Integration of Social Behavioral Modeling for Smart Environments To Improve Energy Efficiency of Smart Cities

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Project period: Feb. 2017 – Feb. 2020
Amount awarded: $802,981

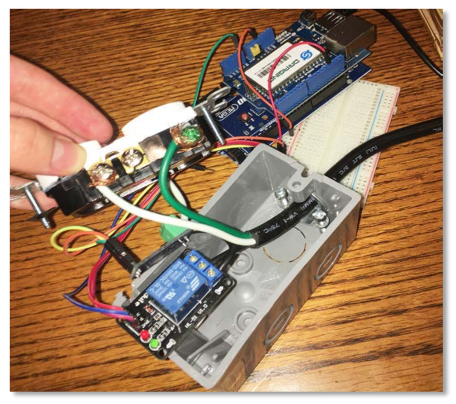
Main Goals

- Understand, model, and predict the social and behavioral aspects involved in the human interaction with residential smart environments
- Design comprehensive framework for energy management which specifically addresses psychological dimensions of user behavior.

Primary Tasks

1. Understand human interactions with smart appliances.
2. Define social behavioral models.
3. Exploit machine learning to refine such models from user behavior.
4. Social-behavior-aware optimization of energy consumption.
5. Community energy optimization in islanded microgrids.
6. Psychological and behavioral factors of efficacy and user engagement.

Clockwise from right: 1) Research facilities at Missouri S&T Solar & Eco Village which host seven competition entries of the US DoE Solar Decathlon for research and residence. 2) Interior and exterior of our Smart Outlet, which monitors real-time energy usage and can remotely power on/off a plugged in appliance; 10-15 outlets will be installed in each of the seven homes. 3) The 2015 Nest Home, where we recently installed the first set of Smart Outlets to monitor baseline energy usage at the appliance level.



Ongoing work

Psychological Model of Smart Appliance Utility

At the basis of our social-behavioral aware energy optimization framework, we define a *psychological model of smart appliance utility* that considers five dimensions of user well-being:

- Physical well-being
- Psychological well-being
- Economic well-being
- Moral well-being
- Social well-being

We examined changes in perceptions of appliance importance across these five dimension and across five different frames for *home energy availability* including:

- Energy & environmental conservation
- Use of a personal power generator
- Reduction of energy bill
- Sharing solar or wind powered generator with others
- Control condition (no mention of energy constraint)

Method

- Online experiment,1500 subjects.
- Randomly assigned to 1 of 5 energy conditions and asked to rank the importance of 27* appliances in contributing to each aspect of well being.
- Also ranked importance of 5 aspect of well being to **Overall** well being to allow for weighting of ranked responses and to calculate overall utility value for each appliance

Results

- Analysis of Variance (ANOVA) using weighted means **Overall** well being showed significant difference in perceived utility for many appliances and between the energy contexts.
- Subset of appliances remained high regardless of contexts (see Table 1).
- Calculated relative utility value for each appliance to quantify user perceptions across multiple dimensions of well-being.

		ANOVA		
Appliance	Rank	F df (4,1452)	*p*	Effect size (η_p^2)
Computer	1	3.003	.018	.008
Phone/Cell	2	3.778	.005	.010
Television	3	5.390	.000	.015
Refrigerator	4	4.230	.002	.012
Air Conditioner	5	2.646	.032	.007

Table I. Highest ranked appliances across all five energy conditions in terms of importance to overall well being.

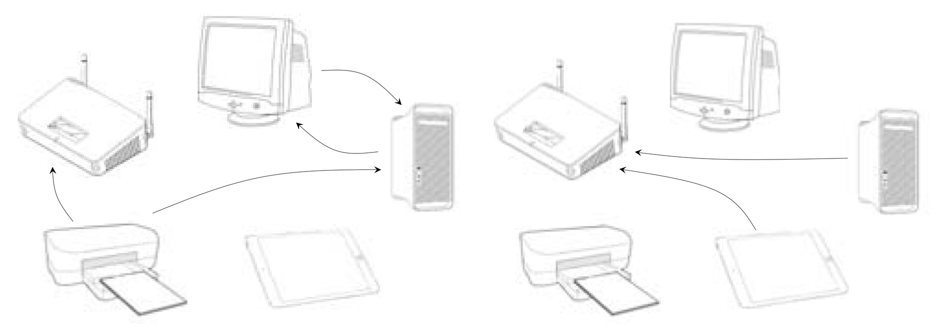
* Complete appliance list

1	Computer	15	Heater
2	Phone/Cell Phone	16	Printer
3	Television	17	Clothes Dryer
4	Refrigerator	18	Microwave
5	Air Conditioner	19	Freezer
6	Lights	20	Fan
7	Treadmill	21	Electric Razor
8	Water Heater	22	Hair Dryer
9	Clothes Washer	23	Dishwasher
10	Oven/Stove	24	Blender/Mixer
11	Radio/Stereo	25	Flat/Curling Iron
12	Clock/Alarm	26	Vacuum
13	Coffee Machine	27	Toaster/Toaster Over
14	Gaming System		

Social-behavioral aware energy optimization

The contribution of an appliance to the psychological wellbeing of a user may not be fully independent from other appliances. Specifically, we identify two forms of dependencies, functional and preference, which are modeled using two directed graphs.

