Modeling Human Behavior for Energy-Usage Prediction

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Abstract. We propose a system that uses a set of mobile sensors to model human behavior of energy usage. This mobile sensor suite can be fit on a keychain or ID/access badge. Data from these sensors, e.g., temperature, visible light spectrum, and 60 Hz electromagnetic field, will be used to give real-time feedback of user's energy consumption and prediction of future energy usage. Feedback of energy consumption will be displayed in an understandable manner on a user interface, e.g., smart phone. A model developed from the available data using machine learning will inform the system about energy consumption patterns and behaviors of users.

Keywords: energy-usage prediction, human behavior, green buildings, sensors.

1 Introduction

Demand of electricity is increasing and will continue to increase day by day throughout the world. A significant amount of electricity is currently generated using nonrenewable fossil fuels. These fuels and similar resources on the earth are limited and depleting rapidly due to increased demand of electricity. Conserving nonrenewable sources for the future is imperative. Also, electricity generation using nonrenewable fuel causes environmental impacts (e.g., global warming, ozone layer depletion, greenhouse gas emissions, etc). Conservation of electricity is the best solution to immediately address these problems. Scientific experts agree with the public recognition of the importance of energy conservation; however, approaches for how to best implement energy-saving strategies remain unclear.

Energy consumption by buildings (residential and commercial) has already exceeded energy usage in the industrial and transportation sector and has reached 20%-40% of total energy consumption [1]. Although environmentally-responsible Green buildings should use less energy than their conventional counterparts, research has shown that some Green buildings consume more energy than expected [2]. In the Swedish city of Malmö, a community of 20 buildings was expected to consume energy in the range of 32 to 107 kWh/m^2 per year. Although a few buildings consumed energy within the range, the remaining consumed in the range of 74 to 356 kWh/m^2 per year. Similarly the Lewis Center at Oberlin College, a multi-purpose facility for Environmental Studies built for maximum energy efficiency, consumed

C. Stephanidis (Ed.): Posters, Part I, HCII 2011, CCIS 173, pp. 298–302, 2011.

120 to 200 kWh/ m^2 per year instead of an estimated 64 kWh/ m^2 per year [3]. One of the major reasons for these startling disparities between estimated and actual energy consumption is lack of knowledge of how different people use energy [4, 5].

Providing informative and immediate feedback to energy users about their energy usage has been found to be an effective way of reducing energy consumption. Such instantaneous feedback has proven to encourage physical activity (e.g., pedometers) and energy conservation, through people's sense of competition [6, 7] or their desire to save money—reducing energy usage by an average of 15% [8]. Fisher (2008) [8] determined that effective feedback for stimulating energy conservation should be:

- Based on actual consumption
- Provided frequently to the user
- Involve an appliance-specific breakdown of energy use
- Presented in an understandable and appealing way

2 Related Work

There are a variety of energy monitoring and feedback systems available in the market today. For example, Kill-A-Watt (p3international.com) and Plogg (plogginternational.com) are promising products that monitor appliance-level energy consumption. TED (The Energy Detective; theenergydetective.com), Wattson panel (diykyoto.com), and GEO's (Green Energy Option; greenenergyoptions.co.uk) Minim and Solo are capable of monitoring whole house's energy consumption. In addition, GEO's Duet, Trio, and Quartet have the ability to monitor energy usage on the level of a whole house as well as down to the individual appliance level.

Overall, at the moment these products are expensive, which is a major hindrance to users adopting them. Importantly, none of the systems available today show an individual's energy usage or provide any information about human behavior.

3 Proposed System

The authors are in the process of developing a system which uses a set of mobile sensors, as shown in Fig. 1. This mobile sensor suite, which can be attached to a keychain or an ID/access badge, will provide measurements of temperature, visible light spectrum, and 60 Hz electromagnetic fields in the vicinity of the user. The proposed system will use data from the sensors to provide real-time feedback on the individual user's energy usage and to predict of future energy consumption.

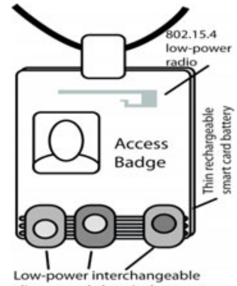

Fig. 1. Wireless sensors on badge

3.1 Mobile Sensor Suite

The compact wireless sensor suite is based on outdoor sensors we developed over 2007-present [9] that connects several different sensor types to a wireless node. This sensor suite moves with the user and can sense changes in illumination and power spikes indicating the user has turned electrical equipment on and off. This real-time energy consumption feedback will be displayed on a smart phone as shown in Fig. 2, which is convenient and one of the most accepted ways of receiving feedback on energy usage [10].

