Occupancy-Based Controls for an All-Electric Residential Community in a Cold Climate

Preprint

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National Renewable Energy Laboratory

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Occupancy-Based Controls for an All-Electric Residential Community in a Cold Climate

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***Abstract*—In residential buildings, rapid improvements in sensors, communication, and information technology have enabled occupancy-based building controls. These controls utilize occupancy information and modify the operation of the heating, ventilation, and air-conditioning (HVAC) system to minimize excess HVAC energy use, especially when the building is unoccupied. This reduces the total building energy consumption and utility bills while maintaining thermal comfort. In this paper, we present two novel occupancy-driven controls—reactive control and predictive control—and compare their performance. We model an all-electric residential community based on a 27-home community in Basalt, Colorado, in the United States. We simulated various scenarios, considering different temperature setback and control algorithms, to analyze the community-scale impact of these occupancy-based controls. The results show that total HVAC energy savings in a building ranges from 1%–20% compared to the baseline scenario without occupancy-based controls. The energy-saving potential is highly correlated with the occupancy pattern and temperature setback in the building.**

***Index Terms*—Energy management, residential community, occupancy-driven controls, reactive control, predictive control**

I. Introduction

Residential buildings account for 21% of total energy consumption in the United States [1]. Approximately 55% [2] of residential energy is consumed by heating, ventilation, and air-conditioning (HVAC) systems to maintain indoor space temperature. Minimizing excess energy use by HVAC systems, especially when a building is unoccupied, can reduce energy consumption and utility bills without affecting occupant comfort. This can be achieved by occupancy-based building controls that integrate building occupancy and comfort information with building controls [3].

Various occupancy detection and monitoring techniques have been developed that utilize data from different sensors, such as passive infrared sensors, smart meters, and carbon dioxide sensors [4]. These recent developments in occupancy detection have paved the path for occupancy-based building controls. These controls can be broadly grouped into three main categories: (a) user-defined schedule, (b) reactive control, and (c) predictive control [5]. In a user-defined schedule, the occupants manually schedule the setpoint temperature using a manual or programmable thermostat. The main drawback of such control arises from the constant interventions required from the occupants. Second, reactive control utilizes occupancy information and adjusts the thermostat setpoint based on occupancy. This can lead to thermal discomfort during the transition from setback to setpoint temperature upon occupants' arrival [5]. Third, predictive control utilizes the current occupancy information as well as future forecast to compute the setpoint temperature. This approach is able to anticipate when occupants will arrive and recover from any setup or setback before they arrive, reducing discomfort. Generally, optimization algorithms are employed to compute the setpoint temperature.

In recent years, there have been several discussions on occupancy-based building controls in residential buildings to minimize energy consumption. Rule-based reactive control with fixed and adaptive setpoints showed 11%–34% savings in [6]. Similarly, a reactive control strategy controlling multiple zonal thermostats within the same building unit is discussed in [7]. Reactive control strategies considering deep setback and completely turning off the HVAC system when the building is vacant are considered in [8]. A predictive HVAC control strategy with occupancy prediction to minimize energy consumption and occupant discomfort is proposed in [9] and [10]. However, a community-scale comparison of reactive and predictive occupancy-based control strategies considering stochastic occupancy schedules has not been performed.

In this project, we developed and simulated two occupancy-based building controls: reactive control and predictive control. First, we developed a rule-based reactive control strategy to adjust the HVAC thermostat setpoint based on occupancy information. Second, we incorporated occupancy information in model predictive control (MPC) of the residential building to holistically control behind-the-meter resources such as HVAC, water heater, photovoltaics (PV), and battery energy storage system. We evaluated the performance of the controls using a model of a residential community in Basalt, Colorado. We utilized stochastic occupancy schedules to represent the variation in the occupancy patterns within the community. Various scenarios considering different temperature setbacks were also considered in the study.

