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

Simone Silvestri (CS – UKY), Denise A. Baker (Psychology – MST) and Jhi-Young Joo (LBNL)

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. Psychological and behavioral factors of efficacy and user engagement.

Figure I. Research facilities at Missouri S&T Solar & Eco Village which host seven competition entries of the US DoE Solar Decathlon for research and residence.

Survey 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.

Appliance	Rank	ANOVA: 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.

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

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.
- 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.

* 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 dependency which is modeled using directed graphs.

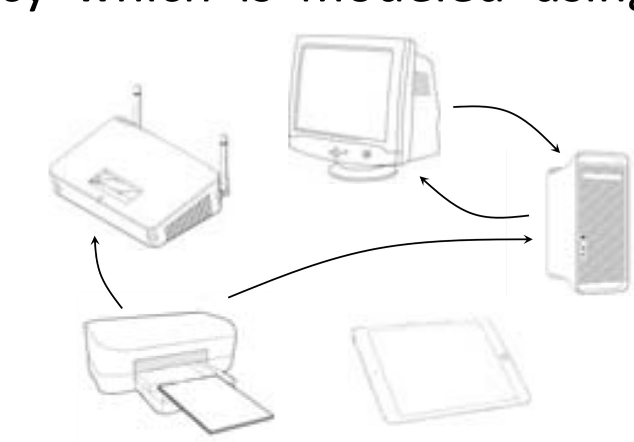


Figure II. Example of dependency graph in an home office setting.

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.

$$\underset{x_i}{\text{maximize}} \sum_{i=1} \left(\alpha u_i z_i^f + (1-\alpha) u_i z_i^p\right),$$

$$\text{subject to}: z_i^f \le x_i,$$

$$z_i^f \le \begin{cases} \sum_{j=1}^{n} \frac{x_j y_{ij}^f}{Y_i^f} & \text{if } Y_i^f > 0, \\ 1 & \text{otherwise,} \end{cases}$$

$$z_i^p \le x_i,\ z_i^p \le z_i^f$$

$$z_i^p \le \begin{cases} \sum_{j=1}^{n} \frac{z_j^f y_{ij}^p}{Y_i^p} & \text{if } Y_i^p > 0, \\ 1 & \text{otherwise ,} \end{cases}$$

$$\sum_{i=1}^{n} x_i e_i \le B\ ,$$

$$x_i \in \{0,1\}, z_i^f \in \{0,1\}, z_i^p \in [0,1]$$

Since the problem is NP-Hard, we propose a heuristics called Acyclic Algorithms.

Algorithm idea:

1. Find Strongly Connected Components (SCCs) in dependency graph.
2. Generate Condensation graph by assigning each SCC to a super appliance
3. Greedily select super-appliances with zero in-degree
4. Remove selected super-appliance and repeat step 3 until budget allows

Algorithm: Acyclic Approach

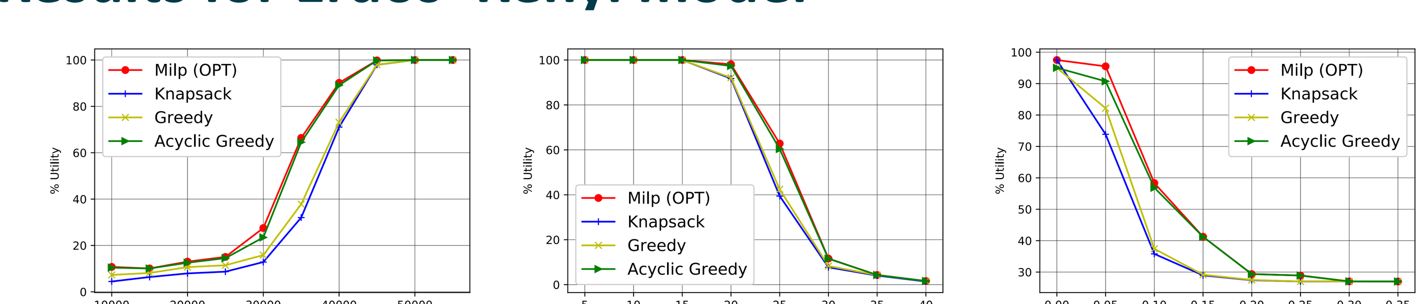
Input: Dependency graph, Sets of appliance utility and power consumption, respectively u_i and e_i for each $a_i \in A$, budget B.

Output: Set of selected appliances S_A.

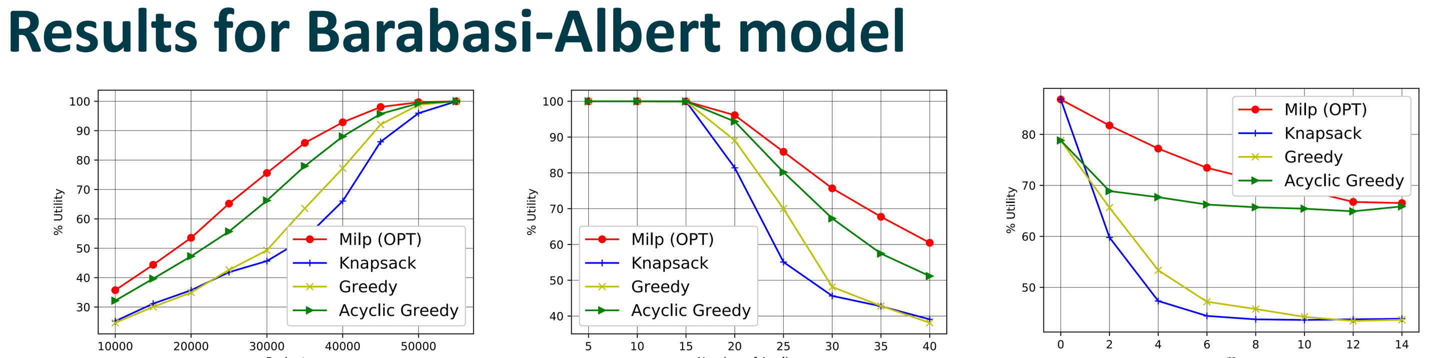
```
Find Super nodes, s_i, by generating reduced dependency graph;
S_A = ∅;
R = A';
while R ≠ ∅; do
    s_i^* = argmax_{s_i ∈ A' \ S_A} U_SB(S_A ∪ {s_i} ∪ D_f(s_i)) / C({s_i} ∪ D_f(s_i));
    if C(S_A ∪ {s_i^*} ∪ D_f(s_i^*)) ≤ B then
        S_A = S_A ∪ {s_i^*} ∪ D_f(s_i^*);
        R = R \ {{s_i^*} ∪ D_f(s_i^*)};
    else
        R = R \ {s_i^*};
Return S_A
```

We compare our algorithms with the optimal solution (OPT) under two synthetic dependency graphs.

Results for Erdős–Rényi model



Results for Barabasi-Albert model



- 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.