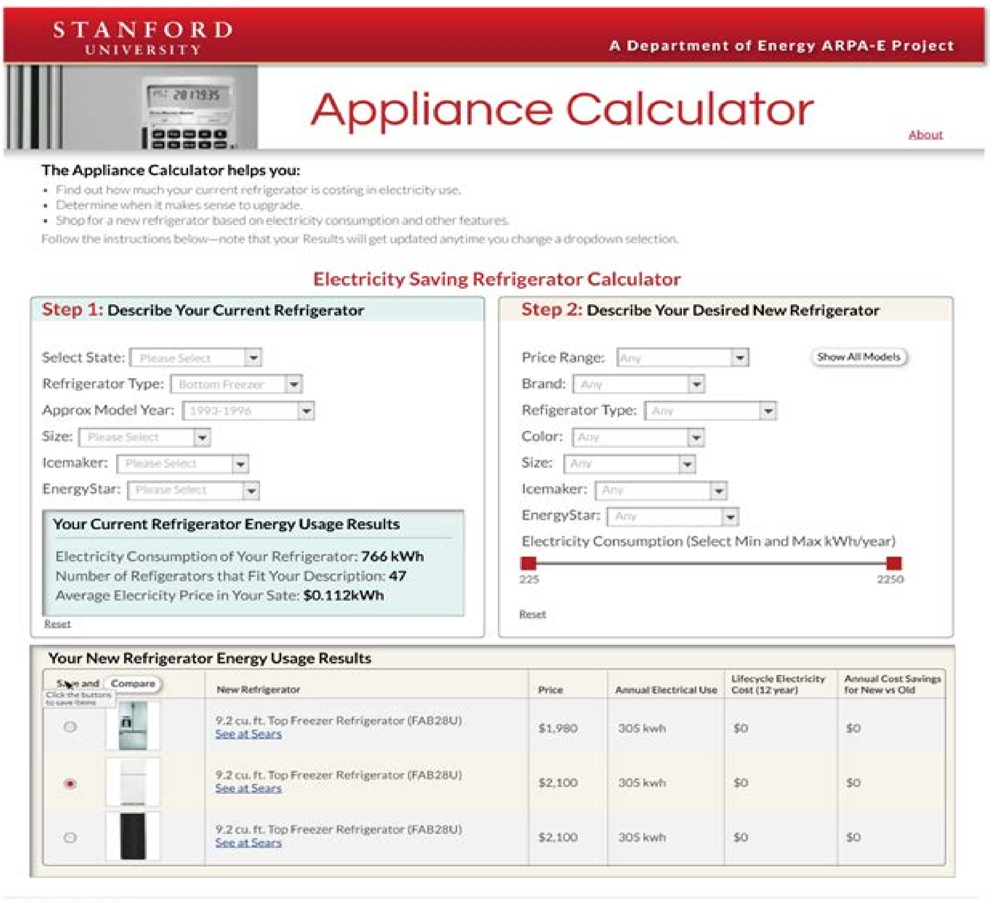
For each user that comes to the website, key information about consumers’ preferences and the impact of framing are tracked:

- Information about the refrigerator currently owned
- Search criteria
- Refrigerator models that were displayed to users
- Refrigerator models that were selected and saved to a “list” to compare

The experimental outcomes consist of the average electricity consumption that each user browsed and saved to the list. Those are the best proxies researchers are able to observe in lieu of purchases. To be more precise, for each user the appliance models that were clicked on and saved to the list are known. For each of those appliance models, researchers also know their electricity consumption. The average of the electricity consumption for all models a user was interested in can then be computed. This average for different versions of the website is reported. Versions with the lower averages are considered the most effective to induce energy efficient purchases.

Figure 7: Screen shot of the Appliance Calculator

(Accessed through Google sponsored links)



Source: Stanford University

3.2.1.4 Results

Experiment 1

The first experiment compared two versions of the appliance recommendation website: a version with a strong emphasis on energy efficiency, and a version with minimal emphasis.

In the version with a strong emphasis on energy efficiency (treatment), products in the search results were displayed with a picture, a short description, price, and three pieces of energy information: kWh/year, lifetime electricity operating costs, and ENERGY STAR compliance. In addition, products were sorted in ascending order of electricity consumption, i.e., the most energy efficient product was always shown first. Finally, the search filters were ordered in a way that the electricity consumption range and ENERGY STAR compliance were shown first.

In the version with minimal emphasis on energy (control), search results only included the picture, a short description, and price information. Moreover, products were sorted in ascending order of price (cheaper product first), and the electricity consumption range and ENERGY STAR compliance search filters were placed at the bottom of the list in the Step 2.

Data from approximately 14,000 users were analyzed for this experiment. Users allocated to the control browsed refrigerator models that consumed 594 kWh/year on average, while consumers in the treatment browsed models that consumed 523 kWh/year. From a regression analysis that controls for month fixed effects, the research team found that the version with the energy focus led to a statistically significant decrease of 69 kWh/year. Using the second outcome variable, the average kWh/year saved to the list was 454 kWh/year for the control and 412 kWh/year for the treatment). The regression analysis suggests a decrease of 85 kWh/year for this outcome variable. In sum, the version of the website with a strong energy focus was successful in nudging consumers toward more energy efficient models.

Experiment 2

The goal of the second experiment was to disentangle the effects of some of the features of the website with a strong energy focus. The two main features to test were the addition of several metrics to measure energy efficiency, and the default sorting that presented the most energy efficient product first.

In this experiment, the research team created a second version of the website (referred as treatment 2) with a focus on energy with a subtle change; the rank of the most energy efficient product was altered, and pushed it further down the list of products at rank six. The two versions of the website with the energy focus were then identical except for this small change in the default rank of the six first products presented. Note that by moving the product ranked first to the sixth position, the rank of the products in rank 2 to 6 was also impacted. This manipulation thus allowed us to isolate the effect of the first sixth ranks. More precisely, the experiment allowed us to determine whether showing a product at rank 2 vs. rank 1, 3 vs. 2, 4 vs. 3, 5 vs. 4, 6 vs. 5, and 1 vs. 6 would impact browsing behaviors.

Data from approximately 20,000 users were analyzed for this experiment. Comparing the two treatments to the version of the website without an energy focus (control), the team found evidence that altering the rank had an important effect on browsing behaviors. Pushing the rank of the most energy efficient refrigerator model down the list increased the average kWh/year browsed and saved to the list relative to the first treatment. The number of users in each treatment scenario does not confirm whether this effect is statistically significant at a 5 percent level. For the first treatment (same treatment as experiment 1), the effect is significant at the 10 percent level.

These results suggest that rank has an important effect on whether consumers consider a product, and may have a bigger effect than energy information. The third experiment suggests that various pieces of energy information may have in fact a very small or even no effect.

Experiment 3

For this experiment, four versions of the website were created, each with a different piece of energy information, in an attempt to determine whether computing out future energy savings from an energy efficient appliance would address the first cost bias, or tendency to select an appliance based on its up-front cost rather than future energy savings. In one version, researchers presented search results with a picture, a short description, price and kWh/year. In a second version, the lifetime electricity costs were added. In a third version, an annual energy savings instead of lifetime of electricity costs was presented. In the fourth version, researchers presented both lifetime electricity costs and annual energy savings, in addition of the other attributes (picture, short description, price, and kWh/year).

Data from approximately 30,000 users were analyzed for this experiment. The results for this experiment suggest that the four treatments led to similar outcomes. That is, they are not statistically significant from one another. This suggests that none of these pieces of information was more powerful than others in nudging consumers.

3.2.1.5 Next Steps

Considering the three experiments together, these results have a somewhat profound implication for behavioral interventions. That is, in Experiment 3, an attempt to produce more energy efficient purchasing behaviors by using an intervention derived from an analysis of what the underlying problem was – the first cost bias – failed to produce an effect. That is, the research team attempted to address the tendency of people to make an appliance purchase decision based on the up-front cost of an appliance rather than the longer term energy savings with implications from Prospect Theory and the intertemporal choice literature. In contrast, in Experiment 1, where the intervention was driven simply by using some of the previously demonstrated most effective behavior change techniques, researchers saw a change in average kWh of between 10-20 percent depending on the measure used. Thus, for quick and effective results, it may make sense to first try the most effective proven behavior change techniques to date.