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The main contributions of this paper are:

1) Community-scale implementation and comparison of various occupancy-based control strategies, including reactive control and predictive control.
2) Incorporating a stochastic occupancy schedule to define a realistic occupancy pattern.
3) Quantitative evaluation of the control strategies using various metrics, including energy savings and thermal discomfort.

The rest of the paper is organized as follows. Section II describes the formulation of occupancy-based building controls and the overall framework for implementing such controls. Section III includes a description of the community and different scenarios considered in this study. Section IV presents the analysis and comparison of various occupancy-based controls. Finally, concluding remarks and future work are presented in Section V.

II. Framework Description

This section describes the occupancy-based control methodology and the framework to evaluate the effectiveness of such controls. The overall framework, shown in Fig. 1, consists of three main components: (a) occupancy-based control, (b) building energy simulator, and (c) stochastic occupancy schedule.

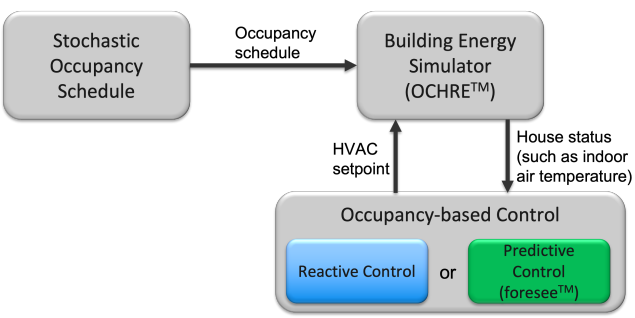

Fig. 1. Framework for evaluating occupancy-based control methods

A. Occupancy-Based Control

1) Reactive Control: These controls react to the occupancy information (i.e., occupied/vacant) gathered from different sensors. In this study, we assume perfect knowledge of occupancy is available to the controllers, representing a best case scenario. The reactive control implements the user-defined setpoint temperature when the building is occupied and implements a temperature setback when the building is unoccupied. A different temperature setback is employed to evaluate the relationship between energy savings and temperature setback.

2) Predictive Control: For the occupancy-based predictive control, we incorporated occupancy information (i.e., occupied/vacant) in **foresee**™, a home energy management system [11], [12]. **foresee** is capable of coordinating and controlling behind-the-meter resources while also considering occupant comfort. **foresee** is formulated as a multi-objective MPC problem, and the objective of the optimization problem, shown below, is to minimize the utility bill, occupant discomfort, and equipment degradation.

$$\begin{aligned}\min \sum_t \{ & \lambda^t b_{\mathrm{m}} P_{\mathrm{g}}^t \\ & + b_{\mathrm{air}}[(T_{\mathrm{air}}^t - T_{\mathrm{air}}^{\max})^2 + (T_{\mathrm{air}}^{\min} - T_{\mathrm{air}}^t)^2] \\ & + b_{\mathrm{wt}}[(T_{\mathrm{wh}}^t - T_{\mathrm{wh}}^{max})^2 + (T_{\mathrm{wh}}^{min} - T_{\mathrm{wh}}^t)^2] \\ & + b_{\mathrm{batt}}(P_{\mathrm{ch}}^t + P_{\mathrm{dis}}^t)\}\end{aligned} \tag{1}$$

where, the first term ($\lambda^t b_{\mathrm{m}} P_{\mathrm{g}}^t$) represents the energy cost, λ^t is utility rate, and P_{g}^t is net building power. The second and third term represent occupant discomfort in air and hot water temperature, respectively. $T_{\mathrm{air}}^t, T_{\mathrm{wh}}^t$ are desired room and water temperature, ($T_{\mathrm{air}}^{\min}$,$T_{\mathrm{air}}^{\max}$) and ($T_{\mathrm{wh}}^{\min}$,$T_{\mathrm{wh}}^{\max}$) are the range of user-defined comfortable room and water temperature, respectively. P_{ch}^t and P_{dis}^t are battery charging and discharging power. b_m, b_{air}, b_{wt} and b_{batt} are the weights for different objective functions.

