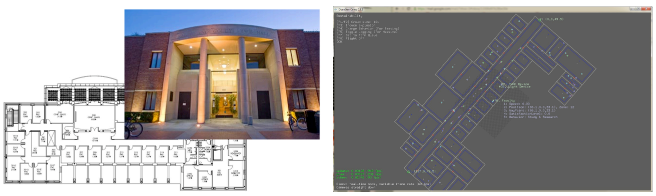
Sustainable Multiagent Application to Conserve Energy (Demonstration)

Jun-young Kwak, Pradeep Varakantham*, Rajiv Maheswaran, Milind Tambe, Farrokh Jazizadeh, Geoffrey Kavulya, Laura Klein, Burcin Becerik-Gerber, Timothy Hayes, Wendy Wood
University of Southern California, Los Angeles, CA, 90089
*Singapore Management University, Singapore, 178902



(a) Educational Building (RGL) (b) Simulation Testbed

Figure 1: The actual research testbed at USC and our simulator

1. INTRODUCTION

Limited availability of energy resources has motivated the need for developing efficient measures of conserving energy. Conserving energy in commercial buildings is an important goal since these buildings consume significant amount of energy, e.g., 46.2% of all building energy and 18.4% of total energy consumption in the US [1]. This demonstration focuses on a novel application to be deployed at Ralph & Goldy Lewis Hall (RGL) at the University of Southern California as a practical research testbed to optimize multiple competing objectives: i) energy use in the building; ii) occupants' comfort level; and iii) practical usage considerations.

This demonstration complements our paper in the AAMAS innovative applications track [4], presenting a novel multiagent building application for sustainability called SAVES (Sustainable multi-Agent systems for optimizing Variable objectives including Energy and Satisfaction). This writeup will provide a high-level overview of SAVES and focus more on the proposed demonstration, but readers are referred to [4] for a more technical description. SAVES provides three key contributions: (i) jointly performed with the university facility management team, our research is based on actual building and occupant data as well as real sensors and devices, etc.; (ii) it focuses on non-residential buildings, where human occupants do not have a direct financial incentive in saving energy; and (iii) SAVES uses a novel algorithm for generating optimal *BM-MDP* (Bounded parameter Multi-objective MDP) policies.

We demonstrate SAVES to show how to achieve significant energy savings and comparable average satisfaction level of occupants while emphasizing the interactive aspects of our application.

2. APPLICATION DOMAIN

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Figure 1(a) shows the real testbed building (RGL) in which SAVES is to be deployed and the floor plan of 3^{rd} floor. This campus building has three floors in total and is composed of classrooms, offices for faculty and staff, and conference rooms for meetings. Each floor has a large number of rooms and zones (a set of rooms that is controlled by specific piece of equipment). The building includes building components such as HVAC (Heating, Ventilating, and Air Conditioning) systems, lighting systems, office electronic devices like computers and AV equipment, and human occupants divided into permanent (faculty, staff, researchers, etc.) and temporary (students or faculty attending classes or meetings, etc.).

As an important first step in deploying SAVES in the actual building, we have constructed a realistic simulation testbed (Figure 1(b)) based on the open-source project OpenSteer (http://opensteer.sourceforge.net/) and validated the simulation testbed using real building energy and occupancy data.

Our simulation considers three building component categories: HVAC devices that control the temperature of the assigned zone, lighting devices that control the lighting level of the room, and appliances. The energy consumption of such building components is calculated based on various parameters designated by the ASHRAE standard and actual energy consumption data in the testbed building. We also built two types of human occupants in our simulation using the agent behavior framework. Permanent occupants follow their regular schedules and temporary occupants stay in the building for classes or meetings and leave once they end. Occupants also have a satisfaction level, modeled as a percentage between 0 (fully dissatisfied) and 100 (fully satisfied).

In this domain, there are two types of energy-related occupant behaviors that SAVES can influence to conserve energy use: individual and group behaviors. Individual behaviors only affect an environment where the individual is located, and group behaviors lead to changes in shared spaces and require negotiation with a group of occupants.

The desired goal in the educational building is to optimize multiple criteria, i.e., achieve maximum energy savings without sacrificing the comfort level of occupants.

3. APPROACH: SAVES

SAVES is composed of two types of agents: room agents and proxy agents (Figure 2). There is a dedicated room agent per office and conference room, in charge of reducing energy consumption in that room. It can access sensors to retrieve room information and energy use and impact the operation of actuators. A proxy agent [5] is on an individual occupant's hand-held device and it has the corresponding occupant's models. Proxy agents communicate on behalf of an occupant to the room agent based on their adjustable

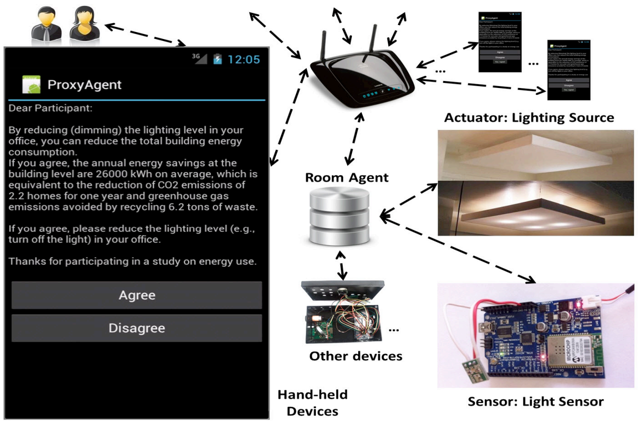

Figure 2: Agents & Communication Equipment in SAVES. An agent in SAVES sends feedback including energy use to occupants.

autonomy – when to interrupt a user and when to act autonomously.