Future research should test additional manipulations to clarify how to best design online appliance recommendation websites to encourage efficient purchases, and which types of behavioral techniques are most effective.

3.2.2 Transportation Lottery

Investigators: Balaji Prabhakar, Pluntke, C, Gomes, N.; D. Merugu, G. O, G. O. M. Mandayam, T. Yue, B. Atikoglu, Adrian Albert, N. Fukumoto, H. Liu, D. Wischik, N.S. Rama

3.2.2.1 Background

In many situations incentives motivate behavior change. However, in many public goods programs the amount of money available for such programs is constrained, and results in relatively small incentives per participant when divided across all participants. Evidence shows that small piece-rate monetary incentives can actually decrease desirable behaviors because the reward “crowds out” intrinsic motivations; for example, offering $7 per blood donation reduces the amount of blood donated (Mellstrom and Johannesson 2008). However, devising alternative incentive structures (also called mechanisms) using the same total pot of available funds can stretch the perceived value of the incentive. In particular, using a lottery-based system to pay out chunky prizes instead of lower, deterministic payouts can attract more participation in the incentive mechanism. This is especially true when the deterministic payouts are small; e.g., a recyclable refunds only $0.05, saving a kWh of energy only saves about $0.10, and an off-peak trips saves 5-10% fuel relative to traveling in the peak hour. In these cases the effort of taking the right action seems hardly worth the payoff. Lottery-like payment mechanisms are much more effective, exploiting the fact that in games with low stakes players are much more risk-seeking.

If such an incentive mechanism were developed, it could be applied in a variety of contexts: time shifting of electricity use in the home, recycling, step programs for increasing exercise, and beyond. In the project reported here, road traffic congestion was targeted, in part because collaborations were much more readily established with transportation related agencies than with electric utility companies. Traffic congestion is a serious issue in many cities around the world. It has worsened considerably in the past few years, causing an enormous wastage of time and fuel. For example, a study (Schrank and T. Lomax, 2005) of several urban areas in the U.S. reports that in 2005 an estimated 4.2 billion hours of time and 2.9 billion gallons of fuel were wasted due to congestion. This amounts to a total loss of about $78.2 billion, up from $73.1 billion in 2004. See the cited U.S. Dept of Energy (2006) and U.S. Dept. of Transport reports for other reports of the effects of congestion in the U.S. In urban areas, increased vehicular traffic has also led to severe pollution and parking problems.

3.2.2.2 Objectives

Prabhakar aimed to develop a sweepstakes or raffle-like incentive program that would stretch the value of monetary rewards so that the energy behavior change would be maximized for a given amount of money. He also aimed to develop a computational system to support the program, and demonstrate the program’s effectiveness.

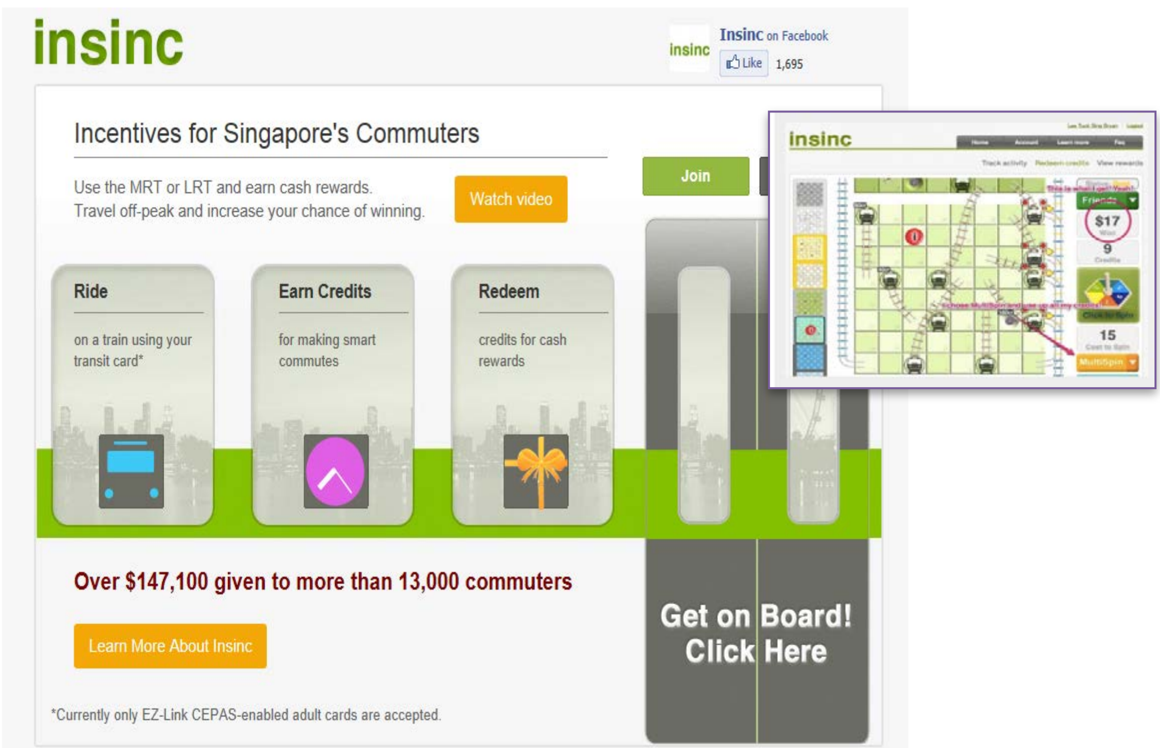
3.2.2.3 Methods

The Insinc project (analogous to the Capri, Steptacular and Instant programs; http://scsn.stanford.edu/projects.php) was developed to incentivize commuters to travel at uncongested times by giving them different numbers of credits (corresponding to cash) for shifting to off-peak travel, mode shifting (from private to public transit), or recommending a friend - as monitored through transportation sensors. Then individuals could choose to participate in a simple game of chance – that looked similar to chutes & ladders - to win a shot at a larger amount of money. Formative work on the project showed that adding a simple game of chance and social networking greatly improved engagement with the system.

Insinc was launched on January 10, 2012, as a six month research pilot by Stanford University and the National University of Singapore with the principal aim of shifting Singaporean rush hour commuters to off-peak times using Insinc. Commuters were invited to register for the program online. Partnerships with National University of Singapore and the Land Transport Authority of Singapore facilitated marketing and participant recruitment efforts, and they supplied incentive payments for the participants, though Prabhakar developed and supported the online system for the program.

Figure 8: Website Landing Page

(Program's game of chance (inset), for the "Insinc" transportation lottery)



Source: Stanford University, Land Transport Authority of Sinapore

3.2.2.4 Outcomes

INSINC enjoyed high word-of-mouth recruitment. In six months recruitment reached 21,000 users. The researchers defined "peak-shift" to be the change in percentage of peak trips made by a group of users after they signed up for Insinc. Overall, 7.5 percent of all Insinc trips were shifted off peak. Users who made regular peak-hour trips before joining Insinc shifted their peak trips by more than 11 percent. A $p < 0.05$ level of significance was observed for using public transit and shifting time of use in the optimal direction for those users. Thus, it was shown that entering individuals into a lottery and compensating only a small number of lottery winners achieved significantly shorter commute times and reduced fuel consumption and congestion. Publications related to this work can be found at:

http://peec.stanford.edu/energybehavior/projects/transportationlottery.php

3.2.2.5 Future Work

INSINC was extended for a further 18 months (July 2012 to December 2013) after the initial 6 months. A wealth of data gathered from this period is expected to yield additional insights. The software developed in part through this project, and general approach, are now being applied in other settings and to address additional societal issues.