To incorporate occupancy information, the parameters T_{air}^{min} and T_{air}^{max} are adjusted based on occupancy. When the building is unoccupied, the range of comfortable temperature (T_{air}^{min}, T_{air}^{max}) is increased to provide flexibility for reducing the HVAC energy consumption. When the building is occupied, the occupant-defined comfortable temperature range is maintained. The default occupant-defined temperature range is considered as $\pm 1°C$ around setpoint temperature.

The building constraints are:

$$\begin{aligned}T_{\mathrm{air,diff}}^t = \beta_1 T_{\mathrm{air,diff}}^{t-1} + \beta_2 (T_{\mathrm{out}}^t - T_{\mathrm{air}}^{t-1}) \\ + \beta_3 (I_{\mathrm{h}}^t C_{\mathrm{h}} - I_{\mathrm{c}}^t C_{\mathrm{c}}) + \delta^t\end{aligned} \tag{2a}$$

$$T_{\mathrm{air}}^t = T_{\mathrm{air,diff}}^t + \beta_4 \tag{2b}$$

$$0 \le I_{\mathrm{c}}^t \le 1 \tag{2c}$$

$$0 \le I_{\mathrm{h}}^t \le 1 \tag{2d}$$

Equation (2a) and (2b) is an autoregressive exogenous (ARX) model, which represent the building model [12]. T_{air}^t is the indoor air temperature, δ^t is the indoor temperature change due to solar and internal heat gain, and T_{out}^t is the outdoor temperature. $\beta_1 - \beta_4$ are the coefficients of the ARX model, pre-trained using building simulation data. I_h^t and I_c^t are heating and cooling duty cycle, and C_h and C_c are heating and cooling capacity. Further details on **foresee**, including additional constraints for other appliances such as water heaters, PV, and energy storage, can be found in [11], [12].

B. Building Energy Simulator

An analysis of the impact of occupancy-driven control warrants an accurate building energy model capable of incorporating the external control signals. We used the Object-oriented, Controllable, High-resolution Residential Energy (OCHRE) model [13] for the residential buildings of the community in this study. OCHRE models the building envelope using

a reduced-order resistor-capacitor equivalent thermal network model. OCHRE also includes grid-interactive and controllable models for residential HVAC, water heaters, PV panels, battery energy storage, and electric vehicles. OCHRE includes models for different HVAC systems, such as air conditioners, air-source heat pumps, furnaces, boilers, and baseboards. The HVAC models in OCHRE are provided with thermostat deadband control by default, but can receive the controls from external controllers such as the occupancy-based controls. Further details on the OCHRE model are provided in [13].

C. Stochastic Occupancy Schedule

Many building energy modeling and analysis tools utilize a "smooth" occupancy profile that represents the average energy consumption of an appliance. The average consumption of appliances are computed based on data from a large number of residential buildings. The smooth schedule-based occupancy models work well when annual energy consumption is the primary concern; however, they may not capture the realistic behavior of occupants, thus impacting peak demand of the buildings.

To address this issue, we integrated a stochastic occupancy model into the residential buildings to model the building occupancy and major end-use appliances. The model first employs a clustering technique (i.e, K-means) to identify distinct patterns of building occupancy and occupant behavior. Second, the model uses a homogeneous Markov chain to realistically simulate occupant behavior [14].

III. Case Study

A. Community Description

The community considered for the case study in this paper is called Basalt Vista, located in Basalt, Colorado, in the United States. The community is located in a cold and dry climate zone (IECC climate zone 6B [15]). There are a total of 12 multifamily buildings, either duplexes or triplexes, comprising 27 dwelling units in the community. Each home in the community is either a 2-, 3-, or 4-bedroom unit with a total area of 107 to 156 square meters [16]. Basalt Vista is an all-electric community equipped with rooftop PV and energy storage, making the community approximately a net-zero community. Each unit, or house, has a PV system with the capacity ranging from 7.6 kW to 11.85 kW. Four houses of the community are also equipped with a 12-kWh battery. The HVAC system installed in all the homes is a minisplit heat pump (MSHP), and the water heating system is a heat pump water heater.

