Reduction of HVAC system runtime due to occupancy-controlled smart thermostats in contemporary multi-unit residential building suites

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Abstract. Previous studies in single family homes have demonstrated a reduction in space conditioning energy demand through the use of occupancy-controlled smart thermostats. This technology has the potential to reduce space conditioning demand in multi-unit residential buildings (MURBs) as well, however no previous studies have tested the performance of smart thermostats in this building type. Field data were collected from 56 thermostats installed in two condominium buildings located in Toronto, Canada. Thermostats installed in each suite were operated using through three different control scenarios during the monitoring period: 1) a baseline scenario, where the thermostat is operated as a standard programmable thermostat, 2) an occupancy-based control scenario, and 3) a load-shifting control scenario. Baseline runtime data collected while the thermostats were operated as a standard programmable thermostat was used in combination with weather data and a supervised learning regression algorithm (Random Forest) to estimate the baseline runtime for each suite on days that the occupancy-based control strategy was running. When the estimated baseline runtime derived from the regression model was compared with the actual system runtime while the occupancy-based control strategy is running, an average reduction in suite HVAC system runtime of 17% was found.

1. Introduction

High-rise multi-unit residential buildings (MURBs) are the most prevalent source of housing in urban regions and represent almost 12% of all dwellings in Canada [1], with that number expected to grow significantly over the next 20 years [2]. In these buildings, heating, ventilation, and air conditioning (HVAC) typically accounts for approximately 50% of all building energy use, so reducing HVAC energy use is key to managing electricity and natural gas consumption, as well as associated greenhouse gas (GHG) emissions. Contemporary buildings, constructed within the last decade, typically do not require the replacement of major envelope or mechanical components nor do they have a large portion of their reserve funds available for comprehensive energy retrofits in the short-term. Therefore, low-cost retrofits such as the optimization of existing system performance and resident engagement in energy conservation are the most appropriate approaches to reducing HVAC energy use for recently constructed buildings.

Contemporary condominiums are typically equipped with an in-suite thermostat used to control the terminal units (e.g. fan coil or heat pump). However, these thermostats are usually non-programmable and, at best, programmable, requiring occupant effort to appropriately program set-points. Research has shown that, in the US, traditional programmable thermostats are only programmed about half of the time [3], with 65% of those that are programmed using overnight setbacks and 56% using daytime set-backs [4]. Occupancy-controlled smart thermostats present an opportunity to reduce HVAC energy use at the suite-level by reducing terminal unit runtime when the
suite is not occupied, without having to rely on the occupant to properly program the thermostat. While some industry studies have demonstrated the effectiveness of occupancy-controlled smart thermostats in single-family homes [5,6], no performance-based field studies have been completed in existing condominiums or high-rise apartment buildings. Pritoni, et al studied the effect of smart thermostats on energy use in university residence halls [7] however, as the occupant behaviour of university students may vary significantly from the behaviour of condominium or apartment residents, the results of this study may not be reflective of the potential energy use changes in these buildings.

In order to determine the impact of occupancy-based control mechanisms in MURBs, data were collected and analysed from 56 smart thermostats installed across two downtown Toronto condominium buildings. Data on suite occupancy, temperature, thermostat runtime as well as local weather conditions were recorded. This paper examines the difference in runtime between suite-level HVAC systems operated with a standard, programmable thermostat and those operated using an occupancy-based control strategy in contemporary MURBs.

2. Recruitment and Studied Buildings

Participants for this study were recruited as part of a larger study on the energy and comfort impacts of smart thermostat retrofits in contemporary condominium buildings. The two buildings were selected based on their vintage, location, suite-level HVAC systems, and the willingness of their condo boards to allow building HVAC system monitoring and provide assistance in participant recruitment. Individual suite occupants were then recruited through information sent out by email through the condominium board. Resident recruitment strategies and compensation for their participation in the study were approved by the Research Ethics Board at the University of Toronto.

The two buildings included in the study are located in downtown Toronto, two blocks apart from one another. Both buildings are recently constructed, highly-glazed condominium buildings, but have several key differences in HVAC system and structure. The characteristics of both buildings are outlined in Table 1.

| Table 1. Key Characteristics of Studied Buildings |
|-----------------------------------------------|
| **Building A** | **Building B** |
| Year Construction Completed | 2012 | 2014 |
| Suite HVAC System | Fan Coil Unit (FCU) | Water-loop Heat Pump (WLHP) |
| Number of Floors | 17 | 22 |
| Number of Units | 343 | 357 |
| Number of Participating Units | 27 (7.8%) | 30 (8.4%) |
| Suite Size | 35 m² – 85 m² | 48 m² - 129 m² |
| Suite Type | 1 Bedroom and 2 Bedroom | 1 Bedroom, 2 Bedroom and 3 Bedroom |