3.3 Community Based Interventions

3.3.1 Girl Scout “Girls Learning Energy and Environment” (GLEE) Program

Investigators: Thomas N. Robinson, Nicole Ardoin, Hilary Schaffer Boudet, June Flora, Carrie Armel, Manish Desai

Partner: Girl Scouts of Northern California

3.3.1.1 Background

Community-based programs have been widely used with success in public health, and they have also been used in the environmental domain. For example, in the Hood River weatherizing project, initially less than 10% of customers signed up for a voluntary program in response to traditional marketing communications, but this number increased to 85% of households in 2 years when the project switched to relying heavily on local residents, such as Citizen Advisory Councils, schools and churches (Cavanaugh, 1995). Key advantages of using community programs include the ripple effect from word of mouth, enhanced learning and mastery through direct experience or observation of others, and the ability to provide personalized messaging. Further, these approaches can be cost-effective by tapping into pre-existing diffusion channels and making the intervention highly structured and easy to replicate.

3.3.1.2 Objectives

Our goal was to apply behavioral theories and methods used in public health promotion to increase children’s energy-saving behaviors and reduce family/household energy use. Youth were targeted for several reasons. First, attitudes and values start developing at an early age (Bryant & Hungerford, 1977) and are difficult to change once established (Asunta, 2003). Moreover, the earlier children embrace sustainable lifestyles, the longer they have to influence families, schools, and communities to embrace sustainable activities and policies (Leeming et al., 1997). Finally, empirical research shows that it is effective to target children when trying to influence family and household behaviors (Cornelius et al., 2013; Damarell et al., 2013; Robinson & Borzekowski, 2006).

3.3.1.3 Methods

Two curricula were evaluated – one focused on behaviors Girl Scouts and their families could do to save energy in their residences and another focused on behaviors Girl Scouts and their families could do to save energy in their food and transportation choices – in a clustered randomized controlled trial from December 2010 to February 2012. The research team worked with the Girl Scouts of Northern California to recruit 30 fourth- and fifth-grade troops and their families in Santa Clara, San Mateo and Alameda counties in the San Francisco Bay Area to participate in this study. (This represents 4 percent of the total of 748 fourth- and fifth-grade troops in the area.) Multiple recruitment strategies were used, including placing advertisements in regular electronic mailings from the Girl Scouts regional office to troop leaders as well as in-person solicitation at monthly troop leader meetings.

Troops were the unit of randomization. Fifteen troops were randomly assigned to the residential energy condition and fifteen troops were randomized to the food/transportation condition after completing baseline assessments. By contrasting the two curricula – one focused on reducing home energy use and the other on reducing food and transportation energy use – each curriculum served as an active control for the other. This created a true randomized controlled experimental trial, the strongest design for testing causality. The evaluation consisted of a baseline survey for all participants prior to the first troop meeting, followed by five sessions of the relevant curriculum, a posttest survey after the fifth session and a follow-up survey conducted between 2.5 and 10.7 months after the fifth session. All Girl Scouts received one of the experimental curricula, taught by a trained member of the research team with troop leaders present.

Troops ranged in size from 4 to 21 girls, with an average of 11 girls per troop. By troop, survey return rates at baseline averaged 98.7 percent for Girl Scouts and 88.5 percent for parents. At post-test, survey return rates averaged 94.9 percent for Girl Scouts and 91.4 percent for parents. At follow-up, survey return rates averaged 83.3 for Girl Scouts and 82.5 percent for parents. Multiple imputation techniques were used to handle missing data, for a total of 313 Girl Scout participants (149 residential; 164 food/transportation) and 318 parent participants (151 residential; 167 food/transportation). In addition to self-reported behavior change through the surveys, researchers also collected data on monthly electricity and gas usage from one-third of the parent participants; analysis of this data is currently underway.

3.3.1.4 Outcomes

Preliminary analysis of the fully collected data indicates pre-post differences in child-reported behaviors between the two treatment groups for both sets of behaviors. Substantial changes occurred for behaviors that require adult assistance, such as adjusting refrigerator and hot water heater temperatures, replacing incandescent bulbs with compact fluorescent light bulbs, and adjusting tire pressure. Preliminary findings also suggest increases in pre-post child-reported knowledge of energy issues from both curricula. These preliminary results are very promising and suggest the efficacy of these two curricula in changing energy efficiency-related behaviors in girl scouts and their families.

3.3.1.5 Future Work

Subsequent analysis will test the efficacy of the curricula in changing child-reported behavior at follow-up, parent-reported behavior, as well as electricity and gas usage in the subset available. Demographic, socio-cultural and psychological moderators and mediators of intervention effects will also be assessed to examine the mechanisms of change, evaluate intervention delivery variables and their relationships to outcomes, and identify the appropriate target audiences for subsequent dissemination.

CHAPTER 4: Evaluation and Modeling

Three projects focused on developing methods for evaluating the effectiveness of energy programs, and modeling the effectiveness of interventions to guide future work

4.1 Google Power Meter Evaluation

The goal of energy disaggregation is to find a breakdown of this signal into multiple components

4.1.1. Background

Readily available, easily accessible, real-time information delivered via technology is reported to produce important declines in residential energy consumption (Faruqui et al. 2010; Ehrhardt-Martinez et al. 2010). Designing interventions that use feedback technologies and rely primarily on information as a means of changing energy behaviors have been promoted as cost-effective policies (Fischer 2008; EPRI 2009) and possible alternatives to traditional price incentives (Allcott and Mullainathan 2010).

Estimates of the energy savings from feedback technologies vary widely, from none to as much as 20 percent (Faruqui et al. 2010; Ehrhardt-Martinez et al. 2010). There are three main factors at the source of this heterogeneity in outcomes. First, studies have employed different research designs. Second, the features of the feedback technology, such as timeliness, data display, interactivity, sociability, and controllability play a significant role in inducing energy reductions and have varied substantially across studies. Third, there is significant heterogeneity in the characteristics of the population of consumers participating in feedback interventions. Although several studies have looked at the impact of feedback technology, providing insights as to how study design, features of the technologies and characteristics of the people using them impact the energy savings estimates, several questions remain. To determine if feedback technologies are cost-effective measures to manage energy demand it is necessary to assess whether they provide persistent energy savings and how they change consumption profiles. Previous studies have remained silent on these questions due to limitation in study design and data available (EPRI 2009).

4.1.2 Objectives

The goal of this research was to provide an estimate of the potential for electricity savings for households that have access to real-time feedback technology, and to document how this technology changes consumption profiles and impacts the persistence of energy savings. The feedback technology, Google Powermeter, resembles the technologies being deployed by several utilities in the US and elsewhere.

4.1.3 Design and Methods

We used a randomized controlled trial to overcome issues of selection bias and to estimate treatment effects. Households participating in this study were recruited in collaboration with Google, both in their California offices and with several offices across continental US. Employees (N=1743) from the company voluntarily enrolled their households for the study. As part of enrollment all participants were required to install The Energy Detective (TED) device (purchased by the company), complete an online survey and be randomly assigned to no-feedback (untreated control) or feedback (treatment) conditions. Only households in the feedback treatment condition were given access to the feedback technology initially. Households in the control condition were given access to the feedback technology after three months. The study took place between February, 2010 and October, 2010.

4.1.4 Results

Summary

Over the period of the field trial, March through October 2010, a statistically significant reduction in electricity use of 5.7 percent was found. However, an examination of persistence of effects over time shows that there is only a brief period of significant reductions in electricity consumption; by week four all statistically significant reductions have ended. In examining time of day reductions, the largest reductions were observed initially at all times of the day but as time passes, morning and evening intervals show larger reductions. Evening reductions faded but morning reductions were sustained for eight weeks. However, the return to baseline in other day and evening periods cancelled out statistical significance in overall reductions. Thus, overall statistically significant reduction effects lasted for four weeks.

Overall effects

Ideally, the researchers' analytic models would be identified using electricity billing data for the months preceding the experiment; however, researchers did not have access to this data. These models rely on that after May 28, 2010, both the control group and the treatment group had access to the feedback technology. Under the assumption that the treatment effect is constant over time, when households in both groups have access to the technology, any differences in average consumption levels can be attributed to household specific fixed effects.

Results from the estimation of the fixed effects model show that the average treatment effect consists of a decrease in electricity use of 5.7 percent per hour (this works out to about 0.05kwh in absolute terms), significant at the 5 percent level.