The MSHP system in the community has a variable frequency drive operating at different speeds to meet the heating and cooling requirements. A local proportional integral derivative controller adjusts the variable frequency drive's speed ratio based on measured room temperature and setpoint temperature. The MSHPs are sized larger than the typical size recommended by industry standards (ACCA Manual J [17]) to ensure the MSHP can meet the heating requirement during the coldest time period. The baseline heating and cooling setpoint temperature is assumed based on typical setpoint temperatures for this region and building type [18].

TABLE I
Description of scenarios

Scenario	Scenario name	HVAC control	Setpoint change	Simulation time
1.0	Baseline	Deadband	None	Annual
2.1	Reactive (2)	Reactive	2	
2.2	Reactive (4)		4	
2.3	Reactive (6)		6	
3.1	Predictive (2)	Predictive	2	
3.2	Predictive (4)		4	
3.3	Predictive (6)		6	

B. Scenario Description

We analyzed several different scenarios, summarized in Table I, to evaluate the performance of the occupancy-based controls. Three scenarios were created based on the HVAC controls implemented. The first scenario is the baseline scenario where the HVAC is controlled using a deadband thermostat controller typically found in residential buildings. The second set of scenarios implemented reactive control, and the third set implemented predictive control, as mentioned in Section II. The depth of the setback significantly impacts the energy-saving potential and occupants' comfort. Such depth of setback is classified into (a) conservative setback (up to $3°C$ temperature deviation from setpoint temperature) and (b) deep setback (greater than $3°C$ temperature deviation from setpoint temperature) [5]. We considered three different depths of setback including $2°C$, $4°C$, and $6°C$, representing both conservative and deep setback for reactive and predictive control scenarios. In **foresee** of predictive control scenarios, highest preference (and weight) is provided to utility cost, followed by user discomfort and equipment degradation, respectively.

IV. Results

A. Stochastic Occupancy Schedule

Various occupancy schedules were generated to represent the variation of occupancy pattern in the 27 houses of the community using the stochastic occupancy schedule. Some variability in the number of occupants was included to cover a range of scenarios (e.g., one occupant in house b1, compared to four occupants in house b20). The total number of hours in a year with a specific building occupancy level is shown in Fig. 2. The occupancy level with 0 (represented by blue bars) denotes that the building is vacant. We can observe that the number of hours the building is vacant varies across homes of the community. The minimum occupancy in a house is 52% (house b20) of total time, whereas the maximum occupancy is greater than 99% (house b19) of total time in the community.

B. Controller Operation

The operation of the controller for a specific day, January 15, for a single home is shown in Fig. 3. The shaded region signifies the time period that the house is vacant. We can observe that the baseline control maintains the same temperature setpoint irrespective of the occupancy information

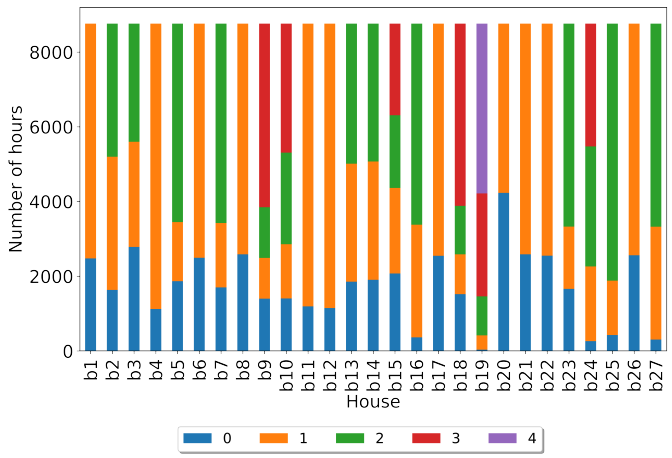

Fig. 2. Summary of the annual occupancy in each house at the Basalt Vista community. Each bar shows the occupancy level of each home (in hours) across the entire year.

of the building. The reactive controls strategies, reactive (2), reactive (4), and reactive (6), decrease the thermostat setpoint by $2°C$, $4°C$, and $6°C$ when the building is unoccupied. The predictive control maintains the temperature lower than the reactive control counterpart just after the occupant leaves but maintains a higher setpoint before the occupant arrives home to reduce the HVAC energy consumption and maintain occupants' comfort.

