Solar Decathlon Competition: Towards a Solar-Powered Smart Home

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Abstract

Alternative energy is becoming a growing source of power in the United States, including wind, hydroelectric and solar. The Solar Decathlon is a competition run by the US Department of Energy every two years. Washington State University (WSU) is one of twenty teams recently selected to compete in the fall 2017 challenge. A central part to WSU's entry is incorporating new and existing smart home technology from the ground up. The smart home can help to optimize energy loads, battery life and general comfort of the user in the home. This paper discusses the high-level goals of the project, hardware selected, build strategy and anticipated approach.

Introduction

Alternative power sources have been at the forefront of scientific research for the last several years (Dresselhaus and Thomas 2001). With global climate change becoming an ever present risk for the future, alternative energy sources are becoming a requirement instead of a luxury item. The U.S. Department of Energy (DOE) is running the Solar Decathlon Competition in 2017 to challenge researchers to create sustainable living through solar powered homes ready for immediate deployment. The Washington State University (WSU) team is creating a home for this competition utilizing expertise in electric power, advanced materials and smart systems.

Impact

The Solar Decathlon provides a venue for the public to imagine the possibilities of a healthy, comfortable and energy-efficient future. The WSU entry seeks to maintain that tradition by creating a home that employs smart grid technologies and previews how homes will function within a smart city context. This Decathlon is timely, given President Barack Obama's recent launch of the "Smart City" initiative, which aims to help communities employ data so they can more efficiently manage resources, improve city services and handle the effects of climate change (Washburn et al. 2009).

The WSU entry will feature a home operating system that coordinates between the grid, various mechanical/electrical/plumbing (MEP) systems, plug level loads and will be designed to learn occupants' preferences through a network of sensors. The system will include an intuitive interface for the inhabitants to engage with smart systems at the scale of the home, the neighborhood, the city and the globe. Moreover, it will provide inhabitants with the ability to visualize and understand the impact of human living patterns. The system will be designed to be adaptable and modifiable for operation in the demand/response environment of a smart grid, both during and following the competition.

Project Objectives

A set of objectives were designed in response to the Solar Decathlon goals and objectives developed by the U.S. DOE's Energy Efficiency and Renewable Energy Office. The goal is a net-zero energy home that promotes principles of occupant well-being, environmental stewardship and adaptability (see Figures 1 and 2).

The WSU team has four objectives:

A Design an *agent-based control system* that can adapt to new conditions and future innovations.

B Design a *healthy and comfortable physical environment* that can adapt to new conditions and future innovations.

C Design energy and water systems that can adapt to new conditions and future innovations, creating *balance resource system*.

D Design structure and skin systems that are strong, resilient, superinsulated and adaptable to new conditions and future innovations, creating a *high performance building envelope*.

Smart Energy

The solar smart home system is designed to function within the context of a smart city, interfacing with the smart grid. As renewable energy is generated this system allows us to control energy at the source, redirecting it as needed in a centralized way to use and store energy from the grid more efficiently.

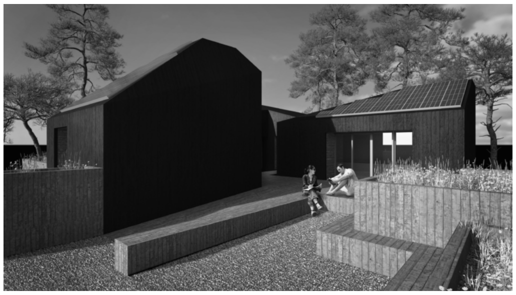

Figure 1: Smart Home Rendering

With real time data from this smart building platform, buying and selling energy from the transactive grid can be optimized throughout the day. In turn the home must be able to effectively store energy for future use. The WSU team are evaluating the application of hydrogen fuel cell implementation versus a more traditional battery system for energy storage within the home.

In addition to controlling the flow of energy throughout the home, a heat recovery approach will be used to capture and reuse energy. Heat Recovery Ventilators can help control the flow of air in and out of the home. These ventilators pull air in, capture heat from the air and then expel it out. Working in pairs, one pulling air in while the other releases it, these ventilators allow the home to capture energy used to heat the built environment before it leaves the envelope. In addition, the system uses water heat recovery to pull heat energy from water that has been warmed for use within the home, creating a closed system of energy recovery throughout the home.