3. Methodology

Thermostats installed in each suite are operated using through three different control scenarios during a one-year monitoring period: 1) a baseline scenario, where the thermostat is operated as a standard programmable thermostat and 2) an occupancy-based control scenario. A sample schedule of the control strategy programming is displayed in Table 2. Participants were not informed as to what control strategy was running on what days, although thermostat display information may have provided clues on which strategy was running. This paper will examine the difference in the runtime
of suite-level HVAC systems operated with a standard, programmable thermostat and those operated using an occupancy-based control strategy in contemporary MURBs. Baseline runtime data collected while the thermostats are being operated as a standard programmable thermostat were combined with local weather data and then a regression algorithm was used to estimate the baseline runtime for each suite on days that occupancy-based control was used. Baseline runtime derived from the regression model was then compared with the actual system runtime collected while the occupancy-based control strategy is running to assess the estimated performance of the strategy.

| Day of Week | Sunday | Monday | Tuesday | Wednesday | Thursday | Friday | Saturday |
|-------------|--------|--------|---------|-----------|----------|--------|----------|
| Control     | SP₁    | SP     | SP      | Occ₂      | Occ      | Occ    | SP       |
| Strategy    |        |        |         |           |          |        |          |

1: Standard Programmable - SP, 2: Occupancy - Occ

### 4. Model Development and Accuracy

The Random Forest algorithm, a supervised machine learning algorithm, which uses multiple decision trees for regression, was used for the estimation of baseline thermostat runtime for days when the occupancy-based control strategy was running. The Random Forest algorithm is widely accepted to be an accurate, unbiased predictive model and is able to run well on large datasets, and handle many input variables as well as missing data points. In order to generate predictions, input data is randomly divided into subsets which are used as the training input for individual decision trees. Once trained, each decision tree will make a prediction for the HVAC runtime given the suite and weather conditions for which the prediction is required. The runtime estimates from the individual decision trees are then averaged to determine the final prediction for the conditions.

The Random Forest algorithm was implemented using the Scikit-learn library in Python [8]. The algorithm was used to predict baseline runtime for hourly intervals using nine predictors including: current suite temperature, current suite humidity, desired suite temperature, desired suite temperature for cooling, desired suite temperature for heating, time of the day, day of the week, and outdoor air temperature, humidity and pressure. Each model was trained using between 434 and 2524 hourly intervals of thermostat data from days the standard programmable thermostat control strategy was running. While all of the thermostats were polled for data during the same time period, the amount of data collected for each thermostat varied due missing data for some periods, usually as a result of limited thermostat internet connectivity.

#### 4.1 Model Accuracy

An individual Random Forest model was trained for each suite using 1000 decision trees. During the model training process, 25% of the collected runtime and suite condition data for each suite was reserved in order to test the model accuracy. Model accuracy was tested by using the trained model to develop runtime predictions for the suite using the reserved suite and weather condition data and comparing the model-predicted HVAC runtimes with the corresponding actual observed HVAC runtimes for the associated suite and weather conditions. When the baseline scenario runtime predictions were compared against the actual thermostat data reserved for testing, the model runtime prediction error ranged from 2.3% to 24.5%. The mean runtime prediction error was approximately 12%. After model development, the data for thermostats with an average runtime prediction error above ten percent was discarded, as changes in runtime due to the use of occupancy-control cannot be reliably estimated with such high error. Assessment of the difference between the runtime resulting from the occupancy-based control and the predicted runtime from the hypothetical programmable thermostat operation (base case) was performed on the reduced dataset, which was comprised of 31 thermostats with an average predictive error of 7.2%.
4.2 Model Predictors

The predictors used, the interval they were measured over, how they were aggregated to hourly periods, and the significance of the predictor in the final model are outlined in Table 3. Note that suite characteristics, such as orientation and building floor, are not included as predictors and predictor significances are shown as ranges as individual Random Forest models were developed for each suite in order to capture the differences in predictor significance for different suites. Developing models for each individual suite allowed for the model to capture variances in suite characteristics and occupant behaviour which may not be able to be captured easily in a single model, given the information at hand.

**Table 3. Random Forest Predictors**

| Predictor                          | Measurement Interval | Hourly Aggregation Method | Predictor Significance Range (Average) |
|------------------------------------|----------------------|---------------------------|---------------------------------------|
| Suite Air Temperature              | 5 min                | Mean                      | 0.02 – 0.56 (0.20)                    |
| Suite Humidity                     | 5 min                | Mean                      | 0.02 – 0.39 (0.16)                    |
| Thermostat Temperature Setpoint    | 5 min                | Mean                      | 0.01 – 0.79 (0.19)                    |
| Outdoor Air Temperature            | 1 hour               | N/A                       | 0.009 - 0.14 (0.06)                   |
| Outdoor Air Pressure               | 1 hour               | N/A                       | 0.01 – 0.28 (0.06)                    |
| Outdoor Relative Humidity          | 1 hour               | N/A                       | 0.006 – 0.14 (0.05)                   |

The temperature in the suite over the prediction interval was the most significant predictor of runtime in most of the models, likely as it is influenced and dependent on other predictors (e.g. indoor temperature is in itself a function of the indoor temperature setpoint, outdoor air temperatures, and HVAC system runtime during the previous interval). Future model iterations will test the impact of removing the suite temperature variable on the significance of other predictors in order to better understand their impact on HVAC system runtime.

