Demo Abstract: EnergyTrack– Sensor-Driven Energy Use Analysis System

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ABSTRACT

We design and demonstrate a sensor-driven energy use analysis system, *EnergyTrack*, that continuously analyzes, evaluates, and interprets building energy use in real-time. The system incorporates an energy usage model that simultaneously considers the energy consumption of end-loads, occupancy changes, and occupant utility. The *EnergyTrack* testbed is implemented in a commercial building office space. We demonstrate our occupancy estimation algorithm as well as energy analysis results that are based on these occupancy estimates. These results include energy wastage tracking, consumption anomaly detection, and visualization of energy-break down by end-loads, building zones, and consumers.

Categories and Subject Descriptors

H.1 [**Information Systems**]: Models and Principles; C.3 [**Special-Purpose and Application-Based Systems**]: Real-time and Embedded Systems

General Terms

Design, Algorithms, Performance, Measurement

Keywords

Smart Grid, Demand Side Management, Measurement & Verification, Wireless Sensor Network

1. INTRODUCTION

Demand side management (DSM) has emerged as a promising way to balance the grid's electricity demand and supply without increasing the grid's generation capacity. In order to facilitate DSM, it is crucial to have reliable, accurate, and verifiable methods to continuously perform Measurement & Verification (M&V). M&V is the process of using measurement to assess the energy consumption for pre- and post-DSM periods. When M&V is continuously performed, so as to provide energy managers with constant feedback to help them control energy use, it has been shown that an additional 7–12% of energy savings can be achieved when compared to one-time M&V methods. However, it is difficult to practice such continuous M&V due to the lack of low-cost solutions to automate this process within an acceptable level of accuracy.

In this paper, we attempt to address the problem by proposing a middleware architecture for a sensor-driven energy use analysis system, *EnergyTrack*, that continuously analyzes, evaluates, and interprets energy usage in buildings using real-time sensor data. We develop an energy usage model that quantitatively incorporates the intuition that the energy usage efficiency of a load is maximized when the maximum number of concerned occupants experience the highest utility from its operation. *EnergyTrack* systematically quantifies useful and wasted energy use by jointly considering occupancy and occupant utility using this energy usage model. For occupancy information, which is a crucial component of our energy usage model, *EnergyTrack* estimates real-time occupancy of buildings using complementary measurements obtained from PIR and CO2 sensors. Our proposed middleware architecture and energy use analysis framework is employed for designing *EnergyTrack*, through seamless integration of four sub-system modules: sensor network, database, data analytics engine, and user interface.

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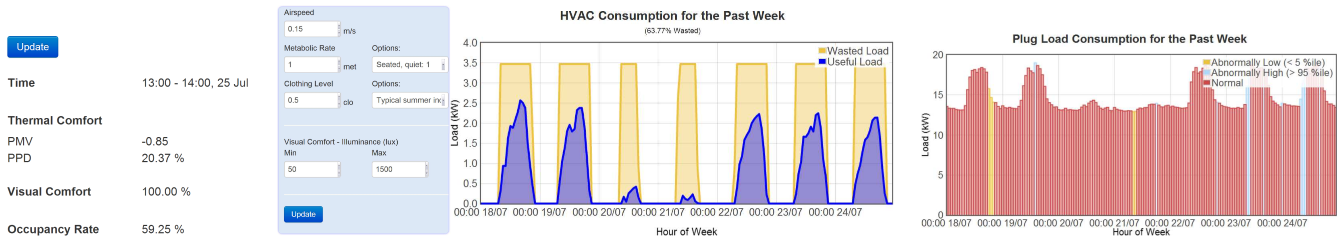
2. SYSTEM DESCRIPTION

EnergyTrack is designed with a multi-layered and modular architecture to facilitate flexibility and scalability. Figure 2 shows the overall system architecture of *EnergyTrack*. It consists of three main layers: Sensor Data Layer (SDL), Model Parameter Layer (MPL) and Energy Analytics Layer (EAL). It is supported by the Data Collection Network (DCN) and User Interface Layer (UIL). The DCN is an abstraction of network infrastructure to deliver sensor data (e.g., temperature or power measurements) to the SDL. The UIL allows users to easily modify the configuration settings of *EnergyTrack* and access various analytical results. The SDL provides a long-term repository for raw data collected from the DCN. The MPL consists of functions to estimate the following key model parameters: occupancy level, mean utility, and end-load states. It also performs a time series analysis that finds the temporal correlation of end-load energy consumption with parameters, such as occupancy level. In particular, it finds the best linear or quadratic fitting function of energy consumption for the estimated occupancy levels.