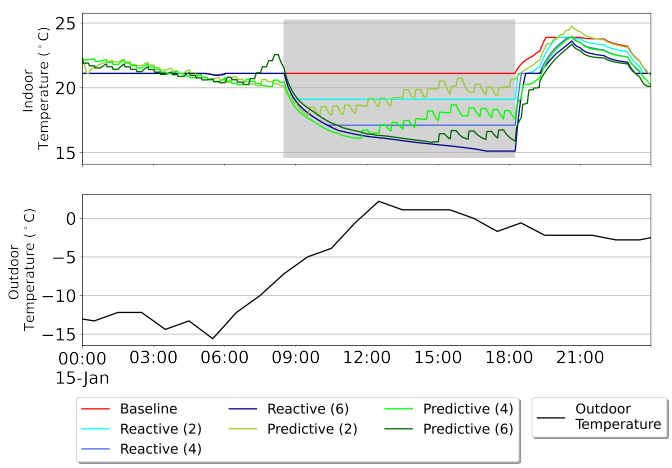

Fig. 3. HVAC control results from baseline, reactive control, and predictive control scenarios on a typical winter day for a single home

C. Energy Savings

The total HVAC energy savings with occupancy-based controls for the community is shown in Fig. 4. For each control strategy, the energy savings increased with an increase in depth of temperature setback. The increase in depth of setback provides flexibility to the occupancy-based controls to save more energy when the building is unoccupied. Similarly, the predictive controls with cost-saving preference saved more energy compared to the reactive controls.

The distribution of HVAC energy savings across the houses in the community is shown in Fig. 5. The orange line shows

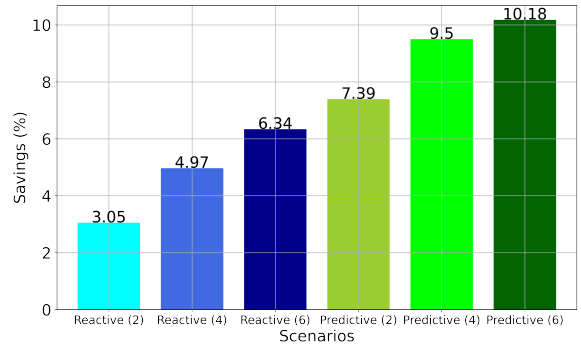

Fig. 4. Total HVAC energy savings calculated at the community level with reactive and predictive controls

the median of the savings distribution, and the edges of the box represent interquartile (1st and 3rd quartile). The variation in HVAC energy savings, for both reactive and predictive control, is due to differences in occupancy patterns between the occupants.

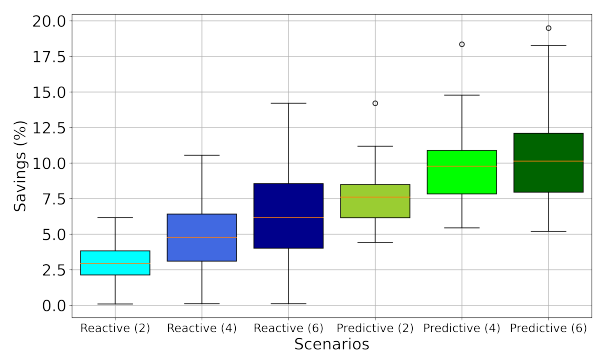

Fig. 5. Distribution of HVAC energy savings of individual homes under different control scenarios