5. Results

The difference between the actual runtime resulting from the occupancy-based control strategy and the predicted runtime from the algorithm, which represents the potential runtime reduction that can be achieved with the occupancy-based control strategy, is calculated using the following equation:

\[ \Delta \text{Runtime}_{\text{Predicted reduction, Hour}} = \text{Runtime}_{\text{Baseline, Predicted, Hour}} - \text{Runtime}_{\text{Occupancy Actual, Hour}} \]

Occupancy runtime data was collected and compared to baseline predicted runtime for an average of 1794 hourly intervals per suite. Table 4 summarizes the findings of the analysis.

**Table 4. Potential Suite-based HVAC system runtime reduction from use of occupancy-control strategy**

|                                | Building A | Building B | Overall |
|--------------------------------|------------|------------|---------|
| Sample Size (Model Error ≤10%) | 15         | 16         | 31      |
| Average Hourly Baseline Runtime| 26 ± 1.3 min | 18 ± 1.5 min | 22 ± 1.4 min |
| Average Hourly Occupancy-Controlled Runtime | 22.7 min | 14.6 min | 18.6 min |
| Average Runtime Reduction (mins/hour) | 3 ± 1.2 mins/hr | 3 ± 1.5 mins/hr | 3 ± 1.4 mins/hr |
| Average Runtime Reduction (%)   | 12 ± 6%    | 21 ± 9%    | 17 ± 7% |
When the actual system runtime during occupancy-based control test periods was compared with the baseline runtime predictions estimated using the Random Forest model, average suite hourly runtime changes were between a 15 ± 1.4 minutes/hour runtime reduction to a 4.1 minutes/hour runtime increase. On average, across the 31 thermostats included in the assessment, suite HVAC system runtime decreased by 3 ± 1.4 minutes/hour. In terms of percent change in hourly runtime, the greatest reduction in HVAC system runtime in a particular suite was 69 ± 11% and greatest increase in HVAC system runtime was 14 ± 11%. On average, a 17 ± 7% reduction of HVAC system runtime was found using the occupancy-based control strategy, with 67% of suites demonstrating an overall decrease in HVAC system runtime. Twelve suites had an average hourly reduction in runtime of over 22%, with three of these demonstrating average hourly runtime reductions between 61% and 69%. The average percent reduction in thermostat runtime by suite is shown in Figure 1. Likely, suites that have low or no reductions in HVAC runtime using the occupancy-based control strategy are suites in which residents work from home, are retired, or in which parents are at home with young children during the day.

![Figure 1. Percent reduction in thermostat runtime by suite for all suites.](image)

Further work with this data set will explore the relationship between the amount of time the suite is occupied and the change in system runtime when using the occupancy-based control strategy. The increase in runtime seen in two of the suites when the control strategy is running is currently unexplained. One possibility is occupant discomfort and interference with the thermostat immediately after arriving home. Further investigation into the available data is required. The change in suite runtime when the occupancy-based control strategy was in place was significantly different between the two buildings. Building A, which uses FCUs as the suite level HVAC supply system, had an average reduction in hourly runtime of 12 ± 6%, while Building B, which uses WLHPs as the suite level HVAC supply system, had an average reduction in hourly runtime of 21 ± 9%. Further investigation is required to determine whether this difference in runtime reduction is a result of building or occupant characteristics.

6. Conclusions
Occupancy-controlled smart thermostats offer the possibility for significant reductions in suite level HVAC system runtime. In this study, data on thermostat runtime and suite conditions were collected from 56 thermostats across two condominium buildings. Data were collected under two different control regimes: 1) a baseline scenario, where the thermostat is operated as a standard programmable thermostat and 2) an occupancy-based control scenario. The Random Forest algorithm was used to develop regression models for each thermostat and to predict baseline scenario suite-level HVAC system runtime during periods where the occupancy-based control strategy was running. Comparison of the estimated baseline runtime with the collected occupancy-based control runtime data showed significant predicted reductions in system runtime for the majority of suites. On average, an average
hourly runtime reduction of 17% was found across the suites. Future work will explore the influence of different suite and occupant characteristics on runtime savings.

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