Time of Day effects

An aspect of this primary research goal is to use the unique real time data to inform the team's understanding of time specific electricity use and reductions. Periods between high and low household membership activity were distinguished, which allowed the researchers to infer whether savings are attributable to habitual behavioral change (such as turning off lights) or to one time behaviors that are more structural in nature (such as installing energy efficient appliances or house insulation). Change in habitual behaviors should lead to reductions that are observable at periods of high occupancy while the latter class of actions should lead to reductions in the baseload levels of consumption.

The largest reductions in electricity consumption due to feedback occur during the morning and evening peak periods: between 5 am and 10 am, electricity consumption decreases by 12.2 percent in average and between 8 pm and 11 pm electricity consumption decreases by 8.2 percent on average. While energy savings during the middle of the day and night are insignificant, savings during the morning and evening peaks are large and significant. Savings occur at periods when household members occupy the house and engage in household functions, such as eating, entertainment, cleaning and household maintenance. Based on this finding,it is argued that electricity use reduction during household activity is consistent with changes in energy behaviors that pertain to habits.

Persistence at different times of day. Researchers find that in the first two weeks after having access to real time electricity feedback, electricity consumption decreases in all time periods. Beginning at the third week, reductions during the day (10 a.m. - 4 p.m.) and the night (11 p.m. - 4 a.m.) fade away. In the long-run, only reductions during the morning and evening peak periods persisted.

4.1.5 Future work

This paper points out the challenges of conducting rigorous experimental work in the field; sufficient experimenter control, adequate funding, and expert staffing are all necessary for robust trials of feedback and energy consumption. Researchers also discuss some of the inherent challenges of this type of work; the heterogeneity of electricity consumption, the relatively low predictability of levels of that consumption, size of samples needed for detection of effects in the face of large heterogeneity, and necessity of data collected over periods of one year or more to adequately assess seasonal and weather effects – and, importantly, achieving persistence through interventions of this type. In addition to attempting to address these issues, future work can expand on analysis techniques to improve learnings from trials such as these, as well as to offer utilities and government entities trusted approaches to quantifying the impacts of behaviorally oriented programs.

4.2 Social Media Analytics through Twitter Explorer

Investigators: Martha Russell, Markus Strohmaier and Jan Pöschko, Technology University of Graz, Austria; Rafael Perez and Neil Rubens, University of Electro-Communications, Tokyo; June Flora, Jiafeng Yu and Marc A. Smith, mediaX at Stanford University

4.2.1 Background

The term social media describes the online tools and platforms that people use to share opinions, insights, experiences, and perspectives with each other. Social media can take many different forms, including text, images, audio, and video. Understanding conversations in online social media has the potential of providing program planners and communication campaign mangers unique insights into individuals' thoughts and verbal productions about energy efficiency and climate change. With the increasing adoption of social media (73 percent of teens and 72 percent of young adults (Lenhart et al., 2010)), new opportunities are available for studying the role of online conversation in persuasion.

In 140 characters or less, the concerns, interests and public narratives about energy efficiency and climate change can be identified through tweets. Twitter conversations also reflect the social aspects of information diffusion through conventions such as retweets and other conversational responses, through the membership and social distance of these conversations, and in overtime changes in frequency and form of the networks. With Twitter, a particularly popular type of social media that has proven relevant in a number of societal challenges and conversations recently, the social response to societal or national events, as well as to media coverage of these events, and persuasive communication campaigns can be observed. Twitter is both a medium and the message (Savage, 2011).

4.2.2 Objectives

Our goals were to track and analyze social media conversations related to energy efficiency and climate change in order to gain insights about consumer attitudes and behavior. By understanding the larger context of public sentiment about changing energy behavior, the research team looked to create insights on the context – cultural, economic, social – where the Stanford Energy Behavior Initiative intervention projects were being conceived and implemented. Their broad research question asked, "How can social media reflect consumer sentiment about energy and campaigns to reduce residential use of energy."

4.2.3 Methods

Using an eco-linguistic taxonomy to describe energy use opinions, energy efficiency behaviors, frames, metaphors, technologies, and also to determine standard sources of energy information such as the Department of Energy (DOE) and Environmental Protection Agency (EPA), the research captured Tweets containing those terms, parsed identified elements of the communications, curated the data, and archived the data for access. The analysis of this eco-linguistic-filtered social media was aimed at understanding the frequency, context and potential persuasive influence of social media conversations about changing energy behaviors (Russell et al., 2011).

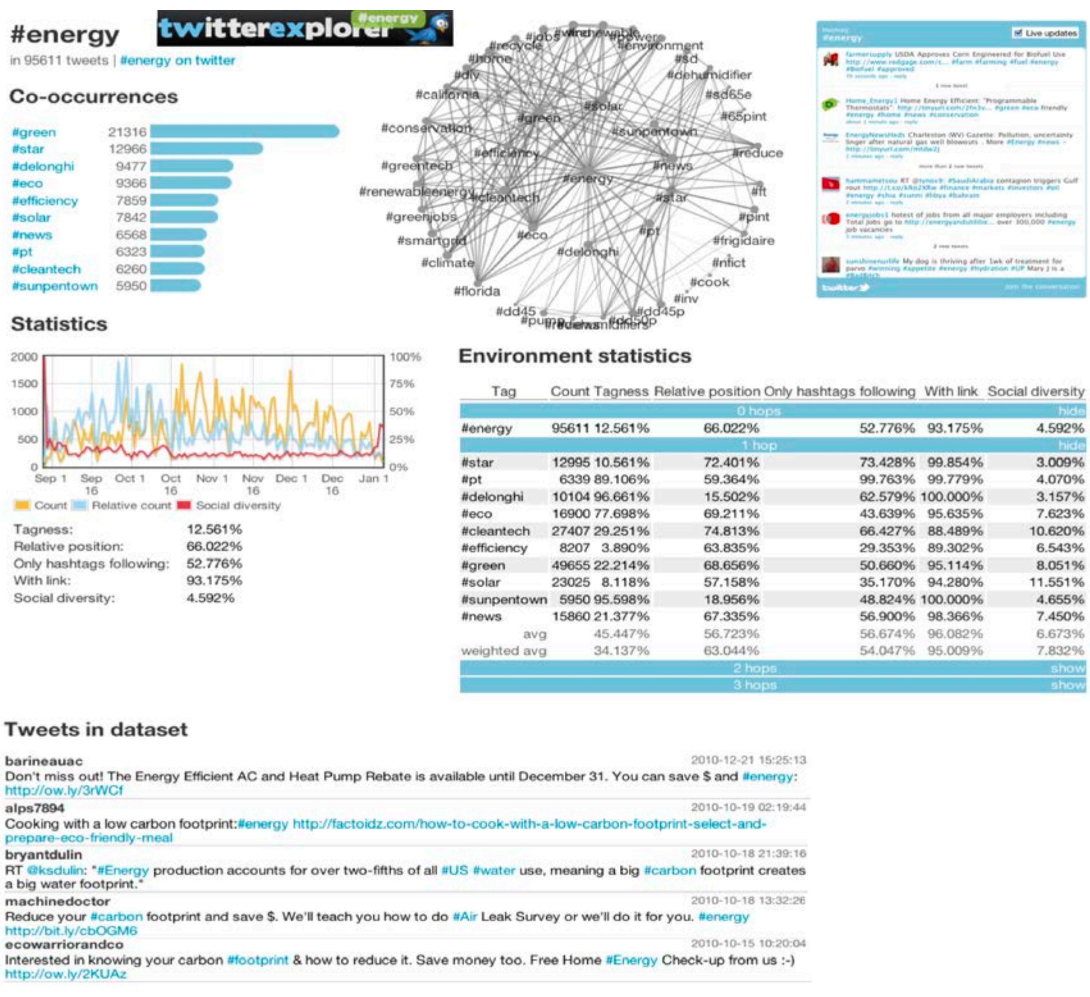
Data was collected from the messages, users and content of the hashtags that occurred between September 3, 2010 and March 31, 2013. Conversations were processed to be overtime mentions of predetermined ecolinguistic terms and co-occurrence of related hashtags in Twitter. Three techniques were used to cull discernable patterns from the large quantities of data and portray the data visually: content analysis of the full Tweets, network analysis of co-occurring hashtags, and semantic analysis of the co-occurring hashtags and their authors.