Room agent reasoning is based on a new model called BM-MDPs, which is one of the contributions of this research. BM-MDPs are responsible for planning simple and complex tasks. These tasks include negotiating with groups of individuals to relocate meetings to smaller rooms to save energy, negotiating with multiple occupants of a shared office to reduce energy usage in the form of lights or HVACs, and others. BM-MDPs must reason with multiple objectives, but simultaneously must reason with the uncertainty in the domain, and we ended up building BM-MDPs to address both these challenges and requirements.

BM-MDPs are a hybrid of MO-MDPs [2] and BMDPs [3]. Similar to BMDPs, the transition and reward functions in BM-MDPs have closed real intervals. Whereas BMDPs are limited to optimizing a single objective case, BM-MDPs can i) optimize over multiple objectives (i.e., a vector of reward functions) with ii) different degrees of model uncertainty.

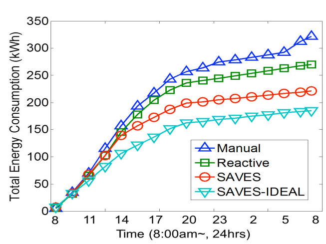

Figure 3: Energy Savings

Figure 3 shows the cumulative total energy consumption on the y-axis in *kWh* and time on the x-axis as obtained in our simulator (Figure 1(b)). SAVES (based on the BM-MDP policies) achieved energy savings of 31.27% with an actually measured compliance rate (68.18%) and up to 42.45% with the ideal compliance rate (i.e., SAVES-IDEAL: occupants *always* accept the suggestions provided by the SAVES room agents) when compared to the manual control strategy. The manual strategy represents the current strategy operated by the facility management team in RGL (Figure 1(a)). In addition to energy savings, we compared the average satisfaction level of human occupants under different control strategies in the simulation testbed. Similarly to Figure 3, SAVES reliably showed higher average satisfaction level (70% or higher) than other control strategies as it plans ahead of the schedules using BM-MDP policies.

4. DEMO

We demonstrate SAVES[1] using the 3^{rd} floor of RGL. Our demo consists of two parts. The first part uses our verified simulation testbed (Figure 1(b)) that is capable of communicating and negotiating with simulated occupants in the building and participants in the demo. The simulation environment is shown on the screen during the entire demo so that people are aware of the situation. The demo engages people by asking them to provide energy saving suggestions: we give them the detailed data of RGL 3^{rd} floor including energy rates of different rooms/zones, occupants' information, occupants' comfort levels, etc. Then, we ask them to make suggestions to reduce energy consumption. In particular, we provide three possible energy behaviors to participants in the demo: reduce the temperature by X°F in room/zone Y, dim the lighting level to Z in room/zone A, and relocate a meeting in conference room B to a smaller office C, where X, Y, Z, A, B, and C are user-chosen variables. We implement those suggested energy behaviors in the simulation environment and compare the performance between SAVES and participants' suggestions. Since our demo handles multi-objective optimization problems, we compare a rate of energy savings as well as the resulting comfort level changes.

The second part focuses on demonstration of proxies on the actual hand-held devices based on the following simple meeting relocation scenario considering group behaviors.

Group Meeting Relocation Negotiation Example Consider a meeting that has been scheduled with two attendees (P_1 and P_2) in a large conference room that has more light sources and appliances than smaller offices. Since the meeting has few attendees, the room agent can negotiate with attendees to relocate the meeting to nearby small, sunlit offices, which can lead to significant energy savings. The room agent handles this negotiation based on BM-MDPs. There are three objectives that the room agent needs to consider during this negotiation: i) energy saving, ii) P_1's comfort level change, and iii) P_2's comfort level change. The room agent first checks the available offices. Assuming there are two available offices A and B, the room agent asks each attendee if she or he will agree to relocate the meeting to one of the available offices. In asking an attendee, the room agent must consider the uncertainty of whether an attendee is likely to accept its offer to relocate the meeting. Since asking incurs a cost (e.g., cost caused by interrupting people), the room agent needs to reason about which option is preferable considering P_1 and P_2's likelihood to accept each option and the reward functions for each option to reduce the required cost and maximize benefits. Assuming A is preferable, the optimal policy of the agent is "ask P_1 first about A"–"if P_1 accepts, ask P_2 about A"–"if P_1 does not reply, ask P_1 about A again"–"repeat the process with B"–"if both agree, relocate the meeting"–"if both disagree, find other available options."

Each participant is provided with a mobile phone having a proxy agent on it. A proxy agent has a pre-set adjustable autonomy. Room agents initiate negotiations with simulated occupants or participants in the demo to conserve energy during the simulation, and SAVES specifically provides suggestions for energy savings to participants via mobile phones (as shown in Figure 2).

[1]SAVES demo: http://www.youtube.com/watch?v=LtdbroGTFmE

5. REFERENCES

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