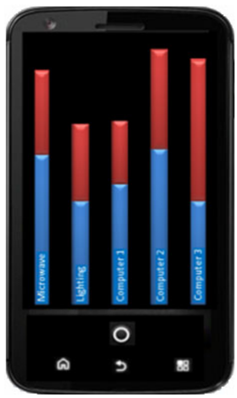

Fig. 2. Example interface display on smart phone

Mobile sensor data, combined with data about the buildings' age, historical energy usage pattern and type of HVAC equipment, outdoor weather conditions, and localization data from the sensor resources in a user's mobile phone [11-13] which include cellular signal level, GPS, Wi-Fi level, cameras, and accelerometers, would give an accurate hour-by-hour energy usage estimate.

Three new sensors that will be added under this project are temperature, lighting spectrum, and electromagnetic field sensor.

Temperature sensor: This low-power integrated circuit converts temperature to a serial data stream upon request. This device can also be programmed to set an alarm flag when a minimum or maximum temperature is attained. Temperature sensing will help the system infer the user's location, the user's energy needs, and any changes in heating/cooling caused by a HVAC system switching on.

Lighting spectrum sensor: This circuit is based on a four-input analog-to-digital converter (DS2450, Maxim Semiconductor) interfaced with photoresistors having light filters centered at four different wavelengths. The relative intensity data will be used to infer the intensity and type of light in the user's vicinity.

Electromagnetic field sensor: This amplifier is tuned to pick up 60 Hz signals at a coil. The amplified signal is rectified and connected to a DS2450 A/D converter. Signals suddenly exceeding a threshold DC voltage mean that the user has switched on an appliance, while slowly-varying signals are more likely caused by the user moving closer to a transformer or electrical outlet.

3.2 Machine Learning

The task of machine learning will be to measure and then model an individual's energy usage patterns and classify users accordingly (Fig. 3). For example, if average power consumption per person is 50 kWhr/day, future research could determine if in a building populated by a large number of people whether perhaps 50% of them have one type of energy-usage pattern (e.g., average energy user), 35% of another pattern (e.g., above-average), and 15% of a third pattern (e.g., below-average). Various algorithms, including neural networks and support vector machines (SVM), will be tested for generating models of energy use related to human behavior.

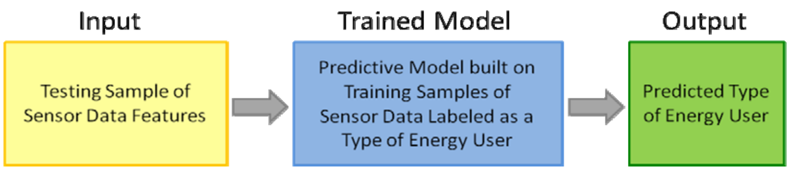

Fig. 3. Overview of a trained predictive model of energy use

Fig. 4 depicts a mock-up of data that could potentially be produced by the mobile sensor suite. Graphs show energy consumption of three users for personal computers, a shared microwave, and shared lighting.

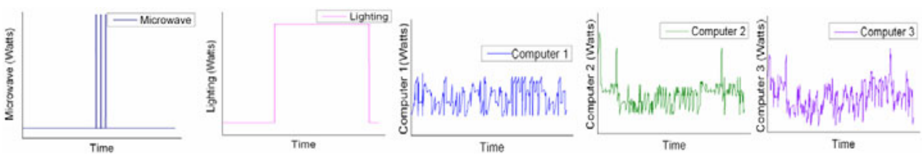

Fig. 4. Example energy usage data by appliance (e.g., microwave, lights, computers)

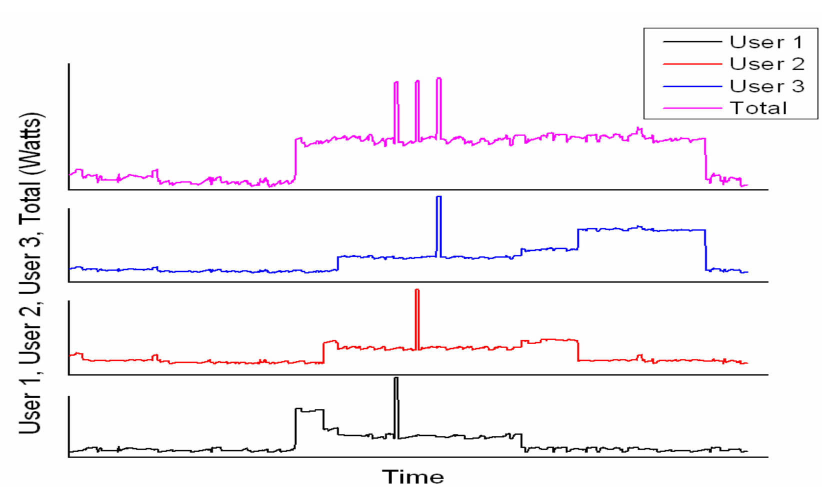

Fig. 5. Mock-up of energy consumption of three users over time with energy events attributed to individual devices (e.g., microwave)

Data from the sensors will be used to compose a comprehensive assessment of the energy use in an area as well as energy consumption that can be attributed to individual users in an area, as shown in Fig. 5.

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