Data were acquired on a daily basis by utilizing the NodeXL Twitter Importer module (Smith et al., 2009), which captured the latest messages containing energy related keywords. The dataset was then parsed and analyzed by utilizing Hadoop Map Reduce distributed processing on the Amazon's EC2 computing cloud. Data for these Tweets was then passed to other applications—Excel, NodeXL, Gephi and TwitterExplorer—for further analysis and visualization. TwitterExplorer (Russell et al. 2011), developed separately, was used to analyze and visualize the latent semantic structures embedded in energy-related conversations on Twitter. TwitterExplorer visualizes semantic relations between terms used in Twitter messages based on different aggregation and similarity measures; semantic similarity between terms is calculated based on co-occurrence of terms within messages (Tweets).

We analyzed samples of the 3+billion filtered Tweets that used the ecolinguistic terms included in this study. Several analytical lenses were tested in this study: frequency, periodicity, valence, co-occurence, and context. Through several methods, the research team were able to describe snapshots and detect changes over time in the conversation as well as identify conversation stimulating events, such as national policy, new technology launches, and media events.

Figure 9: Twitter Explorer Interface

(for data collection and analysis of tweets that include specified keywords)



4.2.4 Outcomes

The data, tools and initial analysis of this study represent first steps towards more refined analytical approaches that help understand the large scale conversations taking place on Twitter and elsewhere. This study demonstrated the feasibility of using data mining techniques to gather and analyze vast amounts of data from ongoing social media conversations and of analyzing the data for meaningful metrics that describe conversations about energy consumption behavior.

Our exploration confirmed that conversations about energy-related issues are, indeed, taking place in social media, specifically Twitter, and that these communications can be studied to better understand how to use technologically-enhanced word-of-mouth to stimulate user-generated persuasion. Using content analysis of full Tweets, network analysis of co-occurring hashtags, and semantic analysis of the co-occurring hashtags and their authors, this preliminary investigation identified descriptors, concerns, actions, and issues. It was confirmed that studying Twitter communications can provide actionable means for assessing engagement, identifying influencers, and identifying word-of-mouth communities that can accelerate change in energy efficiency behaviors.

Using network analysis of hashtags researchers analyzed and visualized contextual relationships of among the salient terms used in social conversations and identified several clusters of related issues, revealed by the co-occurence of hashtags. The research team used social and linguistic structures of communication (repeat communications and varied types of Twitter communication conventions such as pictures, hashtags, retweets, and URLs) to analyze the self-organizing communities of consumers. These communities share many of the characteristics of issue publics, and further research on similarities and differences to other issue publics is needed in order to understand how to create, grow and sustain word-of-mouth persuasion for energy behavior change. Tools that permit visualization of vast quantities of user-generated content about energy and sustainability were demonstrated.

4.2.5 Future Work

Based on these initial results, it was recommended to continue data collection and developing analytical methods and tools that can: track public opinion related to energy consumption; analyze domain-specific, user generated content on social media platforms; identify and track indicators such as semantics and social roles; identify and explore patterns and disruptions; identify and benchmark grassroots resources such as author networks; characterize opportunities for resource transformation; and build semantic models to understand the aggregations of conversation streams.

To accelerate exploration of these important issues, the Twitter Energy data is available for other researchers. Against the urgency of climate change and the need to mobilize widespread changes in energy consumption, other researchers were encouraged to join the team in a research agenda that includes: analyzing and characterizing energy consumption behavior; tracking public opinion related to energy consumption; analyzing domain-specific, user generated content on social media platforms; identifying and tracking leading indicators of attitude and behavior change; and identifying patterns and disruptions that can accelerate change and provide alerts for emergency response.

4.3 Diffusion Modeling of Behavioral Interventions

Investigator: Jeff Shrager

4.3.1 Background

A central goal of the Stanford ARPA-e project is to achieve energy reductions by using feedback from sensors to inform decisions regarding which behavioral manipulations to deploy. Given this goal, it is important to be able to predict as accurately as possible, how different possible manipulations will move the needle toward this goal. Even if the exact amount of energy that might be saved under various manipulations cannot be predicted, the research team might be able to at least rank-order the possible manipulations. Such a ranking, crossed with cost, would be used in choosing which manipulations to employ.

The most accurate way to conduct such analyses is, of course, through real, clinical-trial-like experiments, and this is the approach taken by some other Stanford ARPAe subprojects (e.g., the Girl Scout project). Unfortunately, real world experiments are extremely time consuming and costly, and can only be conducted on a small number of manipulations. Moreover, because one would assume that the efficacy any such manipulation will depend upon many features of the setting in which they are applied, one would have to run a huge number of experiments to tease out all of these interacting effects.

Although a simulation can never stand in fully for a clinical trial, in many fields they have proven extremely useful in getting a rapid (and very inexpensive) handle on the general response topology. For example, every modern biomedical clinical trial is computationally simulated before being actually run on real patients. These simulations provide very accurate estimates of the number of patients that one needs to run in order to get meaningful results in the real trial.

4.3.2 Objective

The goal of this project is to use computational simulation to estimate the differential efficacy of behavioral manipulations on energy usage applied in various environments. It aimed to specifically develop a general methodology to enable analysts to propose a novel manipulation, and then rapidly and inexpensively explore its potential efficacy under a variety of conditions, and, if desired, to rank these predictions against other proposed manipulations (or, used in another way, to choose in which real-world settings to deploy different manipulations because different manipulations may be predicted to have differential success in these).

4.3.3 Methods

Multi-agent simulation was used in this modeling effort. Muti-Agent simulation has a long history, beginning with Simula67, and leading to SmallTalk, and thence to all modern object-oriented programming languages. It has been extensively applied in many domains including military simulation (where gaming is very big), hardware (e.g., Verilog), socio-economics, and even in politics. Multi-agent simulation can model very complex systems with very complex dynamics in great detail, heterogeneous populations (without averaging), complex internal decision making algorithms, complex communications structures, and are generally relatively easy to develop. It is most powerful and useful when inter-individual interactions are high and the decision choice algorithms are influenced by changing local social parameters. Although multi-agent simulations are most interesting in these domains, they can be powerful in individual (non-social) domains as well, especially in this case where there is a tacit communication via the community's influence on the shared environment and on the shared electrical grid. Also, the utility of an agent based model would in part be in communicating analysis results and exploring consequences from the model – that is, agent based models are probably much better than the way that currently communicated statistical outputs. (A disadvantage of multi-agent simulations is that they are more difficult to utilize for abstraction and optimization; math modeling / algebraic analysis is preferred in this case.)

In the multi-agent simulation, the following steps were carried out: 1. Create /code the model; define the environment (e.g., weather, oil supply); define each agent's possible actions and decision algorithm; define the communications (i.e., "social") graph. 2. Parameterize the decision algorithm, social graph, and environment: Set search ranges for target parameters (independent variables, e.g., interpersonal communication graph structures; intervention manipulation parameters, such as thresholds for interventions and intervention strengths; and so on); set as many "non-target" parameters as are available (e.g., default pricing of categories of energy; population size and subcategories, and default energy usage averages for each population subcategory); Guess at non-target parameters for which data is not available; randomize over all others. 3. Run across search ranges of target parameters and gather data (dependent variables, usually final energy utilization). 4. Interpret results using qualitative dynamics, graphical visualizations, or fitting of the output data to algebraic models (possibly for algebraic analysis, e.g., optimization).

4.3.4 Outcomes

Two models were developed. The "A" model (developed with S. White) was based upon existing modeling technologies and was used to pilot the basic modeling theory and test the hypothesis that very simple manipulations would produce observable differentials in energy utilization. Based upon results from the "A" model experiment, a "B" model, called ESim, was developed, which was more general and built on a cloud-based modeling infrastructure that would, in principle, enable other modelers to experiment with ours and other similar models. Statistical results from these models suggest that approximately 10 percent energy savings could be expected on average, but that this depends critically upon the communicaition model (i.e., social network structure and interaction density).