The EAL uses parameters from the MPL to provide three key features: *a*) Energy Wastage Tracking (EWT); *b*) Con-



(a) (b) (c)

Figure 1: EnergyTrack Implementation: (a) Visualization of real-time parameter estimates: thermal comfort, visual comfort and occupancy level, (b) Energy Wastage Tracking for HVAC with thermal and visual comfort parameters that can be adjusted. The wasted energy is the difference between the total and the useful, (c) Consumption Anomaly Detection for plug loads with anomalous consumptions marked in blue and yellow.

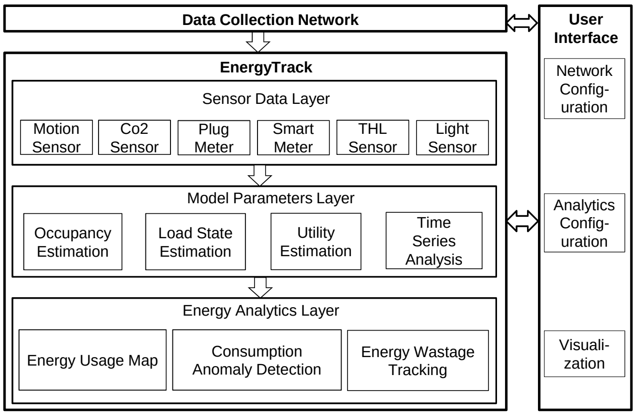


Figure 2: System Architecture of EnergyTrack

sumption Anomaly Detection (CAD); and *c*) Energy Usage Map (EUM). The EWT evaluates energy wastage (or equivalently, potential energy savings opportunities) in real-time using our energy usage analysis model. The CAD detects abnormal consumption periods, where the consumption, given the occupancy rate, falls short of the 5^{th} percentile or exceeds the 95^{th} percentile. The EUM hierarchically maps energy consumption over a tree of end-use loads, occupants, and zones.

3. DEMONSTRATION

We implement the *EnergyTrack* analysis system at our office space in a commercial building, where about 90 occupants work during the business hours of 8am-6pm on weekdays. During the demonstration, we will show various analytical results for our office, which are evaluated by our algorithms in real-time. The results and model parameters are accessible through a web-based User Interface (UI). In particular, we will demonstrate the MPL and EAL of our analytics framework. Figure 1(a) shows the model parameters estimated by the MPL, such as thermal and visual comfort metrics and occupancy rate in our office. For thermal comfort, we adopt the Predicted Percentage of Dissatisfied (PPD) standard. The PPD metric is a function that predicts the percentage of occupants who are dissatisfied with their thermal comfort, given various environment and human conditions such as air temperature, humidity, metabolic rate, and clothing insulation. These environment settings are configurable from the UI or retrieved from the SDL. *EnergyTrack* displays the estimated historical and/or real-time occupancy level that allows users to examine occupancy patterns in our office at various time resolutions.

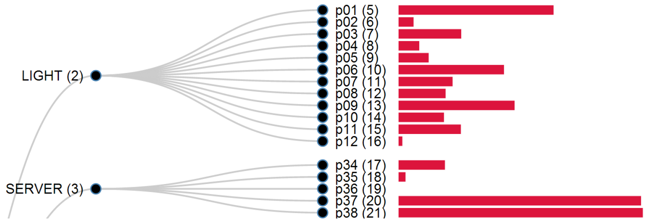


Figure 3: Snapshot of Energy Usage Map by end-load type

Figure 1(b) illustrates the HVAC system wastage in our office, which is calculated using occupancy levels and thermal comfort parameters. We also show the lighting load wastage, which is assessed using the visual comfort parameters. Visitors will be able to adjust these comfort metrics from the UI to see the changes reflected in the wastage calculation at the demonstration site. We will demonstrate the CAD component, by applying it to detect anomalous energy consumptions in HVAC, plug, and lighting loads separately.

The EUM supports viewing energy consumption from various angles (by end-loads, occupants, or zones) and at different levels of detail in a hierarchical manner (i.e., power consumption is further broken down into different dimensions). The EUM is represented by an interactive tree layout to capture the relationships between occupants and end-loads, or between end-loads and zones in our office. Figure 3 shows a snapshot of the EUM of our testbed for a set of lights and servers. In the figure, the length of the red bar on a leaf node indicates its consumption. During the demonstration, visitors will be able to interact with the EUM tree interface. By expanding or collapsing a tree node, they can observe the total energy consumption and energy usage trends during selected periods.

4. ACKNOWLEDGMENTS

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