Related Work

Some past works on smart energy efficiency homes have not considered the comfort of the inhabitants of the home (Kastner, Kofler, and Reinisch 2010). Recently researchers have begun to study consumer comfort in the context of a smart energy efficient home. While the main goal of Solar Decathlon is to create a zero energy usage home, inhabitant comfort is a large concern. Team WSU hopes to achieve a balance between energy efficiency and user experience, with the use of a smart home and machine learning algorithms.

Machine learning and automation for buying and selling power from the grid will be based largely off of past works in decentralized management agents (Ramchurn et al. 2011), dynamic programming management systems (Tischer and Verbic 2011) and deterministic optimization (Scott et al. 2013). These seminal works suggest ways to help modify user behavior as well as aid in the design of the automation that will take place in the home. These works are theoretical in nature, however their results give some indication of what may work in the applied built smart home.

Previously built energy efficient smart homes give an indication of application specific issues and successes. One such house is the Energy Aware Smart Home (Jahn et al. 2010) which used a Hydra middleware to create an energy aware smart home. This home focused on providing feedback to the user through a system of sensors presented on screens in the home and user's smart phone. By providing easily accessible real time energy usage data to the inhabitant of the home, the user is given the opportunity to become more energy aware and change their own habits. However, this system relies on the user to decide upon the balance between comfort and energy efficiency. An automated system may be able to improve energy efficiency to a greater extent without interfering with comfort.

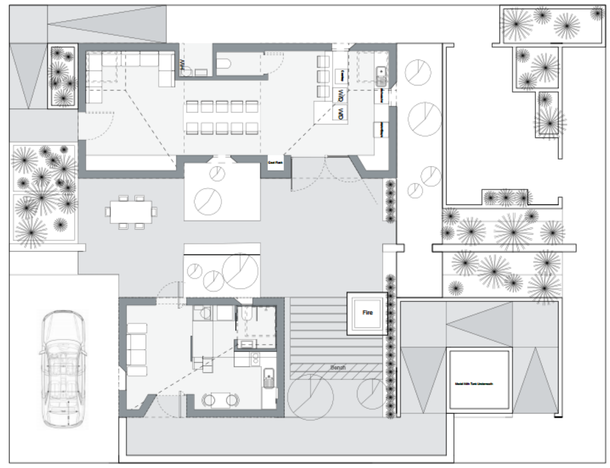

Figure 2: Smart Home Floor Plan

The Automation Systems Group (Kofler, Reinisch, and Kastner 2012) proposed a smart home system that used agent based learning given information about the home and appliances. This research suggested that an automated system could make decisions on behalf of the user by incorporating usage related information. Automated decisions about on/off state of devices in the home can significantly increase energy savings while minimizing the effect on the inhabitant of the home. The WSU team hopes to incorporate these automated systems with appliances, lighting, weather, HVAC, activity and security. The activity of the home and energy reports will be fed back to the user through the dashboard, increasing the users energy awareness.

Smart System Architecture

The solar smart home relies on a complex system of interconnected devices. Each device reports back its state and accepts state changes, but makes no specific decisions on its own. Devices use a number of communication protocols including WiFi, Bluetooth, ZigBee, Z-Wave and Insteon (see Figure 3). Z-wave and Insteon devices report back to a Universal Devices HUB which then reports to a main computer. The central computer also handles traffic from WiFi, Bluetooth and ZigBee devices. The central computer then uses hand-coded heuristics and learned policies to make decisions about what actions the devices should execute and sends back a request to individual devices. The user of the smart home may also make changes to the system by closing

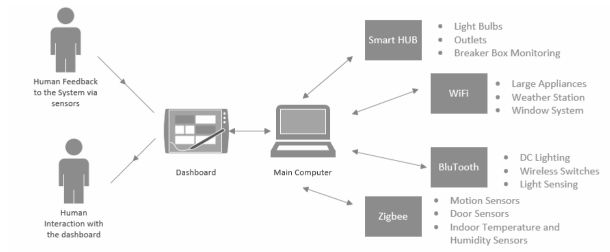

Figure 3: Smart Home System Architecture

windows, turning on or off lights, requesting changes via the user interface, etc. and these changes have an effect on the algorithm and the choices made by the main computer.