4.3.5 Next Steps

A model to guide program design and selection has not been possible in the past, but is now feasible due to the dramatically improved ability to quantify the effects of behavioral programs with sensor data, to an accumulated large body of empirical behavior change literature from which effect sizes can be drawn, and to sufficiently mature modeling approaches. The project reported here was ambitious in attempting this, and much work remains to be done to achieve the goals described here. The tool developed could be used to make predictions, which could then be tested in field trials. Parameters such as effect sizes for a wide variety of behavioral approaches, derived from existing research and evaluation studies, could be incorporated to improve the model. As more studies are behavioral program pilots are run, the true empirical responses to the corresponding programs can be incorporated into the model. A description of the work and a user's guide is online, and the code (both for the model, and for the graphical user interface so that non-programmers can utilize the model to make predictions) is available for others to use; please contact the lead investigator for access jshrager@stanford.edu (it was recently taken down from the web due to server issues, but could be returned to operation).

CHAPTER 5: Summary and Conclusion

5.1 Summary, Impacts, and Next Steps

5.1.1 Summary

This initiative has met its objectives to develop an array of components needed in a system that utilizes smart meter and other sensor data, communication technologies, and behavioral approaches, to achieve significant energy savings. Major work on 19 projects tied to this goal was accomplished, as well as preliminary work on a new integrative Project 20 that is underway with additional funding. A summary of these achievements is included in the table below, and elaborated upon following the table.

CS = Computer Science

E-IPER = Emmett Interdisciplinary Program in Environment and Resources

EE = Electrical Engineering

FS = Freeman Spogli Institute for International Studies at Stanford

H-STAR = Human Sciences and Technologies Advanced Research Institute

ISB = Indian School of Business

MS&E = Management Sciences and Engineering

PEEC = Precourt Energy Efficiency Center

Table 3: Stanford Initiative Projects Potential Applications

Proj. #	Project Name	Investigators & Partners	Potential Applications and Completed Deliverables (Publications for all projects can be found at http://peec.stanford.edu/energybehavior)
Technology			
1	Communication Network	– Levis, Kazandjieva (CS)	Established home area network (HAN) Internet standard for use at scale; use the high granularity data from from plug monitoring mesh network that was developed to inform future computing energy standards First, helped establish the first Internet standard for home area networks (HANs), which is being adopted by industrial consortia such as WirelessHART and ZigBee, and is designed to support innovation. Second, developed a wireless power plug meter that automatically joins a self-assembling, ad-hoc wireless mesh network; the deployed network of 200 meters allowed the team to publish detailed data at a scale orders of magnitude greater than other similar efforts, and is informing future energy standards for computing systems
2	Stanford Energy Services Platform (ESP)	– Armel, Reeves (PEEC) – Bonsai Development Corp.	Improve the ease of implementation and evaluation of energy saving interventions that use sensor data via software platform Software platform that includes data collection services, a database, analytics, and graphical user interface templates for behavioral program deployment and experimentation at Stanford and beyond
Algorithms			
3	Segmentation Algorithms	– Fischer, Rajagopal, Albert, Kavousian (CEE) – Google, PG&E	Energy use and demand forecasting; demand response programs Software to segment commercial and residential customers based on their smart meter data energy consumption patterns. This information can be strategically and cost-effectively used to target customers for energy savings; utility trial in planning phase
4	Learning and Automation	– Aghajan, Khalili, Chen (EE)	HAN energy efficiency (EE) and demand response (DR) automation Software based on adaptive machine learning algorithms utilizing appliance and sensor data to improve TV and lighting automation on the dimensions of user activity, user preferences, and energy savings
5	Disaggregation Technical and Policy Survey Paper	– Armel (PEEC), Gupta, Shrimali, Albert – Bidgely, Venrock	Support the development of algorithms for improved demand side management (DSM) Comprehensive survey paper assessing the benefits of disaggregation (i.e., the statistical separation of the whole building energy signal into appliance level energy use data), overview of state of the art algorithms and their performance, and smart meter data suitability for these algorithms; dissemination of findings through public forums and thousands of downloads

6	Residential Energy Disaggregation Dataset (REDD)	– Kolter, Chadwick, Armel, Flora (CS, PEEC) – Enmetric	Support the development of algorithms for improved DSM Data set collected and made available for developers to improve, train, and test disaggregation algorithms; extensively used.
7	Disaggregation Algorithms	– Ng, Kolter (CS)	Support the development of algorithms for improved DSM Disaggregation algorithms were developed using sparse coding methods to advance the state of the art
Target Behaviors			
8	Energy Behavior Taxonomy	– Flora, Boudet, Roumpani, Armel (PEEC)	Energy saving action recommendations for use in software or programs Database of 250 energy saving actions, their attributes and impact, and barriers. Implementation in Bidgely Inc.'s online recommendation system
9	Identification of Innovative Energy Behaviors	– Armel, Cornelius, Ardoin, Plano, Bridgeland, Morton, Chang, Allen (PEEC)	Energy saving action recommendations for use in software or programs; development of new energy saving technologies Opportunity map identifying energy reducing practices and technical insights from other cultures and time periods, quantifying their potential energy saving impacts across U.S. climate zones, if adapted for developed nations
Behavioral Interventions			
Media Interventions			
11	Online Game	– Reeves, Cummings, Scarborough (Comm) – Kuma Games	Energy savings through media programs Online game utilizing real world energy data, social competition, and retraining of habits through reinforcement; laboratory and field studies suggested changes in energy saving behaviors and consumption.
10	Social Norms	– Walton, Sparkman, Clark, Paunesku, Armel, Luo, Flora (Psy) – Home Energy Analytics, City of Mountain View	Energy savings through media programs Web application that helps consumers track energy use and receive tips; 800+ users, embedded experiments showed the effectiveness of thematically organized tips and collective action framing
12	Immersive Reality	– Bailenson, Bailey, Flora, Armel, Voelker, Reeves (Comm) – DraftFCB	Energy savings through media programs Experimental evaluation of the utility of an immersive virtual environment in promoting energy saving behaviors, with results suggesting that vivid visualizations of energy consumption (e.g., amount of coal instead of KWh) may be more important than the personalization afforded by avatars.

13	Facebook Applications	– Banerjee, Flora, Sahoo, Bhansali, Greenspan, Khakwana, Liptsey-Rahe, Madres, Manley, Omer, Rajendra, Scalamnini, Wong, Stehly, Voelker (ME/Design)	Energy savings through media programs Three Facebook applications to motivate energy reductions and online experimental evaluations of these
Incentive Interventions			
14	Appliance Calculator	– McClure, Houde, Armel (Psy)	Energy savings through nudges Online appliance calculator application; 60,000 users via Google Ads, embedded experiments evaluated the effectiveness of information and framing tools for guiding the purchase of energy efficient appliances and electronics, e.g., selection of 10-20% more energy efficient refrigerators from default sort order (manipulations informed in part by a study with Sears)
15	Raffle Incentive	– Prabhakar, Merugu, Pluntke, Gomes, D. Mandayam, Yue, Atikoglu, Albert, Fukumoto, Liu, Wischik, Rama (EE) – National University of Singapore, Land Transport Authority of Singapore	Energy savings through incentives Online software developed for a raffle-like incentive program to motivate energy savings; 21,000 users, ~10% of trips were shifted off peak to reduce congestion and associated fuel waste
Community Intervention			
16	Community Program	– Robinson, Ardoin, Boudet, Flora, Armel (School of Med & Education) – Girl Scouts, People Power	Energy savings through community based programs Girl Scout “GLEE” curricula; 30 troop study, showed significant changes in self-reported home energy saving actions for both girls and their parents

5.1.1.1 Avenues of Impact

The following elaborates on the deliverables produced and results found for each of the projects. Complementary workshops and other support efforts were also conducted.

Technology

1. Communication network. Levis, in collaboration with a many others, helped establish the first Internet standard for home area networks (HANs), which is being adopted by industrial consortia such as WirelessHART and ZigBee. Specifically, they created an open standard for TCP/IP in home area networks (HANs) as well as an open-source reference implementation of the standard for others to copy, extend, re-use, and improve. This technology will provide greater freedom in data collection, representation, storage, and communication between devices of different manufacturers, as well as lower the barriers to entry, all leading to innovations and improvements in human interfaces to sensor-actuator networks.

