Energy Analytics for Eco-feedback Design in Multi-family Residential Buildings

Sang woo Ham

Abstract

The residential sector is responsible for approximately 21% of the total energy use in the U.S. As a result, there have been various programs and studies aiming to reduce energy consumption and utility burden on individual households. Among various energy efficiency strategies, behavior-based approaches have received considerable attention because they significantly affect operational energy consumption without requiring building upgrades. For example, up to 30% of heating and cooling energy savings can be achieved by having an efficient temperature setpoint schedule. Such approaches can be particularly beneficial for multi-family residential buildings because 88% of their residents are renters paying their own utility bills without being allowed to upgrade their housing unit.

In this context, eco-feedback has emerged as an approach to motivate residents to reduce energy use by providing information (feedback) on human behavior and environmental impact. This research has gained significant attention with the development of new smart home technology such as smart thermostats and home energy management systems. Research on the design of effective eco-feedback focuses on how to motivate residents to change their behavior by identifying and notifying implementable actions in a timely manner via energy analytics such as energy prediction models, energy disaggregation, etc.

However, unit-level energy analytics pose significant challenges in multi-family residential buildings tasks due to the inter-unit heat transfer, unobserved variables (e.g., infiltration, human body heat gain, etc.), and limited data availability from the existing infrastructure (i.e., smart thermostats and smart meters). Furthermore, real-time model inference can facilitate up-to-date eco-feedback without a whole year of data to train models. To tackle the aforementioned challenges, three new modeling approaches for energy analytics have been proposed in this Thesis is developed based on the data collected from WiFi-enabled smart thermostats and power meters in a multi-family residential building in IN, U.S.

First, this Thesis presents a unit-level data-driven modeling approach to normalize heating and cooling (HC) energy usage in multi-family residential buildings. The proposed

modeling approach provides normalized groups of units that have similar building characteristics to provide the relative evaluation of energy-related behaviors. The physics-informed approach begins from a heat balance equation to derive a linear regression model, and a Bayesian mixture model is used to identify normalized groups in consideration of the inter-unit heat transfer and unobserved variables. The probabilistic approach incorporates unit- and season-specific prior information and sequential Bayesian updating of model parameters when new data is available. The model finds distinct normalized HC energy use groups in different seasons and provides more accurate rankings compared to the case without normalization.

Second, this Thesis presents a real-time modeling approach to predict the HC energy consumption of individual units in a multi-family residential building. The model has a state-space structure to capture the building thermal dynamics, includes the setpoint schedule as an input, and incorporates real-time state filtering and parameter learning to consider uncertainties from unobserved boundary conditions (e.g., temperatures of adjacent spaces) and unobserved disturbances (i.e., window opening, infiltration, etc.). Through this real-time form, the model does not need to be re-trained for different seasons. The results show that the median power prediction of the model deviates less than 3.1% from measurements while the model learns seasonal parameters such as the cooling efficiency coefficient through sequential Bayesian update.

Finally, this Thesis presents a scalable and practical HC energy disaggregation model that is designed to be developed using data from smart meters and smart thermostats available in current advanced metering infrastructure (AMI) in typical residential houses without additional sensors. The model incorporates sequential Bayesian update whenever a new operation type is observed to learn seasonal parameters without long-term data for training. Also, it allows modeling the skewed characteristics of HC and non-HC power data. The results show that the model successfully predicts disaggregated HC power from 15-min interval data, and it shows less than 12% of error in weekly HC energy consumption. Finally, the model is able to learn seasonal parameters via sequential Bayesian update and gives good prediction results in different seasons.