The correlation between the occupancy information and HVAC energy savings (kWh) is shown in Fig. 6. The dashed line represents the polynomial curve fit for data of each scenario, showing the general trend of the impact of occupancy on energy savings. The increase in vacancy (or decrease in occupancy) corresponded to an increase in HVAC energy savings because there are more times where setpoints can be adjusted. The predictive controls also exhibited higher savings for the same depth of setback compared to reactive savings. This is mainly due to increased flexibility ($\pm 1°C$) around setpoint temperature for adjusting the temperature and cost-saving preference in predictive control scenario.

D. Thermal Comfort

The thermal discomfort due to the HVAC system control is calculated in discomfort degree hours, but only when the building is occupied. If the indoor air temperature is more than $\pm 1°C$ from cooling setpoint temperature and less than $\pm 1°C$ from heating setpoint temperature, then it is causing thermal discomfort to the occupants and the values are calculated.

TABLE II
COMPARISON OF THERMAL DISCOMFORT AND HVAC ENERGY SAVINGS UNDER DIFFERENT CONTROL SCENARIOS

Scenario	Baseline	Reactive (2)	Reactive (4)	Reactive (6)	Predictive (2)	Predictive (4)	Predictive (6)
Discomfort (C-hrs/yr)	221	244	336	485	319	380	537
HVAC energy savings (kWh)	-	136	222	283	330	424	455

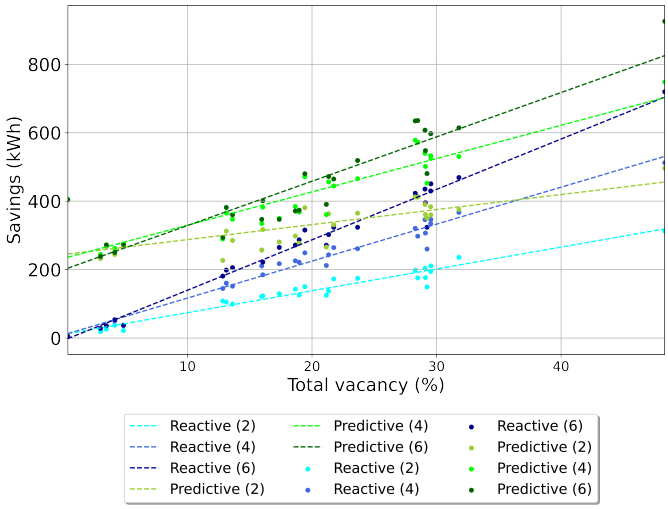

Fig. 6. Correlation between HVAC energy savings and occupancy

There is thermal discomfort due to HVAC system in baseline case, shown in Table II, because the MSHP system is not able to meet the heating load in cold winter days. Compared to baseline scenario, the discomfort increased in the reactive scenarios because there is lag time for HVAC system to maintain the setpoint temperature during the transition from unoccupied to occupied building. In case of predictive control scenario, the discomfort increased because cost savings is set to have higher priority than thermal comfort in **foresee**.

V. CONCLUSIONS AND DISCUSSIONS

This paper presents the community-scale analysis of different occupancy-based building controls. The occupancy-based building controls are capable of reducing energy consumption and utility bills while maintaining consumer comfort. The result demonstrates that there is a wide variation in HVAC energy-saving potential (1%–20%). This variation in energy-saving potential can be attributed to variation in the occupancy pattern in the building. There is a strong correlation between savings and occupancy pattern of the homeowners; in other words, more vacancy in a house translates to higher savings with occupancy-based controls. Similarly, the energy-saving potential also increases with larger temperature setback. With the cost-saving preference in **foresee**, predictive controls had higher energy savings with same depth of setback compared to reactive controls.

Future work may include:

- Incorporating real-time occupancy detection in the occupancy-based control algorithms.
- Validating the performance of occupancy-based controls in a field demonstration.

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