As a second deliverable, this team developed a wireless power plug meter that automatically joins a self-assembling, ad-hoc wireless mesh network to deliver data to collection points (see Figure 1). The open-source design has been used by several follow-on efforts by other groups. Further, the deployed network of 200 such meters in the Stanford CS building for two years to obtain long-term, fine grained power draw measurements allowed the team to publish detailed data at a scale orders of magnitude greater than other, similar efforts, as well as establish the basic methodologies one should follow to measure computing energy. These results are being used by several green computing companies to write future energy standards for computing systems.

2. Stanford Energy Services Platform. This provides the computational backbone for the behavioral interventions and includes three layers: data collection and storage (user, energy, website activity, weather, property, and project data), services (analytics like baselining and peer comparison, registration, surveys, experimental condition assignment, alerts), and presentation (API, widgets, drupal modules). The software is being prepared and documented for use by others.

Algorithms

3. Segmentation and targeting algorithms. See other Summit posters for more info. Researchers used anonymized data from 250,000+ California utility customers with at least one year worth of hourly smart meter data, as well as 10 minute data collected on over 1,000 Google employees. The algorithms developed decompose a customer's consumption into daily load shapes; load shapes are then analyzed in aggregate to obtain a small number of typical loads shapes that characterize the whole population. These shapes can be then utilized to build behavioral models for customers; examine features such as variability, amount of kWh consumed, and thermal response; and more effectively target customers for energy programs. Finally, innovative methods to quantify the energy efficiency of buildings were developed. Tests of the algorithms in utility programs are in the planning phase.

4. Learning algorithms to enhance automation. This project automated the activity of TVs and lights based on human activity, preferences, and energy savings criteria. Data was collected from the electronics and also low resolution cameras that monitored human activity, and machine learning algorithms were developed that incorporated user models and decision-making to predict user behavior, as well as user feedback for refinement. The models were tested with real world data.

Disaggregation

This is the statistical separation of the whole building energy signal into appliance level energy use data. There were three discrete projects:

5. A comprehensive review paper evaluating the benefits of disaggregation, algorithm requirements, and the ability of smart meters to meet these requirements - and which has had tens of thousands of downloads to date.

6. Development of a high frequency data set, to aid algorithm development, testing, and benchmarking. Data was collected for three weeks from each of ~40 homes in Boston, MA and the Bay Area, CA, including 16 kHz whole home data, 3 sec circuit level data, and 1 min plug level data. Data available upon request, and will be publicly posted soon.

7. Algorithm development. Disaggregation algorithms using sparse coding methods were developed to advance the state of the art.

Target Behaviors

A list of target behaviors is useful for populating consumer facing recommendation systems with energy saving actions, and in guiding future work on the development of new energy saving actions. The two discrete projects included:

8. A database of 250 actions that directly reduce stationary residential energy use, and each action's ratings on nine different attributes (e.g., energy savings, fiscal cost, frequency of the action, skill demand). Actions were implementation in Bidgely Inc.'s online recommendation system. This project also analyzed how the actions clustered based on the attributes so they could be more effectively "bundled"in behavior change programs.

9. A collection of energy saving actions from other cultures and throughout history as inspiration for modern day energy saving innovations; their potential energy savings across U.S. climate zones were quantified to provide an opportunity map for future design efforts. (work in progress)

Behavioral Interventions

Media Interventions

10. Online game. This multiplayer game and supporting social media is suitable for use in xperiments and deployment in utility smart meter trials. Power House incorporated real world energy data into some of the game play, leveraged social competition, and

retrained habits through reinforcement. In a laboratory experiment and field study, participants respectively increased their short term energy efficient behaviors (turning off devices) and used significantly less energy during the weeks they used the game. This project received Phase II funding to deploy the game through Facebook.

11. Social norms. 800 self-selected residences received feedback about their energy consumption, energy saving tips, and normative framing in emails sent every other week. It was found that when energy-saving tips were organized thematically (e.g., all heat saving tips, rather than a random mix of tips), the collective-action frame ("We're doing it together!") led to significantly greater reductions than descriptive norms ("Residents here have reduced their energy use by x% this year.") or the thematic recommendations alone.

12. Immersive reality. This work created an immersive virtual shower world and measured its impact on energy related hot water consumption behavior, with results suggesting that vivid visualizations of energy consumption (e.g., amount of coal instead of KWh) are more important than the personalization afforded by avatars.

13. Facebook applications. This project developed three Facebook applications to match the range of motivations exhibited by individuals: Power Tower is social in that it allows one to collaborate with others in a Tetras-like puzzle where pieces are granted based on multiple participants' energy savings; Kidogo is affective in that it allows one to compute their real world energy savings and then microfinance individuals in developing countries based on these savings; and Powerbar is cognitive in that it primary displays energy feedback data. Partner workshops planned for Phase II funding period to disseminate findings.

Policy Interventions

14. Appliance calculator. This application has been used by over 60,000 people via Google Ads. By testing changes in the interface it was found, contrary to expectations, that projecting out cost savings over time does not appear to prompt more energy efficient refrigerator browsing, whereas simply changing the default sort order to put the most efficient appliances on top reduced the average kWh consumption of items selected by 10-20 percent – this suggests that simply implementing the most effective behavior change techniques may be a more effective strategy than a traditional route of analyzing the underlying cause of a problem then trying to address it.

15. Raffle incentive. The Insinc sweepstakes or raffle-like incentive program recruited 21,000 users in six months, with 7.5 percent of all Insinc trips shifting off peak to reduce congestion and associated fuel waste, 11 percent shifting by those previously making regular peak-hour trips, and significant shifting to the use of public transit. A computational platform was also developed (separate from project #2) to support this and similar programs.

Community Intervention

16. Community program. Community-based programs can be much more effective than traditional marketing communications when strategically tapping into existing social networks and providing close support from peers (e.g., 10 vs. 85 percent in the Hood River Project). A five lesson Girl Scout program was developed that resulted in significant changes in self-reported home energy saving actions for both girls and their parents. Phase II funding will link the Girl Scout and Integrative (#20) projects and scale the project to other regions of the U.S.

Data Evaluation and Modeling

17. Google Powermeter evaluation. Over 1000 individuals participated in a randomized controlled trial and showed an average of 6 percent energy savings in the first month or two of using the interface, which resembled many interfaces used on utility or other energy feedback websites. The study thus provided a benchmark for the comparison of other interventions, as well as a rigorous example of experimental and analysis methods for such work. (A note regarding persistence - it may be substantially improved with periodic reminders, as reported by Hunt Alcott (NYU) regarding the Opower program.)

18. Twitter explorer. This project developed Twitter Explorer to mine and analyze data from ongoing Twitter and other social media conversations about energy. For one year, Tweets were collected if they contained ~150 energy related linguistic terms. Using content, network, and semantic analyses of Tweets and hashtags, researchers assessed engagement, identified influencers, and identified word-of-mouth communities. Further work can enable an understanding of how to create, grow, and sustain word-of-mouth acceleration of energy behavior change.

19. Diffusion modeling. This project developed a simulation methodology and tool that allows one to model the energy savings of behavioral interventions according to parameters such as time, behavioral technique used, and social network distance and type. This tool could serve as a foundation for developing similar but more sophisticated tools enhanced with additional parameters and empirical data that could eventually lessen time and cost of developing interventions through predictive modeling, or, used in another way, to choose in which real-world settings to deploy different manipulations.

Thus, the Initiative can be divided into technology, interventions, and evaluation and modeling tools. The Energy Services Platform software provided the technical backbone for the behavioral programs; the analytics were developed to perform personalization, targeting, and other functions to improve uptake and effectiveness of the behavioral interventions; and evaluation tools were developed to help assess the impact of the interventions.

