Data-driven Simulation of Room-level Building Energy Consumption

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ABSTRACT

Building energy consumption comprises a highly complex set of dynamics that critically depend on the behavior of building occupants. A key area of ongoing research is the simulation of energy consumption for evaluation of occupant-centric building design or management interventions (e.g., building layouts, suggestions to occupants). Researchers have shown that standard physics-based simulation tools like EnergyPlus exhibit large errors when compared to measured data, which has largely been attributed to difficulties in handling occupancy data. To address this performance gap, scholars have noted the promise of data-driven simulation tools. However, a key remaining challenge is the integration of granular (e.g., zone- or room-level) occupancy data for prediction of energy consumption at these granular scales. Such analysis can enable rapid simulation of the effects of new building states (e.g., occupancy patterns) for evaluation of potential building interventions (e.g., schedule-shifting). In this paper, we use real-time data from ambient sensors in a testbed and train a data-driven model to predict HVAC energy consumption using occupancy, temperature, humidity, and temporal features, each collected with high spatial and temporal granularity. We find that our data-driven approach out-performs EnergyPlus, even when adjusted with calibration tools (CV(RMSE) improvement of 49% to 84%). We also find that our trained data-driven model is able to make energy predictions in near real-time (sub-second), which enables rapid evaluation of building interventions. Overall, this sensor-based and data-driven approach to building energy simulation can enable new occupant-centric building management strategies that save energy and promote wellbeing in the built environment.