Example of functional and preference dependency graphs in an home office setting.



Functional graph Preference graph

Energy optimization

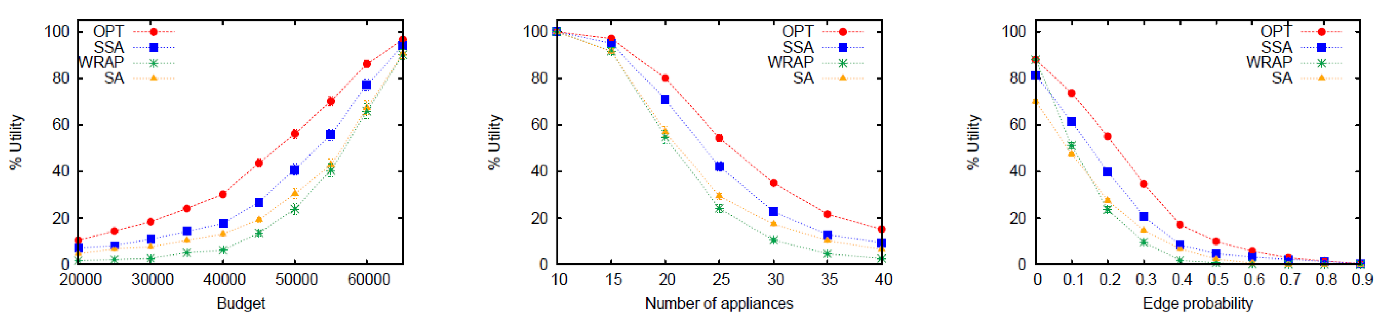
We consider an energy constrained scenario, where for example the user wants to reduce its energy bill or he is running on limited energy resources. We formulate the problem of finding the best set of appliances that maximize the user well being given an energy budget.

$$
\begin{aligned}
&\underset{x_i}{\text{maximize}} \sum_{i=1}^{n} \left(\alpha u_i z_i^f + (1-\alpha) u_i z_i^p\right),\\
&\text{subject to}: z_i^f \le x_i,\\
&\quad z_i^f \le \begin{cases} \sum_{j=1}^{N} \frac{x_j y_{ij}^f}{Y_i^f} & \text{if } Y_i^f > 0,\\ 1 & \text{otherwise,}\end{cases}\\
&\quad z_i^p \le x_i,\ z_i^p \le z_i^f\\
&\quad z_i^p \le \begin{cases} \sum_{j=1}^{N} \frac{x_j y_{ij}^p}{Y_i^p} & \text{if } Y_i^p > 0,\\ 1 & \text{otherwise ,}\end{cases}\\
&\quad \sum_{i=1}^{n} x_i e_i \le B\ ,\\
&\quad x_i \in \{0,1\}, z_i^f \in \{0,1\}, z_i^p \in [0,1].
\end{aligned}
$$

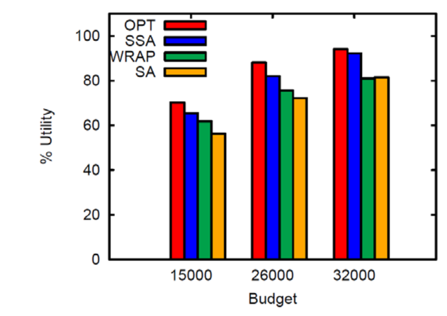
Since the problem is NP-Hard, we propose an heuristic called Smart Simulated Annealing (SSA).

Preliminary results

We compare SSA with the optimal solution (OPT), with a standard simulated annealing (SA) algorithm, and with a recent proposed approach (WRAP) [1]. We first consider synthetic dependency graphs (Erdős–Rényi).



We then consider realistic dependency graphs obtained through large scale surveys. The graphs have 27 appliances, 40 (functional) and 157 (preference) edges.



[1] S. Ciavarella, J.Y. Joo, S. Silvestri, *"Managing Contingencies In Smart Grids Via The Internet Of Things"*, in IEEE Transactions on Smart Grid, Vol. 7, Issue 4, 2016.

This work is supported by the National Institute for Food and Agriculture (NIFA) under the grant 2017-67008-26145.

For more information visit psych.mst.edu/research/smarthome/ or Contact PI Simone Silvestri, silvestri@cs.uky.edu.