5.1.2 Future Steps

ARPA-E is funding Phase II of this Initiative. Five projects have been selected for that work; four existing projects will perform technology-to-market related activities such as scaling to larger consumer populations, and an integrative "Project 20" will aim to pull together aspects of these and other Phase I projects to develop and scale a more comprehensive energy behavior change program. The five projects specifically include:

- Reeves et al. aims to acquire a substantial base of PowerHouse game users on Facebook.
- Fischer and Rajagopal will develop segmentation and baselining analytics using smart meter data, which will support the behavioral program(s), and they will develop data visualization methods.
- Robinson et al. will disseminate highly replicable community-based curriculum materials to facilitate widespread implementation; this will also serve as a scaling channel for another behavioral program(s).
- Banerjee et al. will finish evaluating three research grade Facebook applications and hold workshops to share findings and software design with potential scaling partners.
- Armel et al. will oversee the new integrative "Project 20" aimed towards developing, testing, and performing the initial scaling of a behavioral energy saving program that integrates and augments several of the Phase I and II project elements – in order to create a more comprehensive program. The architecture of the system will include several innovations and a narrative will create a cohesive user experience. Preliminary work on this system was performed with Precourt Energy Efficiency Funds.

In addition, the research team will work towards creating an energy behavior platform that supports sensor data and analytics, for use by Stanford programs and others; attempt to develop a viable business model for Stanford programs which may include incentive, evaluation, and/or scaling components; and disseminate Stanford learnings and tools.

5.1.3 Impacts

Perhaps the most effective way to save energy is to simply not use it; this is in part because every unit of electricity not used (coined "negawatt") avoids the consumption of three to four units of fuel at the power plant (Lovins 2010; Lovins and Browning 2000). Such reduced demand side use has a wide array of benefits: reduced GHG emissions; reduced environmental impact (from GHGs, pollution, etc.); reduced system capacity requirements (reducing the generation, transmission, and distribution investments required of utilities and IPPs to meet electricity demand); improved grid reliability (reduction in outages, etc.); increased energy security (reduction in vulnerability to long-term disruptions of energy supply through volatile fuel prices, energy imports, climate change impact on energy markets, and finite resource exhaustion). Behavioral programs such as ours also provide the benefits of increased consumer appeal of energy efficiency actions (making achieving energy savings easier, promoting their adoption and furthering the benefits they provide), and increased economic activity (for example, through an increase in retrofits, energy efficient appliance purchases), and potentially improved smart grid efficiency and benefits.

The majority of the Stanford Initiative's work to date has been in developing software, algorithms, programs, evaluation tools, and other supporting deliverables, and testing these – precursors to scaling to large populations to achieve the widespread impacts described above. There have been energy saving impacts – for example, the lottery project included over 20,000 participants with an average of 7.5 percent of trips shifted off peak, and the appliance calculator projects totaled over 60,000 participants and those exposed to behavioral "nudges" pursued appliances that used 10-20 percent fewer kWh than their counterparts in the control condition. However, the emphasis on scale will begin with Phase II work, where the research team will refine and integrate the projects, make them commercial grade, and develop and implement scaling approaches. Development work being emphasized in Phase I is consistent with the timeline described in the original grant proposal, with a some delay due to difficulty in getting sensor data, and other technical and logistical issues.

To provide an estimate of the potential energy savings if this work is scaled, the following discussion is included. For an effective program that targets residential electricity use and space heating use, the research team can start with an estimate of lower bound savings up to 12 percent, and upper bound savings of 35 percent, with a middle ground estimate of 23 percent. These figures should then be tempered with the finding that large scale programs tend to achieve lower average energy savings per household than smaller programs, and most of the programs to date have been smaller, thus these figures may be biased upwards. The lower bound of achievable energy reductions is derived from over 50 studies showing that feedback about electricity use causes a reduction in use ranging from approximately zero to 20 percent, with the majority of studies showing savings between 7-16 percent (Darby 2006; Fischer 2008; EPRI 2009). These findings are derived from studies that used feedback as the sole or primary behavior change technique and greater savings may be possible by applying additional techniques (e.g., goal setting, game playing, framing effects, incentive structures, social marketing, and/or competition). It is also worth noting that in these studies, more frequent or appliance-specific feedback results in deeper savings, and savings tend to persist over two years according to a literature review by the Electric Power Research Institute (EPRI 2009) though questions about persistence continue and persistence may occur in some situations such as with periodically repeated programs but not in others (Alcott and Rogers, 2013). The upper bound estimate of 35 percent is derived from case studies (Parker et al. 2006) and a business analysis (McKinsey&Company 2009); there are also communities of households that have achieved much deeper savings, such as the Ninety Percent Reductions Group. The middle ground estimate of around 23 percent is the energy savings potential from behavioral programs, estimated by two independent research groups, that took into account technical potential from common energy saving actions as well as likely population penetration of these actions (Gardner and Stern 2008; Laitner, Ehrhardt-Martinez, and McKinney 2009).

It may be useful to compare these figures to the current widely used status quo energy behavior change savings program in the United States - Opower's home energy report - which achieved approximately 2 percent residential electricity bill savings according to analysis of their first 17 experiments which included 600,000 households across the United States (Alcott, 2011). Another useful comparison is that with the residential, and also total, energy consumption of the United States and of California. In the U.S., about 23 percent of energy is consumed by residential buildings, 19 percent by commercial buildings, and 16 percent by passenger cars and light trucks (Energy Information Administration 2008). In addition, the U.S. Department of Agriculture (USDA) estimates that food-related energy use accounted for about 16 percent of the U.S. energy budget in 2007 (Canning et al. 2010). Greenhouse gas (GHG) emissions follow a similar pattern (EPA 2006; Vandenbergh et al. 2008). In California, residential buildings use 33 percent and 37 percent of the electricity and natural gas respectively, and in commercial buildings these these figures are 37 percent and 16 percent. Furthermore, a 15 percent reduction of total U.S. energy consumption is more than the total yearly energy consumption in Brazil or the UK, or the quantity of fossil fuels that would be saved and GHG emissions reduced in the U.S. by a 25-fold increase in wind plus solar power, or a doubling of nuclear power, based on 2007 figures (Energy Information Administration 2008; Sweeney 2007).

5.2 Conclusions

The Stanford Energy Behavior Initiative, which ran from early 2010 through the summer of 2013, achieved an impressive array of work spanning 20 projects overseen by thirteen investigators across ten departments and five schools, in collaboration numerous students and outside partner organizations. The central objective of the Initiative was to develop the components that would support a system aimed at utilizing smart meter and other sensor data, communication technologies, and behavioral approaches, to achieve significant energy savings. The effort focused on the stationary residential sector, though work is applicable to and has explored transportation, water, and commercial applications. The Initiative can be divided into software and analytics, behavioral programs, and evaluation tools projects. The Energy Services Platform software provided the technical backbone for the behavioral programs; the analytics were developed to perform personalization, targeting, and other functions to improve uptake and effectiveness of the behavioral programs; and evaluation tools were developed to help assess the impact of the programs. Sensor data was used in a myriad of ways: for baselining, segmenting, and targeting; to improve automation; to disaggregate energy use and provide personalized recommendations; to provide users with feedback, comparison with others, and points towards competition, donations, and incentives; to evaluate the effectiveness of energy saving programs; and in other ways. Many deliverables were created from these projects, that could be used to scale programs for widespread impact, and that could be utilized by other groups, and numerous publications were produced describing the methods, findings, and deliverables. Phase II of this Initiative aims to integrate and scale these projects.

GLOSSARY

Term	Definition
CS	Computer Science
DR	Demand Response
DSM	Demand Side Management
EE	Energy Efficiency
EE	Electrical Engineering (Dept. Affiliation in Tables)
E-IPER	Emmett Interdisciplinary Program in Environment and Resources
ESP	Energy Services Platform
FS	Freeman Spogli Institute for International Studies at Stanford
HAN	Home area network
HMD	Head mounted display
H-STAR	Human Sciences and Technologies Advanced Research Institute
IETF	Internet Engineering Task Force
ISB	Indian School of Business
IVET	Immersive virtual environment technology
MS&E	Management Sciences and Engineering
PEEC	Precourt Energy Efficiency Center
REDD	Residential Disaggregation Dataset
RFC	Request for Comments
RPL ("ripple")	Routing Protocol for Low-power and lossy
Smart Grid	Smart Grid is the thoughtful integration of intelligent technologies and innovative services that produce a more efficient, sustainable, economic, and secure electrical supply for California communities.
TCP/IP	Transmission Control Protocol/Internet Protocol

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