Hardware Components

The bulk of the solar smart home will use a system of smart devices. The home will rely on many devices to control energy, comfort and productivity.

Plugs and Electrical Boxes

The smart home contains three main devices to handle home energy usage: Aeon Labs Z-Wave micro smart energy switch for control of standard outlets, Aeon Labs Aeotec Z-Wave Heavy-Duty Smart Energy Appliance Switch Wired for control of large appliances and TED Pro Home with Spyder for electric box data. Z-Wave devices report back to the Universal Devices HUB the wattage, amperage and status of the outlet or appliance. The HUB and TED report back to the computer information about wattage, amperage and states. The computer will then use this data to help users visualize energy consumption, provide real-time monitoring of energy usage, determine when different appliances should be turned off/on and whether to run directly off of solar power or use battery power.

Lighting and Switches

The smart home utilizes several light sources to create comfortable lighting through the day. The system collects information from the weather station on sun rise, sun set and cloud cover, from a series of light sensors throughout the house on reported lumens in varies areas and from the motion sensors on what activity the user is most probabilistically taking part in. This information can make changes on three types of lighting: DC strip lighting built along the edges of major rooms, AC lights plugged into the Z-Wave outlets which utilize wireless EnOcean switches and Insteon LED light bulbs. DC lighting is controlled via a High Side DC Current Sensor Breakout and a small microcontroller with Bluetooth. The current sensor reports back to the microcontroller how much current is being drawn by the strip lighting. The microcontroller then reports the current draw, the on/off state of the strips and the intensity of the light, to the main computer. The Insteon light bulbs report back the on/off state of the bulb and the intensity of the light. The main computer can turn on and off lights, and dim lights depending on the needs of the users and the home's energy availability.

Weather Station, Thermostat, Air Quality, Temperature and Humidity

The team is currently in the evaluation stage for weather stations, thermostats and indoor air quality, temperature and humidity sensors. The weather station and thermostat may be commercially available through companies like Acurite and Ecobee respectively; however the air quality, temperature and humidity sensors may require the purchase of boards and micro controllers to create custom built systems. These systems will report back to the main computer the status of indoor and outdoor environmental states. This data will be used by the machine learning algorithms to make changes to the HVAC system, including heating, windows and vents.

Windows and Vents

Ventilation of the home will in part be controlled by an automated window system. At each window the smart home will collect data on relative pressure. Decisions on when to open windows, which windows to open and at what degree the windows are to be opened will be made by the central computer based on pressure data. In addition to the automated system, each window will contain a manual override. In the case of a rapid increase of air contaminants, temperature, or other concerns, the inhabitants of the home can manually override the system to open the window.

The smart home will communicate to each window through a WiFi capable microcontroller, Digilent WF32. The microcontroller will set the position of a 12V DC motor based on direction from the central computer, which controls the mechanical movements of a standard linear actuator. At any point in time, the smart home can access data on the window's position, state of the manual override and air pressure.

Motion Sensors: Activity and Security

Activity tracking in the smart home will utilize a depth of research started by the CASAS research group (Cook et al. 2013). This group has been building an assistive smart home for those with dementia and other health related needs. The CASAS system uses a set of infrared motion tracking sensors, magnetic door sensors, temperature sensors and a supervised learning random forest algorithm to accurately detect what activity the user is engaged in. These algorithms can now predict a number of basic activities of everyday life including cooking, cleaning, relaxing and preparing to leave the house (Cook, Schmitter-Edgecombe, and Dawadi 2015). This research goes one step further and can predict what behaviors may occur in the future given what has happened in the past (Minor, Doppa, and Cook 2015). This research taken together can help us to create patterns and routines to schedule changes in the homes other systems. This system can also be used to detect intruders when a user is away to act as a security system.

Software

A user's basic experience of a smart home system can be ruined by poor software design (Norman 2005). Care must be taken to assure that the smart home does not make decisions that will adversely effect the user, and if such an event does occur, that the user can quickly recover from the error. Much of this will take part in the ways in which the system handles both uncertainty and user feedback, as well as system dashboard's interface.

System Dashboard

The system dashboard will be handled through an iPad tablet which resides in the space and an iOS notification system for mobile devices. The interface will allow remote changes to be made, schedules to be set and recipes (see below) to be created.

Notification Center

The iOS notification system will allow users to know only those things of most importance to them. This system will utilize reinforcement learning to modify notifications based on specific users. Many new applications for mobile devices send notifications to users. These notifications can become cumbersome for users to attend to throughout the day and are therefore turned off or ignored. A smart home may have a large variety of notifications of varying importance to send to users, such as state changes for the garage, the doors, or the windows, indoor or outdoor temperature, current energy usage, current battery levels, etc. These notifications can become overwhelming to a new user of a smart home.

This research will build on previous work utilizing supervised learning techniques to attempt to reduce the amount of notifications given to a user (Smith et al. 2014; Okoshi et al. 2015). However, the WSU solar smart home will implement several reinforcement learning strategies to collect feedback from users and utilize that information for better notification delivery. In this way, the notification system can modify itself to meet the needs of specific users, instead of attempting to find generalized rules for all users.

Recipes

One goal of the learning system will be to identify common sequences of activities. For example, a user may wake up to an alarm, turn on the lights and then start a pot of coffee. Such a 'get up' recipe could be implemented directly by the user or learned autonomously. Initially, all learned recipes would be suggested to the user and confirmed. Eventually, the home's goal is to learn and apply recipes autonomously, allowing the user to provide feedback if it is not useful or not correctly applied.

Intelligence and Machine Learning

The WSU smart home agent will enable both energy and cost savings by directly measuring, controlling and scheduling devices within a home. While human behavior and energy needs are difficult to predict, many aspects of a home's daily energy schedule can be statistically derived. Home energy management systems can optimize device scheduling to meet user constraints and preferences by estimating the required daily energy use through typical occupant behavioral patterns. Care must be taken to account for uncertainties in the predictions; at times when the model has low certainty the agent must be more cautious than when it has high certainty.

The amount of flexibility that a particular device can exhibit depends on its functional requirements. For example, charging an Electric Vehicle (EV), a requirement for the 2017 contest, can be rescheduled as long as sufficient charge to meet user requirements is stored by its departure time. Electric lighting generally must operate when requested by the user. Some devices can be stopped and started frequently (e.g., a charging EV); some must run for a continuous amount of time once begun (e.g., a washing machine); and others can be set to different output levels operating at some percentage of maximum power (e.g., an EV charging at a fraction of its capacity or a water heater with a variable rate heating element). This makes these devices far more flexible because they can use any existing energy surplus.

By learning occupant behavior and understanding the thermal interactions between the different loads and the home climate, smart agents can more accurately schedule a home's resources or adapt semi-passive energy features to reduce energy use throughout the day. Smart agents, for example, could be directed to close vents in unoccupied rooms when the dryer is running, thus adding sufficient heat to the home.

Open questions

This work in progress leaves a variety of questions yet to be answered. Much of the machine learning involved in handling of energy and automation while also not bothering the user, is a delicate balance which may require feedback from the user to perfect. What kind of feedback is necessary and useful from users? How can we request this information without also creating an annoyance for the user? What algorithms will be most efficient to model the user's preferences?

The smart home will have multiple smaller homes and one large communal area (see Figure 2). Each home will handle an average of two users, while the larger unit could handle a dozen or more users at a time. This complexity may strain activity tracking, energy balancing and any other intelligence included in the home. How do we account for the variety of people in the same space? How do we balance user friendliness and modifiability of this system?

The Internet of things currently has a variety of issues with security in such complex systems (Roman, Najera, and Lopez 2011). Many of the devices are running microcontrollers, which lack the processing power to run advanced encryption techniques, yet a smart home will include a large number of such devices. How do we assure users that the system is safe given the large number of recent hacks on Internet of things devices? How do we balance security and psychological acceptability?

Conclusion

The alternative energy source problem will need to be solved in the near future, and a solar smart home is just one of many ways that may help. The WSU team smart home project can give insight for how to best implement low energy solutions while utilizing machine learning to create a comfortable and efficient home. While there are many questions that will need to be addressed and handled, as hardware and innovation continues to improve these too will hopefully be solved. This research should help to create a better, cleaner tomorrow through technology.

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